

Minerva Access is the Institutional Repository of The University of Melbourne

Author/s:

Assarkhaniki, Zahra

Title:

Enhancing the Sustainable Development Goals (SDGs): Integrating Resilience and Sustainability at the Local Level

Date:

2022

Persistent Link:

<https://hdl.handle.net/11343/326539>

Terms and Conditions:

Terms and Conditions: Copyright in works deposited in Minerva Access is retained by the copyright owner. The work may not be altered without permission from the copyright owner. Readers may only download, print and save electronic copies of whole works for their own personal non-commercial use. Any use that exceeds these limits requires permission from the copyright owner. Attribution is essential when quoting or paraphrasing from these works.

Enhancing the Sustainable Development Goals (SDGs): Integrating Resilience and Sustainability at the Local Level

By

Zahra Assarkhaniki

ORCID: 0000-0001-9769-0404

**Submitted in total fulfilment of the requirements
of the degree of Doctor of Philosophy**

December 2022

Centre for Spatial Data Infrastructures and Land Administration (CSDILA),
Department of Infrastructure Engineering,
Faculty of Engineering and Information Technology,
The University of Melbourne

Abstract

In recent decades, urbanisation and population explosion have adversely affected communities' resilience and sustainability. This problem is more prevalent in developing countries, which are among the most vulnerable communities left behind by most planning and development practices.

Global efforts have been made to manage urbanisation in order to improve resilience to ongoing changes and sustainability of development and accordingly develop a framework to benchmark the two concepts. Even so, there is still a significant gap in the present knowledge at the intersection of resilience and sustainability, as well as the lack of a commonly accepted framework for measuring resilience itself. This prevents us from developing an integrated and commonly accepted framework for measuring resilience. The United Nations Sustainable Development Goals (SDGs) as a widely applied framework to measure the level of sustainable development at the country level has the potential to remove this discrepancy by considering the integration of resilience and measurement of sustainability. As elaborated in Chapter 1 (section 1.1), the framework is criticised for lacking a thorough measurement of resilience being more focused on sustainability.

Thinking of the SDGs beyond “using the framework as the best possible approach” or “considering the SDGs as a failure because of its existing weaknesses”, this thesis acknowledges decades of work by the UN and many countries to build the SDGs framework and its worldwide application and at the same time the existence of some gaps and the opportunities for improvement. This research was thus intended to address one of the major criticisms of the Sustainable Development Goals, namely the lack of comprehensiveness in measuring resilience, as well as addressing shortfalls in current knowledge at the nexus of resilience and sustainability.

In order to integrate a more comprehensive resilience measurement into the SDGs, this research looked at the possibilities for adding a more comprehensive set of resilience indicators into the SDGs. Besides, since the level of community resilience greatly depends on local characteristics, a methodological workflow for the SDGs' localisation was urgently required. Hence, this research aimed to: firstly, integrate the quantification and measurement of sustainability and resilience in the context of the SDGs; and secondly, develop a methodological workflow to advance the approach to fit for purpose at the local level.

To achieve the research aim, firstly, resilience dimensions and quantification have been conceptualised and a framework of baseline resilience indicators has been developed. Later, referring to the baseline indicators to measure each of the resilience dimensions, the aspects of resilience that have been overlooked among the SDGs have been defined. Accordingly, a pool of resilience indicators has been suggested to be integrated into the SDGs. Next, a localised workflow has been created, tested

and evaluated to incorporate additional indicators that significantly contribute to the local SDG Index in the area of interest.

The workflow for integrating resilience and sustainability in the SDGs at a local level contains three steps: 1) Assessing the pool of resilience and the SDGs indicators for data availability and application at the local level; 2) Aligning the indicators to with the local context if required; and 3) Analysing the significance of the indicators in measuring resilience/sustainability at the local level applying the Exploratory Regression method. To evaluate the developed workflow, the hypothesis of the research - that adding resilience indicators will enhance the effectiveness of the SDGs in measuring resilience at the local level - was tested.

To implement the developed workflow, one of the major challenges in the SDGs utilisation is data availability and particularly in informal settlements, Jakarta, the capital city of Indonesia, with a big share of informal settlements has been selected as the case study. For testing the workflow, after executing steps one and two, each of the indicators and accordingly the local SDG Index has been calculated for each of the 286 sub-districts of Jakarta. As indicated, one main obstacle has always been data availability especially when it comes to informal settlements. Here, a novel method is proposed and used to generate the missing data on the location of these settlements applying machine learning (ML) techniques on the available spatial and statistical open data. Finally, the third step has been conducted and selected indicators have later been used to test the hypothesis of this research through developing the Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models. Results from the validation that support the hypothesis prove the effectiveness of the proposed workflow for the integration of resilience and sustainability at the local level in the SDGs.

This research significantly contributes to the present knowledge about resilience and its quantification by conceptualising its dimensions, resolving the inconsistency in the terminology employed in this subject. As well as filling the gap of a common framework to measure resilience. The research also proposes resolutions for enhancing the Sustainable Development Goals as a globally adopted framework for measuring and monitoring sustainability. It does this by addressing the main criticism of the SDGs, which is the limitation in measuring resilience, and developing a workflow for SDGs' localisation.

In contrast to the current approaches for SDGs' localisation that are mainly qualitative (see Chapter 8), the proposed method presents a quantitative robust workflow that can be followed in different cities at various jurisdictional levels. This research also presents a sample solution for coping with data availability issue while also proposing a novel method for the detection of informal settlements using freely accessible data. Furthermore, this research significantly contributes to the present knowledge in

the domain of resilience and its quantification by conceptualising resilience dimensions, resolving inconsistencies in the subject's terminology, and proposing a resolution for filling the gap of a common framework to measure resilience while also addressing a major criticism against the SDGs that is limitation in measuring resilience.

Declaration

This is to certify that:

- the thesis comprises only my original work towards the PhD except where indicated,
- due acknowledgement has been made in the text to all other materials used,
- the thesis is fewer than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices,
- Parts of this work were published as listed in the Knowledge Transfer section.

Zahra Assarkhaniki
December 2022

Preface

Some parts of the research presented in the main body of this thesis have been adapted from author's publications as the following:

- Chapter 4: Assarkhaniki, Z., Rajabifard, A., Sabri, S. (2020). The conceptualisation of resilience dimensions and comprehensive quantification of the associated indicators: A systematic approach. *International Journal of Disaster Risk Reduction*, 51. DOI: [10.1016/j.ijdrr.2020.101840](https://doi.org/10.1016/j.ijdrr.2020.101840)
- Chapter 7: Assarkhaniki, Z., Sabri, S. Rajabifard, A. (2021). Using open data to detect the structure and pattern of informal settlements: an outset to support inclusive SDGs' achievement. *Big Earth Data*, 5(4). DOI: [10.1080/20964471.2021.1948178](https://doi.org/10.1080/20964471.2021.1948178)
- Chapter 6: Assarkhaniki, Z., Sabri, S. Rajabifard, A. Advancing Sustainable Development Goals: Embedding Resilience Assessment. In revision following peer review by Sustainability Science.
- Chapter 8: Assarkhaniki, Z., Rajabifard, A. Sabri, S. An Innovative Workflow for Integrating Resilience Assessment to the Sustainable Development Goals (SDGs): A localised Approach. In revision following peer review by Sustainable and Resilient Infrastructure.

The thesis author was the primary author of all these manuscripts, conceptualised the studies, analysed the data and wrote the first draft of the manuscripts.

This research has also been communicated and the recommendations have been received through presentation in conferences, sessions, workshops, and roundtables as below with urban practitioners from Australia and Indonesia, who are at the forefront of bringing this research to practice:

Presentations at conferences, workshops, and training sessions:

- Partnerships for Sustainable Urban Development: Achieving SDG11, hosted by Resilience for Development Impact Network (RDI), 26 August 2019.
- 2019 Infrastructure Engineering Postgraduate Conference, hosted by the Department of Infrastructure Engineering, the University of Melbourne, 7 November 2019.
- Victoria's ePlan & Smart Cadastre Seminar, 25 February 2020.
- 2020 Infrastructure Engineering Postgraduate Conference, hosted by the Department of Infrastructure Engineering, the University of Melbourne, 26 November 2020.
- 3D Land Administration & Digital Twin Training workshop, hosted by Centre for Spatial Data Infrastructure and Land Administration (CSDILA), 22 September 2021.
- Exploring Concepts of City Leadership through Data, Technology, Digitalisation, hosted by Melbourne Centre for Cities, 24 August 2022.

Communicating the research and receiving recommendations from urban practitioners:

- Land Equity International: Dr. Kate Rickersey (Managing Director) and Ms. Kate Fairlie (Land Admin Specialist) on 18 June 2019.
- Mr. Tony Burns (Executive Director of Land Equity International) on 23 August 2019.
- Victorian Commissioner for Environmental Sustainability: Dr Gillian Sparkes and her team on 11 September 2019.

- Victorian State Government, Strategic Policy: Dr. Ada Young (Director) and her team on 17 December 2019.
- Communicating this research and receiving recommendations from Indonesian urban researchers and practitioners in Symposium Infrastruktur Informasi Geospasial (SIIG) 2021, jointly held by Badan Informasi Geospasial and PPIDS UGM, Indonesia, 07 July 2021.
- Ministry of National Development Planning of the Republic of Indonesia (BAPANAS): A session for communicating the research in the case study of Jakarta with a group of urban planners and policy makers on 20 November 2020.
- Ministry of Agrarian Affairs and Spatial Planning (ATR/BPN), Republic of Indonesia: Communicating the research with a group of experts in spatial planning and surveying and mapping from ATR/BPN in the workshop on Digital Technologies in Spatial Planning and Future Advancements, hosted by Centre for Spatial Data Infrastructure and Land Administration (CSDILA), 30 November 2022.

Award:

- “Best Journal Paper Prize 2020” in the Department of Infrastructure Engineering, University of Melbourne for the paper titled: The conceptualisation of resilience dimensions and comprehensive quantification of the associated indicators.

No work was carried out by the candidate prior to enrolment, and no work has been submitted for other qualifications. No third-party editorial assistance was used for the formatting of this thesis.

Acknowledgement

My sincere and deepest gratitude goes to Professor Abbas Rajabifard and Doctor Soheil Sabri, my supervisors and mentors, who have supported me throughout the PhD journey with their patience, motivation, enthusiasm, and immense knowledge. In addition, I would like to extend my deepest gratitude to Professor Greg Foliente, the chair of the PhD advisory committee, for his constructive suggestions and advice, as well as his kind encouragement throughout the research process.

It is also my sincere gratitude to Land Equity International (LEI) for its support and interest in this research, especially Mr. Tony Burns (Executive Director), Dr. Kate Rickersey (Managing Director of LEI), and Ms. Kate Fairlie (Land Administration Specialist) for their invaluable assistance.

I am also eternally thankful to my family. This dissertation would simply not be possible without the unwavering love and support of my family. A very special thanks is owed to my husband, Masoud, to whom I am indebted for his everlasting care, support, advice, and love. Through life and my PhD journey, he has helped me remain resilient, sharing laughter and tears with me, celebrating with me, and never giving up on me through hardships.

Zahra Assarkhaniki
December 2022

Table of Contents

Abstract.....	ii
Declaration.....	v
Preface	vi
Acknowledgement	viii
List of Figures	xii
List of Tables	xv
List of Appendices	xvi
List of Acronyms	xvii
1 Introduction	1
1.1 Research Background	1
1.2 Research Problem	5
1.3 Research Questions.....	5
1.4 Research Aim, Objectives, and Hypothesis.....	5
1.5 Research Approach and Methodology.....	6
1.6 Thesis Structure	7
1.7 Chapter Summary	8
2 Resilience and Sustainability - Concepts and Measurements	10
2.1 Introduction	10
2.2 Resilience and Sustainability	10
2.3 Integrating the Measurement of Resilience and Sustainability.....	12
2.3.1 Resilience Measurement Methods	13
2.3.1.1 Qualitative Measurement of Resilience	13
2.3.1.2 Quantitative Measurement of Resilience	14
2.3.1.3 Mixed-method for Measurement of Resilience.....	15
2.3.1.4 The approach followed in this research	16
2.3.2 Resilience Measurement Context.....	17
2.4 Resilience and Vulnerability.....	20
2.5 Chapter Summary	21
3 Research Design and Methods	24
3.1 Introduction	24
3.2 Research Methodology	24
3.3 Research Design	25
3.4 Research Methods.....	25
3.5 Conceptualisation	25
3.6 Development.....	26

3.7 Implementation and Evaluation	27
3.8 Chapter Summary	28
4 Conceptualisation and Quantification of Resilience	31
4.1 Introduction	31
4.2 Data Collection Procedure	31
4.3 Data Analysis Process	34
4.4 Conceptualising Resilience Dimensions Based on the Results	38
4.4.1 Economic Dimension	38
4.4.2 Institutional Dimension	38
4.4.3 Infrastructural Dimension	40
4.4.4 Environmental Dimension	40
4.5 Baseline Resilience Framework	41
4.6 Chapter Summary	43
5 Resilience Measurement – The SDGs Versus the Baseline Resilience Framework (BRF)	46
5.1 Introduction	46
5.2 Theoretical approaches	46
5.3 A Global Scale Country-Level Comparison of Resilience Measurement by the SDGs and the BRF	46
5.3.1 Measuring Infrastructure Resilience Using the Baseline Resilience Framework	46
5.3.2 Measuring Infrastructure Resilience Using the SDGs	47
5.4 Comparing the Approaches	49
5.5 Chapter Summary	52
6 An Integrated Framework to Measure Resilience and Sustainability	55
6.1 Introduction	55
6.2 Developing the Integrated Framework to Measure Resilience and Sustainability in the Context of the SDGs	55
6.3 The SDGs Coverage of Resilience Indicators	59
6.4 Enhancing the SDGs: Embedding Resilience Indicators	63
6.4.1 Social resilience	64
6.4.2 Infrastructural resilience	65
6.4.3 Institutional resilience	66
6.4.4 Economic resilience	66
6.4.5 Environmental resilience	67
6.5 Chapter Summary	68
7 Jakarta Case Study Part 1: Data Generation	71
7.1 Introduction	71

7.2 Informal Settlements in Jakarta	72
7.3 Remote Sensing Data for Detecting Informal Settlements	73
7.4 Open Data for Detecting Informal Settlements	74
7.5 Satellite Image Classification for Informal Settlement Detection	75
7.5.1 Pixel-Based Classification (PBC) Using Machine Learning Techniques	76
7.5.2 Methods for Developing the Training Set and the Application of Open Data.....	77
7.6 Satellite Image Classification for Data Generation in Jakarta	79
7.6.1 Land-Uses Classification and Informal Settlement Detection in Jakarta.....	84
7.6.2 Mapping of informal settlements in Jakarta.....	92
7.6.3 Mapping parks and farmlands in Jakarta	93
7.7 Chapter summary.....	94
8 Jakarta Case Study Part 2: Integrating Resilience into the SDGs at the Local Level	98
8.1 Introduction	98
8.2 SDGs' Localisation.....	98
8.3 Innovative Workflow for SDGs' Localisation.....	99
8.4 Testing the Developed Workflow for Integrating Resilience Indicators into the SDGs in Jakarta 102	
8.4.1 Indicators' Assessment for Data Availability and Application in Local Level	103
8.4.2 Indicators' Alignment to the Local Context.....	103
8.4.3 Analysing Indicators' Significance in Measuring Resilience/ Sustainability at the Local Level 106	
8.5 Validation	108
8.6 Chapter Summary	112
9 Conclusion.....	115
9.1 Introduction	115
9.2 Research Aim, Objectives, and outcomes	115
9.2.1 First Objective and Outcome	115
9.2.2 Second Objective and Outcome	117
9.2.3 Third Objective and Outcome.....	118
9.3 Contributions	119
9.4 Recommendations.....	120
References.....	122
Appendices.....	139

List of Figures

[Figure 1.1.](#) Resilience in the SDGs.

[Figure 1.2.](#) Inherent challenges in integrating resilience and sustainability in the context of the SDGs.

[Figure 1.3.](#) Research methodology.

[Figure 2.1.](#) Relationship between resilience and sustainability based on the literature.

[Figure 2.2.](#) Resilience measurement context.

[Figure 2.3.](#) Approaches that link resilience measurement with vulnerability.

[Figure 3.1.](#) Research methodology and applied methods.

[Figure 4.1.](#) Data collection and extraction process.

[Figure 4.2.](#) Citation network analysis of the publications retrieved from Scopus.

[Figure 4.3.](#) Data analysis process.

[Figure 4.4.](#) Schematic overview of the coding process and identifying themes.

[Figure 4.5.](#) Resilience dimensions.

[Figure 5.1.](#) GIS classification of SDG IRI based on the Jenks Natural Breaks Optimisation method.

[Figure 5.2.](#) IRI calculated for the world countries based on the SDGs and the BRF.

[Figure 5.3.](#) Mapping infrastructure resilience based on BRF. Countries are not coloured where data is not available.

[Figure 5.4.](#) Mapping infrastructure resilience based on the SDGs. Countries are not coloured where data is not available.

[Figure 6.1.](#) Conceptual graph for the first two steps of the method for mapping SDGs indicators against resilience dimensions, sub-domains, and variables.

[Figure 6.2.](#) Coding process for BRF indicators.

[Figure 6.3.](#) A sample coding of the SDGs indicators.

[Figures 6.4.](#) Matrix coding for five clusters developed after the coding process.

[Figure 6.5.](#) Parallel coordinate plots (PCP) for each of the five resilience dimensions.

[Figure 6.6.](#) Categorisation of the SDGs based on their coverage of resilience dimensions.

[Figure 6.7.](#) The SDGs coverage for variables of social dimension.

[Figure 6.8.](#) The SDGs coverage for variables of infrastructural dimension.

[Figure 6.9.](#) The SDGs coverage for variables of institutional dimension.

[Figure 6.10.](#) The SDGs coverage for variables of economic dimension.

[Figure 6.11.](#) The SDGs coverage for variables of environmental dimension.

[Figure 7.1.](#) Study areas: Jakarta, Indonesia.

[Figure 7.2.](#) Settling type of informal settlements in Jakarta.

[Figure 7.3.](#) Schematic comparison of Pixel-Based Classification (PBC) and Object-Based Classification (OBC).

[Figure 7.4.](#) Random forest algorithm's schematic function in image classification.

[Figure 7.5.](#) Informal settlements of Jakarta (2015).

[Figure 7.6.](#) Overview of the procedure followed to detect informal settlements.

[Figure 7.7.](#) Street structure in informal settlements in Jakarta.

[Figure 7.8.](#) Steps for using OpenStreetMap (OSM) for developing the training set for the informal built-up class.

[Figure 7.9.](#) First round of land-use and land cover classification on Landsat 8.

[Figure 7.10.](#) Second round of land-use and land cover classification on Landsat 8 using OSM for developing the training set.

[Figure 7.11.](#) Informal and formal settlements detected in Jakarta.

[Figure 7.12.](#) Comparison between the roads detected in the first and second round of classification.

[Figure 7.13.](#) Sample areas (No. 1-6) for magnification of the informal settlement detection by RF.

[Figure 7.14.](#) Colour composite of Landsat 8 pixels in formal vs. informal built-up.

[Figure 7.15.](#) Process for updating the map for the 2015 informal settlements based on the informal settlement detection.

[Figure 7.16.](#) Sample for Excluded Parcels from Informal Settlement Map.

[Figure 7.17.](#) Updated map of informal settlements in Jakarta.

[Figure 7.18.](#) Classified of low and high vegetation on Landsat 8.

[Figure 8.1.](#) Proposed workflow for incorporating resilience indicator into the SDGs through a local approach.

[Figure 8.2.](#) The SDGs Addressing the Resilience of Physical Infrastructure.

[Figure 8.3.](#) Maps of indicators measured in sub-district level.

[Figure 8.4.](#) Creating the travel time map using the points for public transport and road layer.

[Figure 8.5.](#) Jakarta's pilot local SDG Index for physical infrastructure at sub-district level.

[Figures 8.6.](#) Map of standard residual for GWR model developed based on each of the scenarios.

[Figure 8.7.](#) Jakarta's pilot local SDG index for physical infrastructure and the areas for informal settlements.

[Figure 8.8.](#) Jakarta's pilot local SDG Index for physical infrastructure and the areas for informal settlements vs areas with convenient access to public transport.

[Figure 8.9.](#) Map of the observed local SDG Index vs the predicted index by GWR model based on the third scenario.

[Figure 9.1.](#) Evolution of the United Nations Agendas from MDG to post-2030 Agenda.

List of Tables

[Table 2.1.](#) Resilience measurement context.

[Table 4.1.](#) Resilience dimensions addressed in the reviewed literature.

[Table 4.2.](#) Similarity matrix to compare frequently addressed dimensions (FADs) with peripheral dimensions (PDs)

[Table 4.3.](#) Comparison of Frequently Addressed Dimensions (FADs) with Peripheral Dimensions (PDs).

[Table 5.1.](#) Indicators to measure infrastructure resilience in BRF.

[Table 5.2.](#) SDG9 Indicators related the achievement of resilient infrastructure.

[Table 5.3.](#) Infrastructure Resilience Index (IRI) based on SDGs and BRF.

[Table 6.1.](#) Cosine similarity between the SDGs framework and the BRF for each of the resilience dimensions.

[Table 7.1.](#) Proposed classes for the classification of Landsat 8 in Jakarta.

[Table 7.2.](#) Confusion Matrix of RF for the first round of classification.

[Table 7.3.](#) Confusion Matrix of RF for the second round of classification.

[Table 8.1.](#) Results from the assessment of the SDG and resilience (BRF) indicators of physical infrastructure for data availability and local application

[Table 8.2.](#) Exploratory regression results for the variables' significance and collinearity.

[Table 8.3.](#) Models' Summary of the results (for 262 observations).

List of Appendices

[Appendix 1](#). Baseline resilience framework (BRF).

[Appendix 2](#). the national-level data for the selected SDGs and BRF indicators.

[Appendix 3](#). BRF indicators to measure resilience.

[Appendix 4](#). SDG indicators and their relevance to resilience dimensions.

[Appendix 5](#). Sensitivity analysis results.

List of Acronyms

A	Agriculture
ADB	Asian Development Bank
AFor	Area of formal settlements to the residential area
ANN	Artificial Neural Networks
AOpe	Area of public open spaces to the residential area
ARos	Area with access to quality roads to the residential area
ATra	Area with convenient access to public transport (450m) to the residential area
BA&P	Business Activity and Production
Bph.	Biophysical
BPS	Badan Pusat Statistik
BRF	Baseline Resilience Framework
C	Cultural
CCa.	Community Capital
SE	Socio-Economic
Co.	Communication
CSt.	Community Strength
DSRM	Design Science Research Methodology
DT	Decision Tree
E	Employment
E&I	Economic Infrastructure
E&K	Education and Knowledge
Ec.	Ecological
Eco.	Economic
Eco.C	Economic Capacity
Ed.	Education
EI	Economic Infrastructure
En.C	Environmental Capacity
Env.	Environmental
ER	Emergency Response
FAD	Frequently Addressed Dimensions
FS	Financial Services
G	Governmental
GDP	Gross Domestic Product
GPA	Grade Point Average
GWR	Geographically Weighted Regression
HC	Households' Capacity
He.	Health
HI	Health Infrastructure
Ho.	Housing
HR	High Resolution
I	Income
IFRC	International Federation of Red Cross
Inf.	Infrastructural
Ins.	Institutional
IRI	Infrastructure Resilience Index
IURCI	Urban Resilience Capacity Index
kNN	k-Nearest Neighbours
L	Land
ML	Machine Learning
MR	Medium Resolution
mtry	number of variables
N	Natural
NIR	Near Infrared
NoHo	No. of Hotels per 10,000 persons
NoSh	No. of indoor shelters per 10,000 persons

ntree	number of trees
OBC	Object-Based Classification
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Square
OSM	OpenStreetMap
P	Preparedness
Pr.	Production
P&D	Population and Demographic
PBC	Pixel-Based Classification
PCP	Parallel Coordinate Plot
PD	Peripheral Dimensions
Ph.	Physical
RF	Random Forest
RR	Recovery Response
S	Social
SB-PSS	Scenario-Based Planning Support System
SC	Social Capital
SCC	Social-Cultural Capital
SDGs	Sustainable Development Goals
SP	Social Protection
SVM	Support Vector Machine
SWIR	Shortwave Infrared
UN	United Nations
UNDP	United Nations Development Programme
VGI	Volunteered Geographic Information
VHR	Very High Resolution
VIF	Max Variance Inflation Factor
WOS	Web of Science
WSD	Weighted Standard Deviation

CHAPTER 1

INTRODUCTION

1 Introduction

1.1 Research Background

Natural and man-made hazards and at the top of these are climate change and urbanisation, have been affecting cities and communities at alarming rates in recent decades (“Land Tenure Studies: Land Tenure and Rural Development,” 2002; Magis, 2010; C. Zhang et al., 2016). Climate change wields damaging effects on water resources, agriculture, forestry, fisheries, ecological systems, and human health (Elasha et al., 2005) through heatwaves, bushfires, floods, droughts, and storms (Haines et al., 2006; Price & Bradstock, 2014). Urbanisation, on the other hand, not only is directly threatening the resilience and sustainability of human and ecological systems (Nelson & Palmer, 2007; United Nations, 2018; C. Zhang et al., 2016), but consolidates the effects of climate change (Nelson & Palmer, 2007). Urbanisation intensifies the impacts of heatwave by its warming effects (the most warming effects after barren areas) (Chung et al., 2004; Lim et al., 2005), which is caused by an increase in energy consumption, changes in land use and land cover, and removal of vegetation (Chung et al., 2004). It also strengthens the danger posed by drought by degrading the quality of rainwater (Das et al., 2010) and increases flood risk due to increased imperviousness (Huong & Pathirana, 2013).

Urbanisation imperils the resilience and sustainability of human systems with significant population shifts in a short space of time. Currently, about 55% of the world’s population lives in urban areas. The share of the urban population will increase up to 60% by 2030. This will be more pronounced in developing countries, which will have the bulk of the world’s unplanned population growth - estimated at 95% - by 2030 (United Nations, 2018). Urbanisation and unplanned population growth are creating high demand for and pressure on housing and the available land. In developing countries, this trend takes the form of land-use change, informal land transactions, and the expansion of informal settlements (Lavigne & Durand-Lasserre, 2009). Informal settlements – otherwise known as slums – emerge as unplanned, illegal, and irregularly structured built-up areas almost deprived from basic infrastructure and urban services (McLaren, Coleman and Mayunga, 2005). Informal settlements are not only among the most vulnerable communities because they lack access to civic infrastructure and are left behind in most development and planning practices, they also threaten the resilience and sustainability of the city as a whole by putting pressure on their surrounding formal settlements’ infrastructure.

Global efforts have been made to manage urbanisation in order to improve resilience to ongoing changes and sustainability of development (Redman, 2014; C. Zhang et al., 2016). Both sustainability and resilience aim to improve the quality of human life (Xu et al., 2015). However, on the one hand, resilience refers to the ability to prepare for, absorb, recover from, and adapt to stresses and adverse events (Lam et al., 2016;

L. K. Siebeneck & Cova, 2012) that the current generation face (Ahern, 2011). Sustainability, on the other hand, is focused on improving the quality of the present generation's life without compromising the environmental, social, and economic interests of both present and future generations (Collier et al., 2013; Marchese et al., 2018).

To deal with the temporal limitations rooted in the differences of the two concepts, benchmarking future development should integrate the measurement of resilience and sustainability. Scientist have developed integrated frameworks to measure concepts (Jarzebski et al., 2016; Milman & Short, 2008; Saunders & Becker, 2015; Seager, 2008; United Nations, 2017). However, such frameworks are either mainly designed for a specific context that are not applicable to other cases (e.g. measures both sustainability and resilience of urban water systems) or fail to measure both concepts although aim to do so, for example including only resilience indicators (see section 2.3 for more details).

One major obstacle in developing an integrated framework to measure the two concepts, that is also a gap in the state of the art, is the lack of a fundamental agreement on what resilience is, what are its dimensions and accordingly a commonly accepted framework for measuring resilience. Such a framework was developed for sustainability and adopted by 193 members of the United Nations in September 2015 as a blueprint for promoting a sustainable future across the globe, called the 2030 Agenda for Sustainable Development (*Transforming Our World: The 2030 Agenda for Sustainable Development*, 2015). The 2030 Agenda presents the well-known Sustainable Development Goals (SDGs) framework that is not context-specific and accepts resilience as a component and prerequisite to achieve sustainability; it has the potential to integrate the measurement of both concepts.

The 2030 Agenda for Sustainable Development introduces a set of 17 sustainable development goals (SDGs) and 196 targets that are measured by a framework of 231 unique indicators as of the year 2022 (UNDP, 2016; UNSD, 2020). Indicators are quantifiable variables used to measure the characteristics of each target (Cutter, 2016). They are then combined to create the SDG Index, a single numeric value representing the level of sustainable development attained by a country (Guillaume Lafortune, Grayson Fuller, Jorge Moreno, Guido Schmidt-Traub, 2018).

The SDGs have been applied by different levels of governments, research, and industry entities. Several cities have implemented the SDGs in their policy-making and everyday practice. The Global Vision | Urban Action program was launched by the New York City's Mayor's Office for International Affairs to apply the SDGs as an international language to communicate sustainability innovations and challenges (NYC Mayor's Office for International Affairs 2018). The city of Utrecht in the Netherlands has declared itself a "Global Goals City" in which the SDGs are applied as an opportunity to achieve a healthy urban

environment (Deininger et al., 2019; Deppy Keranidou & Hans Sakkers, 2018). The SDGs have generally been firmly anchored in the European countries as the heart of policy-making. Eurostat, the statistical office of the European Union, is responsible for monitoring progress in achieving the SDGs (Schleicher-Tappeser, 2014). Referring to Asian institutions, IGES (Institute for Global Environmental Strategies) in Japan is a pioneer in studying the connections between the SDGs targets so that the best political decisions are made in the Asia-Pacific region and globally (X. Zhou & Moinuddin, 2017).

Despite the potential of the SDGs to be chosen as the framework for integrating resilience and sustainability, it is criticised for incorporating not enough resilience indicators to effectively address the broad scope of resilience as a concept. Bahadur et al. (2015) have argued that the SDGs directly address resiliency only in six targets (1.5, 2.4, 9.1, 11.5, 11.b, 13.1) among 196 targets and in 4 unique indicators (1.5.1, 1.5.2, 1.5.3, 11.b.1) among 231 indicators (Bahadur et al., 2015) ([Figure 1.1](#)). Analysing the correspondence between SDG11 (make cities and human settlements inclusive, safe, resilient and sustainable) and some of the global resilience frameworks, Diaz-Sarachaga and Jato-Espino (2019) have illustrated that this framework is not comprehensive enough to evaluate resilience and should be enriched (Diaz-Sarachaga & Jato-Espino, 2019).

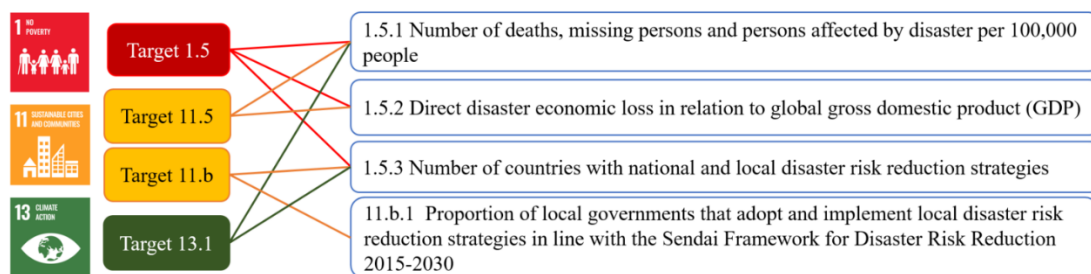


Fig. 1.1. Resilience in the SDGs (Adapted: from Bahadur et al. 2015)

The limited numbers of indicators is considered to be inadequate for incorporating resilience in the SDG Index. This is because, in order to measure resilience as a multidimensional concept (Cumming, Barnes, Perz, Schmink, Sieving, Southworth, Binford, Holt, Stickler, & Van Holt, 2005), a long list of indicators is required to be integrated into the SDGs (Bahadur & Pichon, 2016; Schipper & Langston, 2015). Besides, the four resilience indicators in the SDGs only focus on disaster resilience. A more inclusive framework, however, should include the measurement of resilience to both extreme events (disaster) and persistent stress, for instance climate change and urbanisation (Alessa et al., 2008; Bahadur et al., 2015; Brenkert & Malone, 2005; Folke, Carpenter, Walker, Scheffer, & Chapin, 2010).

This is a major challenge, as there is a risk that without resilience, any extreme event, or shocks might demolish all efforts towards achieving the SDGs. As an example, indicator 3.8.1 measures the coverage of essential health services based on a series of quantitative indicators, such as “the number of hospital beds per 10,000 people” (UNSD, 2023). One major concern, however, is what happens if enough hospital beds are available, but the hospital is built in a flood-prone area? In this case, health services could be inaccessible and useless at time of disasters. This is an example of how overlooking resilience could affect or even reverse the SDGs’ computations and estimations of sustainability.

This challenge of incorporating a more comprehensive measurement of resilience into the SDGs also highlights an inherent challenge that is considering the importance of local characteristics in the measurement of resilience. There is a limitation in the present knowledge of the application of the SDGs at the local level (e.g. cities) and consideration of the local characteristics. According to the United Nations Development Programme (UNDP), the SDGs’ localisation can be defined as “translating the aspirations of the goals and targets into implementable plans and programs on the ground” (UNDP, 2019). Yet, it is not clear how local practitioners can formulate and implement the global framework (Fenton & Gustafsson, 2017).

In addition, one inherent challenge in localisation is data availability. The challenge is exacerbated in developing countries with a high percentage of informal settlements due to the lack of statistical data on these settlements (P. Jones, 2017), their high level of vulnerability and the significant impact they have on local resilience and sustainability. The most recent global crisis, the COVID-19 pandemic, has exposed inequality and vulnerability of the urban poor due to the challenges to tracking the virus, access to healthcare services, infrastructure (e.g. transport), and water and sanitation. All these threaten the resilience of entire cities (UN-Habitat, 2020). The Organisation for Economic Co-operation and Development (OECD) has estimated that developing infrastructure for the expanding urban population will cost \$71 trillion by 2030, about 3.5% of the forecasted global Gross Domestic Product (GDP). Ignorance of informal settlements leaves such expensive development with a critical gap and puts more pressure on governments. For this reason, it is crucial to consider informal settlements when assessing cities and the communities’ resilience and sustainability, in order to design evidence-based and data-driven budget allocations that can address critical challenges in future developments.

This research addresses three inherent challenges in integrating resilience and sustainability within the Sustainable Development Goals framework, namely: (i) adding a more comprehensive set of resilience indicators; (ii) taking local characteristics into account when measuring resilience and sustainability; and (iii) the availability of local-level data ([Figure 1.2](#)).

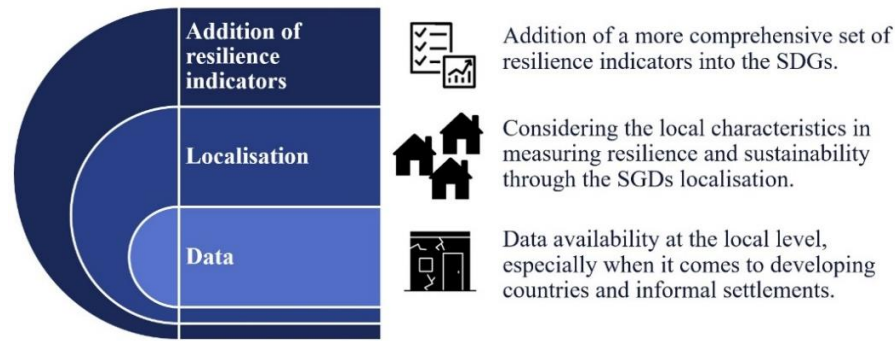


Figure 1.2. Inherent challenges in integrating resilience and sustainability within the Sustainable Development Goals (SDGs) framework.

1.2 Research Problem

Global efforts have been made to achieve sustainable development, many of which overlook the essence of resilience as a component of sustainability to achieve sustainable development. Without resilience, any extreme event or disaster could demolish all the efforts toward sustainable development. The problem is more pronounced in the global south countries which are home to many informal settlements that are among the most vulnerable and deprived communities. Therefore, to achieve inclusive and equitable development globally, benchmarking both sustainability and resilience considering both formal and informal settlements is crucial. Yet, the difference between the temporal scales in which resilience and sustainability are measured (short-term and long-term respectively), has challenged the development of an integrated framework for measuring the two concepts.

The United Nations Agenda 2030 for Sustainable Development (SDGs) applied globally provides a framework to measure sustainability and resilience at national levels. However, the framework is criticised for its limited understanding and inclusion of resilience. Besides, little is known about the application of the framework at the local level and this problem is more pronounced when it comes to measuring resilience which is highly dependent on local characteristics.

1.3 Research Questions

1. To what extent do the SDGs measure resilience?
2. How to integrate a more comprehensive set of resilience indicators into the SDGs?
3. How can the SDGs be localised so that they are fit for purpose at the local level?

1.4 Research Aim, Objectives, and Hypothesis

Aim: The aim is to strengthen resilience measurement in the SDGs, to be used as a framework for measuring and monitoring both sustainability and resilience, as well as developing a methodological workflow that functions well at the local level.

Hypothesis: The addition of the resilience indicators will enhance the effectiveness of the SDGs in measuring resilience at the local level.

Objectives
1. Identify and explain the overlooked aspects of resilience in the SDGs. 2. Develop a methodological workflow that integrates the proposed indicators into the SDGs at the local level. 3. Evaluate the effectiveness of the proposed workflow strategy.

1.5 Research Approach and Methodology

To articulate the approach for this research, the framework suggested by Creswell (2014) has been adopted (Creswell, 2014). Here, since the aim of this research is to strengthen resilience measurement in the SDGs that is a framework of objective indicators, a quantitative research approach is formulated and it consists of three components: research methodology (philosophical worldview), research design, and research methods elaborated in Chapter 3. In brief, the general orientation of this research is driven by the Design Science Research Methodology (DSRM). This method is widely used to examine causal relationships, that identifies causes that influence the outcome in quantitative studies (Geerts, 2011; Creswell, 2014). In this research, causes are defined as the indicators that significantly contribute to measuring resilience/sustainability at the local level, and outcome is the local SDG Index. Applying DSRM, this research is conducted in three phases (Figure 1.3) that are elaborated in Chapter 3. Phase 1 (grand level) is the conceptualisation to develop a shared understandings of the concepts of resilience, its dimensions, and scope.

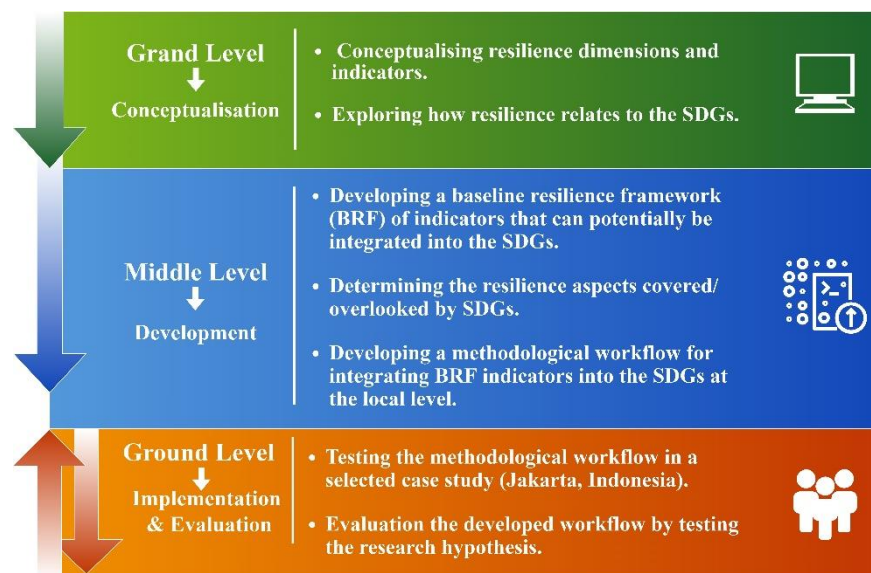


Fig. 1.3. Research methodology consisting of three main phases: conceptualisation, development, and implementation & evaluation.

In the second phase (middle level), the development phase, a baseline resilience framework (BRF) of indicators has been developed as they have the potential to be incorporated into SDGs. The pool of indicators is fundamentally built based on an analysis of the areas of resilience assessment that have been overlooked in the SDGs. Next, a workflow has been designed to embed resilience indicators into the SDGs in order to enhance this framework to facilitate the measurement of resilience and sustainability at the local level. The final level (ground level) is the actual implementation and evaluation level.

1.6 Thesis Structure

To achieve the research objectives the structure of this thesis is structured as follows:

Chapter 2: Resilience and Sustainability – Concepts and Measurements

This chapter first defines resilience, resilience measurement methods, and how they relate to bonding concepts such as vulnerability. Next, it explores the connection between resilience and sustainability, in general, and the SDGs in particular. Finally, it argues the possibility of developing a joint framework to measure resilience and sustainability with reference to the published literature on this topic.

Chapter 3: Research Design and Methods

This chapter explains the research methodology that is chosen according to the defined research problem and questions. Later, the chapter outlines the research design and the proposed methods to answer the research questions and to achieve the research objectives.

Chapter 4: Conceptualisation and Quantification of Resilience

This chapter focuses on the main issue to developing a common framework to measure resilience that is due to the lack of consensus on its dimensions, measurement, and quantification methods. This chapter determines the similarities and differences among diverse resilience dimensions addressed in the literature and defines the key dimensions. Later, the chapter develops a baseline resilience framework (BRF) incorporating pools of baseline quantitative indicators to measure each key dimension of resilience.

Chapter 5: Resilience Measurement - The SDGs Versus the Baseline Resilience Framework

Here, the focus is on the measurement of resilience and exploring the possibility of and the need for having a commonly accepted framework, so the resilience measured by the SDGs and the BRF have been compared. As a sample dimension, infrastructure resilience has been measured at a national level throughout the world using the indicators from the SDGs and BRF. Having assessed the differences and similarities between the two frameworks, the chapter concludes that the two frameworks should be integrated in the context of the SDGs in order to be used as a common framework for measuring resilience.

Chapter 6: An Integrated Framework to Measure Resilience and Sustainability

In this chapter, to answer the first research question and to integrate resilience indicator into the SDGs as suggested in Chapter 5, the SDGs indicators are compared with the indicators of the BRF to determine the aspects of resilience that have been well covered in the SDGs and vice versa. The chapter later proposes indicators to be integrated into the SDGs so that all the relevant aspects of resilience that have been overlooked in this framework, are in fact covered.

Chapter 7: Jakarta Case Study Part 1: Data Generation

This chapter introduces the selected case study, which is Jakarta, the capital city of Indonesia. This case study starts with looking at a critical dataset that was missing. Jakarta is home to many informal settlements, and this is a critical factor in its overall resilience and sustainability. Yet a recent map of its informal settlements was not available. As part of the case study, informal settlements have been detected using machine learning techniques. Presented here are the process and the results of the informal settlements detection and mapping them in Jakarta.

Chapter 8: Jakarta Case Study Part 2: Integrating Resilience into the SDGs at the Local Level

This chapter presents a novel workflow for integrating resilience assessment into the SDGs through a localised approach. This chapter also presents the results from the second part of the case study, which is the implementation and evaluation of the developed workflow. Finally, the workflow is evaluated by testing the hypothesis of the research.

Chapter 9: Conclusion

This chapter summarises the main findings of the research, and then provides the theoretical and practical implications of findings. Also provided here are the recommendations, an explanation of the research limitations and suggestions for future research on this topic to pursue.

1.7 Chapter Summary

This chapter presented an overview of the topic being investigated in the thesis, and the research questions, aim, objectives, and hypothesis. The research problem is rooted in the necessity for a more inclusive evaluation of resilience in the endeavours to achieve sustainable development. The research process presented in this chapter starts from exploring the possibility of applying the SDGs as a framework to integrate the measurement of resilience and sustainability. It was followed by suggestions about how to enhance the SDGs, developing a workflow for its application at the local level, and finally testing the propositions in Jakarta, Indonesia.

CHAPTER 2

RESILIENCE AND SUSTAINABILITY - CONCEPTS AND MEASUREMENTS

2 Resilience and Sustainability - Concepts and Measurements

2.1 Introduction

Accelerating challenges that are occurring in cities and communities have triggered a growing interest in the evaluation of resilience and sustainability of future urban development. The UN Sustainable Development Goals (SDGs), in which resilience has been incorporated as a component of sustainability, can potentially serve as a framework to integrate the measurement of the two concepts. Yet, it has been argued that the framework does not inclusively cover measurement of broad resilience aspects (Bahadur et al., 2015; Diaz-Sarachaga & Jato-Espino, 2019). This exploration commences with examining the validity of the above criticism. To determine the extent to which the SDGs are capable of measuring resilience, this chapter discusses how resilience relates to sustainability in general and to the SDGs, in particular. This chapter first conceptualises resilience and sustainability and how they are related. Next, resilience measurement methods are reviewed to determine how and what type of resilience measurement could be integrated into the SDGs.

2.2 Resilience and Sustainability

Resilience was first used by physical scientists to describe the characteristics of springs and the stability of materials and their resistance to external shocks, derived from the Latin root *resi-lire*, meaning to spring back (Davoudi et al., 2012). The concept was eventually defined in engineering as the ability to return to steadiness following a disturbance which could be any type of uncertainty (Holling, 1986). A further application of the concept appears in ecology. Ecological resilience refers to a natural ecosystem's ability to adapt and persist when faced with adversity (Adger, 2003). Unlike engineering resilience that was determined by how quickly a system bounces back, in ecological resilience, multiple equilibrium possibilities are acknowledged rather than a single, stable equilibrium (Davoudi et al., 2012).

Later, a socio-ecological resilience concept was proposed, which suggests that the nature of systems can change over time irrespective of external disturbance and rarely return to their previous position after adversity (Folke, Carpenter, Walker, Scheffer, Chapin, et al., 2010). The concept of evolutionary resilience emphasises the complex, interconnected socio-spatial systems that operate at multiple scales and timescales rather than viewing places as isolated units. It has become increasingly popular in planning studies to use this concept as an umbrella theme that encompasses topics such as ecosystem services, low carbon cities (Rizzo, 2020).

At the same time as the first definition of resilience was emerging, sustainable development was defined in 1970 by the World Commission on Environment as "development that meets the current needs of the

present without compromising the future ability of future generations to meet their own needs" (The World Commission on Environment and Development, 1987). It quickly gained prominence as a keyword that has become a central part of many discussions in diverse fields as the search for achieving environmental balance in place of dominance over nature (Clarke & Clegg, 200 C.E.).

The growing interest in resilience and sustainability discussions has led to controversial debates on the similarities and differences of these concepts (Ahern, 2011; Marchese et al., 2018; Xu et al., 2015). Resilience is generally referred to as the ability to prepare for, absorb, recover from, and adapt to stresses and adverse events (Ahern, 2011; Lam et al., 2016; L. K. Siebeneck & Cova, 2012). Sustainability, on the other hand, is defined as meeting the needs of the present without compromising the environmental, social, and economic interests of the present and future (Adams, 2006; The World Commission on Environment and Development, 1987). Sustainability, therefore, can be considered as the ability to ensure that various aspects of life remain functional over time (The World Commission on Environment and Development, 1987). Exploring the literature on the intersection of resilience and sustainability, five different types of relationships between the two concepts can be identified ([Figure 2.1](#)).

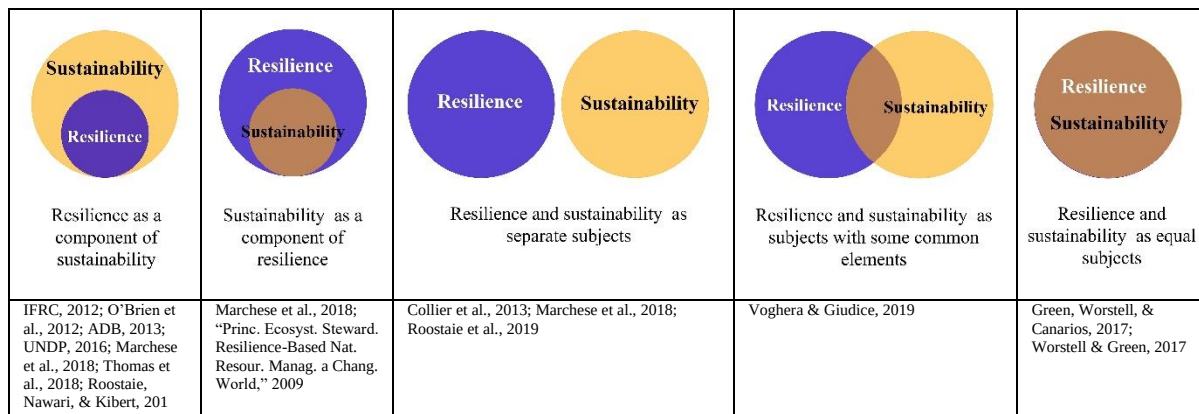


Fig. 2.1. Relationship between resilience and sustainability based on the literature.

The first group of literature considers resilience as a component of sustainability (Marchese et al., 2018; Roostaie et al., 2019). It can be seen in the model presented by Allen et al. (2019) to evaluate the sustainability of food systems. They suggest an assessment tool that uses indicators to evaluate the sustainable food system, including some that measure resilience to drivers of the system's vulnerability (Allen et al., 2019). This approach has been widely addressed by non-profit organisations or agencies. The Asian Development Bank (ADB) uses a definition of resilience building on this nexus between sustainability and resilience as the ability of countries, communities, businesses and individual households to resist, absorb, recover from, and reorganise in response to disruptive events, without endangering their

sustained socio-economic advancement and development (ADB, 2013). Similarly, following the acceptance of the International Federation of Red Cross (IFRC) (IFRC, 2012) and the Intergovernmental Panel on Climate Change (IPCC) (O'Brien et al., 2012) of this approach, the SDGs were developed based on it in 2015 (UNDP, 2016).

The second group accepts sustainability as a component of resilience with an emphasis on the key role of managing a system's sustainably so that it remains resilient (Marchese et al., 2018; "Princ. Ecosyst. Steward. Resilience-Based Nat. Resour. Manag. a Chang. World," 2009). On the other hand, some of the literature examines resilience and sustainability as concepts with separate objectives. This group emphasises that due to the major differences in the spatial and temporal scales of the two concepts (elaborated in the next paragraph) (Collier et al., 2013; Marchese et al., 2018; Roostaie et al., 2019) as well as the specific features of any contexts, the weight might be either on resilience or sustainability to build a strong community (Lew et al., 2016). The fourth group brings together the joint elements of the two concepts that can be jointly evaluated, such as the need for reflective capacity, flexibility of the process, and robustness (Voghera & Giudice, 2019). Finally, the fifth group equates sustainability to resilience mostly by either considering resilience as an alternative for sustainability or vice versa (Green et al., 2017). For instance, Worstell and Green (2017) have created a resilience/sustainability index using resilience indicators (Worstell & Green, 2017).

Generally, both sustainability and resilience seek to improve the quality of human life (Xu et al., 2015). However, resilience is mainly judged as process-oriented which relates to a short space of time before, during, or after a disaster, and trying to maintain the processes of a system and its functionality (Marchese et al., 2018; Rus et al., 2018). Sustainability, on the other hand, is understood to be outcome-oriented, considering long-time effects and prioritising the outcomes of a system's functions (Costanza & Patten, 1995). The differences and similarities suggest that benchmarking future development upon either resilience or sustainability might be a poor approach.

2.3 Integrating the Measurement of Resilience and Sustainability

Several frameworks have been built based on the relationships between the two concepts as illustrated in [Figure 2.1](#). However, some of these frameworks are designed for a specific field of study or context. For example, Milman and Short (2008) developed the Water Provision Resilience Framework that measures both sustainability and resilience of urban water systems (Milman & Short, 2008). Similarly, Saunders and Becker (2015) introduce a framework to measure resilience and sustainability in the wake of an earthquake in New Zealand, which cannot be used elsewhere the objectives differ (Saunders & Becker, 2015).

Other integrated frameworks measure either resilience or sustainability despite accepting one as a component of the other. For example, in the framework developed by Jarzebski et al. (2016) for assessing the social–ecological system sustainability of community-based forest management, resilience indicators have been applied as a factor that is fundamental for achieving sustainability (Jarzebski et al., 2016). Although aiming to measure both concepts, the framework only incorporates resilience indicators. In a similar way, Green et al. (2017), measured eight qualities of resilient food systems as a sustainability/resilience index (Green et al., 2017).

Generally, there are two main limitations of the reviewed integrated frameworks. One is their context-specific nature, with a limited number of indicators to assess a specific issue (earthquake, water provision, etc.), and the other is their failure in measuring both concepts. Of the current integrated frameworks, the UN SDGs unify both resilience and sustainability metrics and provide the opportunity to compare sustainability between countries (Zamboni, 2017). However, this framework has been criticised for incorporating not enough indicators to measure resilience given the multidimensional nature of the concept (Bahadur & Pichon, 2016; Cumming, Barnes, Perz, Schmink, Sieving, Southworth, Binford, Holt, Stickler, & Holt, 2005; Schipper & Langston, 2015). To cover the gap for a joint framework to jointly measure resilience and sustainability, this research aims to strengthen resilience measurement in the SDGs. However, the prerequisite to achieve the aim is to explore how comprehensively the SDGs measure resilience and how the framework can be enhanced, resilience measurement methods must first be reviewed.

2.3.1 Resilience Measurement Methods

A variety of methods have been used to assess resilience, including quantitative, qualitative, and mixed approaches. These methods are briefly explained in this section.

2.3.1.1 Qualitative Measurement of Resilience

Qualitative assessment is mainly done through survey questionnaires, in-depth interviews, focus group discussions, and self-assessments. These methods provide an in-depth and bottom-up evaluation of resilience without allocating quantities to the assessing features and qualities. For instance, Harte et al. (2009) conducted an in-depth interview to define the factors that had enabled households in an informal settlement to respond and recover from a fire (Harte et al., 2009). In another example, Sharifi et al. (2017) conducted a focus group discussion including both researchers' and practitioners' experiences in urban resilience theory and practice, in an attempt to define the central elements of the built environment that influence community resilience (Sharifi et al., 2017).

2.3.1.2 Quantitative Measurement of Resilience

Despite qualitative methods, quantitative ones follow several approaches to measuring resilience using a group of indicators to represent the functionality and characteristics of a system by numerical values (Woolf et al., 2016). Indicators used to measure resilience are either objective or subjective. Subjective indicators are graded based on people's insights (Oladokun et al., 2017; Woolf et al., 2016). For example, Marshall and Marshall (2007) measured the level of social resilience by conducting a survey questionnaire. Here, 17 questions were asked, such as "I can cope with small changes in the industry" and responses were rated from strongly disagree to strongly agree (values 1 to 4, respectively) (Marshall & Marshall, 2007). Quantitative measurement of resilience using subjective indicators can be confused with qualitative methods. The difference derives from the numerical value that is given to the level of resilience in this method (Creswell, 2014).

Objective indicators are conversely measured based on computable data such as statistical and census data (Cutter et al., 2010, 2014; Hung et al., 2016; Moghadas et al., 2019; L. Siebeneck et al., 2015). For instance, in the SDGs framework, indicator 1.5.4 stands for poor people's resilience to extreme events (1.5.4: Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies) (UNSD, 2020). Generally, this approach offers the possibility to compare various case studies and time frames through standardised metrics. Meanwhile qualitative and quantitative methods that use subjective indicators reflect the communities' views at the scale and time they were surveyed. Despite some drawbacks of using objective indicators such as data availability issues (Knippenberg et al., 2019) or following a top-down approach that might not reflect all the features in smaller context, this method has been widely accepted and tested in the frameworks, tools, and case studies (Chu et al., 2017; Hu et al., 2018; Kim & Park, 2018; Li, Lam, et al., 2016; L. Siebeneck et al., 2015; J. Song et al., 2017; Tan et al., 2017; C. Zhang et al., 2016) due to the defined advantages.

For the purpose of this research that is to integrate sustainability and resilience indicators in the context of the SDGs, the quantitative method based on indicators is preferred. In addition, since the SDGs' method to measure resilience and sustainability is based on calculating objective indicators, the review of this group of indicators is the focus.

Quantitative assessment of resilience by indicators: As explained, in several case studies resilience has been quantitatively assessed by indicators that are either objective or subjective. Based on the type of indicators, quantitative assessment of resilience employs three main approaches: evaluating subjective indicators, measuring objective indicators, and assessing resilience using a combination of both types of indicators (mixed-method). In the first approach, subjective indicators evaluate resilience. Those are the

indicators rated based on the experience, judgment, and wisdom of the experts (DasGupta & Shaw, 2015; Oladokun et al., 2017; Woolf et al., 2016) self-assessment (Beauchamp et al., 2019), or household surveys and interviews (Alam et al., 2018; Jacobi et al., 2018; L. Jones & D'Errico, 2019; Khalili et al., 2018; Khatibi et al., 2019; Lokonon, 2019). Woolf et al. (2016), relying on this approach, present a framework to evaluate community resilience in slums in the Kenya Slum Upgrading Programme in 2007 (Woolf et al., 2016). The framework consists of 49 indicators that are part of 16 subcategories, and four categories of external resources, assets, capacities, and qualities to quantitatively assess community resilience in slums. These indicators are later rated by residents through a household survey. Indicators' ratings are then averaged, to assess the level of resilience in different categories based on equal weightage. The results reveal the areas of strength and weakness in regard to slums' resilience.

Although the methods that rely on perception and experience help to depict the construct of resilience in a case study as a bottom-up approach, they are criticised for their level of accuracy (Stratford et al., 2010). The robustness of the result depends on the amount of data collected, i.e. number of samples (Woolf et al., 2016), as well as capturing the changing trends in case studies and updating the data, which is very expensive and time-consuming (Cai et al., 2018). More importantly, subjective methods do not provide results that can be used to compare the level of resilience in different countries, such as what is achieved by the SDGs. Scholars who adopt the second approach conduct quantitative assessment using objective indicators. For instance, Fu and Wang (2018) have developed an index to measure urban resilience to any disturbances by calculating Urban Resilience Capacity Index using 42 objective indicators (Fu & Wang, 2018). The index is later included in a built-in scenario-based planning support system to support policy by predicting the effects of all planning scenarios or policies on urban resilience. The approach has many advantages, including relying on a tangible definition of resilience and the possibility of comparison among different case studies through standardised metrics (L. Jones & D'Errico, 2019). However, some obstacles to this method include data availability and the need for a large list of indicators to measure resilience (Bahadur & Pichon, 2016; Cai et al., 2018; Schipper & Langston, 2015).

2.3.1.3 Mixed-method for Measurement of Resilience

In a mixed-method assessment, resilience is assessed through a combination of qualitative and quantitative approaches. This method takes advantage of focus groups, interviews, and questionnaires to collect more data, mainly where census and statistical data are scarce (Kaye-Blake et al., 2019; Mavhura & Manyena, 2018; Mohammed et al., 2018a; Quandt, 2018). As an example, DasGupta and Shaw (2015) applied a mixed-method of 25 indicators to measure the level of resilience of coastal communities to climate-related disasters in 19 coastal administrative blocks of Indian Sundarbans in 2013 and 2014. (DasGupta & Shaw, 2015). To calculate the resilience score, the subjective indicators were assessed through a questionnaire survey of

administrative officials. Objective indicators, on the other hand, were measured using census and statistical data, as well as available reports, handbooks, and research papers.

Applying the third method helps to overcome the paucity of data by conducting field surveys in which subjective indicators are measured. However, it compromises the precision of the results (since the calculation of subjective indicators and subsequent resilience index depend on human ranking) and affects the compatibility of the results. With this in mind the SDGs framework follows the second approach by evaluating 231 unique objective indicators (as of the year 2022) to calculate the SDG Index. Therefore, to achieve the aim of this research the second and third approaches (objective and mixed-methods) are chosen and reviewed to extract and create a pool of objective indicators to measure resilience (results presented in Chapter 4) indicators.

2.3.1.4 The approach followed in this research

The SDGs' approach to calculate the SDG Index for countries, similar to many other resilience frameworks (Avila-Foucat & Martínez, 2018a; Chu et al., 2017; Roy et al., 2019; Tambo, 2016a) is to aggregate indicators through equal weighting. The SDG Index demonstrates the level of sustainability in countries by first normalising the indicators' values linearly to a scale between 0 and 1 (Equation 1) and then aggregating the indicators, applying equal weighting (Equation 2):

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

Where: x is raw data value; $\max/\min$ denote the highest and lowest value for the indicator, respectively; and x' stands for the normalised value after rescaling.

$$I_i(N_i, N_{ij}, I_{ijk}) = \sum_{j=1}^{N_i} \frac{1}{N_i} \sum_{k=1}^{N_{ij}} \frac{1}{N_{ij}} I_{ijk} \quad (2)$$

Where: I_i is the SDG Index for country i ; N_i is the number of goals for which the country has data; N_{ij} represents the number of indicators for goal j for which country i has data; and I_{ijk} denotes the score of indicator k under goal j for country i (Guillaume Lafortune, Grayson Fuller, Jorge Moreno, Guido Schmidt-Traub, 2018).

This approach makes it possible to add and exclude indicators and provide the opportunity for proposing more indicators to measure resilience. However, the indicators should be applicable to any case with different spatial and temporal features. It is therefore very important to understand the connections between resilience measurement and the context. The next section attempts to analyse whether there are any links between the indicators and the context in which resilience has been measured.

2.3.2 Resilience Measurement Context

Literature, in which resilience is measured using objective indicators, has employed different approaches to demonstrate the context in which it is measured. The first step in most of the research is to define "resilience of what?" and "resilience to what?" (see [Table 2.1](#)). Temporal and spatial scales are further defined to elaborate on when and whose resilience is measured ([Figure 2.2](#)). "Resilience of what" answers the question of whose resilience is being measured, and this can vary from a household to a country (spatial scales), while resilience to what defines the stress to which people are exposed, from persistent stress (e.g. urbanisation and climate change) to extreme events or disasters (e.g. flood, drought, outbreak of a disease, etc.). Resilience to what also specifies the temporal scales of the stress by defining whether resilience is measured before the stress (pre-event), during the stress (during event), or after it (post-event) (Assarkhaniki et al., 2020).

The measurement of resilience to persistent stress is usually done during the event, while resilience to extreme events is measured either based on baseline conditions (pre-event) or post-disaster status. Therefore, the answer to "resilience of what?" has an indirect relationship with temporal scales ([Table 2.1](#)).

Generally, it can be concluded that the resilience context is defined based on the spatial and temporal scales in the literature. Also, the links among different scales in which resilience is measured ([Figure 2.2](#)) show how the spatial and temporal scales are connected. For instance, community resilience can be measured in pre-event conditions (Ainuddin & Routray, 2012; Fu & Wang, 2018; Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019; Kim & Park, 2018; Scherzer et al., 2019; L. Siebeneck et al., 2015; Singh-Peterson et al., 2014; Yoon et al., 2016), during the event (Abdrabo & Hassaan, 2015), and post-event (Kliskey et al., 2019). Conversely, pre-event resilience can be measured in a different spatial scales that ranges from a community (Kim & Park, 2018) to a country (L. Siebeneck et al., 2015).

By comparing resilience measurement where different scales are employed, it can also be inferred that indicators to measure resilience are in many cases interchangeable. For example, "% Labour force employed" is used as an indicator in all temporal scales of pre-disaster (Li, Lam, et al., 2016), post-disaster (Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019), and during the event (Abdrabo & Hassaan, 2015). Similarly, "Principle arterial miles per square mile" is an indicator that is used in measuring the resilience of a community (Scherzer et al., 2019), city (Moghadas et al., 2019), and country (Hiete et al., 2012). The possibility of interchangeable use of indicators has led to a less understood approach to measure resilience called baseline resilience. In contrast to defining indicators that measure resilience of what, and to what, this approach aims to measure baseline (or general) resilience, which provides a baseline index for resilience to any stress or extreme event (from disasters to persistent stress) (Fu & Wang, 2018;

Green et al., 2017; Kaye-Blake et al., 2019; Tan et al., 2017). In baseline resilience, the general factors that might help a group of people to survive an adverse event are measured, such as availability of shelter, hospital beds, or any type of insurance that might help a community to respond to any type of stress, from a pandemic to a flood.

Table 2.1. Resilience measurement context.

	Temporal Scale	Spatial Scale								Resilience Capacity		
		Local Scales *				National Scales *						
Source	Pre-event	During event	Post-event	Household	Community ¹	City	State	Provinces	Country	Resilience of	Resilience To	Adaptive Capacity
(Kaye-Blake et al., 2019)	✓				✓					Rural communities	General (any future stress)	
(Mihunov et al., 2019)			✓						✓	Community	Drought hazard	✓
(Manyena et al., 2019)										Urban community	Disaster	✓
(Scherzer et al., 2019)	✓									Community	Disaster	
(Moghadas et al., 2019)	✓					✓				City	Flood	
(Kammouh et al., 2018)					✓					Urban community	Disaster	
(Mihunov et al., 2019)	✓								✓	Community	Drought	
(Fu & Wang, 2018)	✓					✓				City	General	✓
(Kim & Park, 2018)	✓				✓					Community	Disaster	
(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)	✓				✓					Community	Disaster	
(Hu et al., 2018)		✓					*	*	*	Social-Ecological system	Economic development	
(Cutter & Derakhshan, 2018)	✓				✓				✓	Community	Disaster	
(González et al., 2018)	✓					✓				Cities and communes	Disasters	✓
(J. Song et al., 2018)				*	*	*				Local	Typhoon disaster	
(Links et al., 2018)			✓		✓					Community	Disaster	✓
(J. Song et al., 2017)		✓								City/community	Flood	
(Tan et al., 2017)	✓					✓				Resource based Cities	General	✓
(Delgado-Ramos & Guibrunet, 2017a)		✓				✓				City	Urban changes	
(Green et al., 2017)	✓			*	*	*				Agri-food System	General	
(Tumini et al., 2017)	✓		✓		✓					Local communities	Disaster	
(Araya-Muñoz et al., 2016)		✓				✓				City	Climate change	✓
(C. Zhang et al., 2016)		✓					*	*	*	Socio-ecological system	Urbanisation	
(Cutter, 2016)	✓				✓					Community	Disaster	
(Hung et al., 2016)	✓					✓				Urban areas	Climate hazard	✓
(Yoon et al., 2016)	✓				✓					Community	Disaster	
(Li, Lam, et al., 2016)			✓				✓			City	Earthquake	
(Li, Wang, et al., 2016)			✓		✓					Community	Seismic hazard	
(Kotzee & Reyers, 2016)	✓					✓				Social-ecological system	Flood	
(Cutter, 2016)	✓				✓					Community	Disaster	
(Asadzadeh et al., 2015)	✓									-	Disaster	
(Abdrabo & Hassaan, 2015)		✓				✓				Urban centres	Climate change	
(L. Siebeneck et al., 2015)	✓							✓		Community	Disaster	
(Burton, 2015)	✓				✓					Community	Natura hazards	
(Cutter et al., 2014)	✓				✓					Community	Disaster	
(DasGupta & Shaw, 2015)	✓				✓					Community	Climate related disasters	
(Singh-Peterson et al., 2014)	✓				✓					Community	Disaster	
(Ainuddin & Routray, 2012)	✓				✓					Community	Disaster	
(Hiete et al., 2012)	✓								✓	Regional	Disaster	
(Cutter et al., 2010)	✓				✓					Community	Disaster	

1 Community is defined as “a group of people with diverse characteristics who are linked by social ties, share common perspectives, and engage in joint action in geographical locations or settings” (M. MacQueen, Kathleen McLellan et al., 2001).

A mediating approach that can be considered as the bridging approach between baseline resilience and spatio-temporally specified resilience is evident the frameworks that measure resilience to disaster. The research that follows this approach, similar to general resilience, develops an integrated framework of indicators that measure resilience to any type of disasters (Cutter, Burton and Emrich, 2010; Hiete *et al.*, 2012; Ainuddin and Routray, 2012; Singh-Peterson *et al.*, 2014; Cutter, Ash and Emrich, 2014; Asadzadeh, Kötter and Zebardast, 2015; Siebeneck, Arlikatti and Andrew, 2015; Yoon, Kang and Brody, 2016; Cutter, 2016; Tumini, Villagra-Islas and Herrmann-Lunecke, 2017; Kim and Park, 2018; Links *et al.*, 2018; Cutter and Derakhshan, 2018; González *et al.*, 2018; Kammouh *et al.*, 2018; Manyena, Machingura and O’Keefe, 2019; Scherzer, Lujala and Rød, 2019; Kammouh, O., Zamani Noori, A., Cimellaro, G.P.; Mahin, 2019).

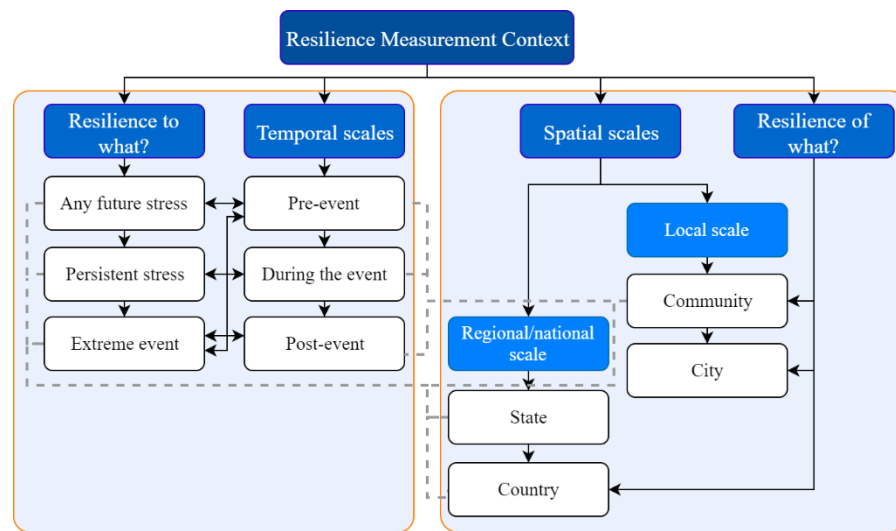


Fig. 2.2. Resilience measurement context. Dashed lines represent the links between temporal (left block) and spatial (right block) scales.

The SDGs follow the second approach of measuring resilience, that is baseline resilience. Therefore, to integrate a more comprehensive set of resilience indicators into the SDGs, a set of baseline indicators can be devised and the objectives of the resilience measurement in every case will define which proportion of the set should be measured in local contexts. It should be noted that the indicators to measure baseline resilience are not limited to resilience discussions; they also exist at the intersection of resilience with bonding concepts such as vulnerability (Urruty *et al.*, 2016). In the next section, the relationship between resilience and vulnerability is investigated, based on which indicators from the vulnerability literature to measure baseline resilience can be extracted.

2.4 Resilience and Vulnerability

One of the concepts that has been linked to resilience in many studies is vulnerability. Although theoretically resilience and vulnerability are separate concepts (Jacob et al., 2013), four types of relationship between these two have been identified in studies that use objective indicators to measure the concepts ([Figure 2.3](#)). Many researchers believe there is a negative linear relationship between resilience and vulnerability, where a more resilient community is less vulnerable ([Figure 2.3.a](#)) (Angeon & Bates, 2015; Buckle et al., 2001; Hiete et al., 2012; Imran et al., 2019). Some research has developed indicators of vulnerability and resilience of communities based on this assumption (Alessa et al., 2008; Brenkert & Malone, 2005; Jacob et al., 2013; Kliskey et al., 2019). For instance, Kliskey et al. (2019) measure the vulnerability of water resources by a set of indicators, such as “percentage of land area set aside in protected area status”. The values quantified by the indicator have later been used as a sign of high resilience in highest values (positive impact) and high vulnerability in lowest values (negative impact). Indicators from this type of framework can be extracted to measure resilience by taking into account their positive (+) or negative (-) impacts on the overall index.

In other research resilience and vulnerability have been characterised as overlapping concepts ([Figure 2.3.b](#)) (Menoni et al., 2012; Norris et al., 2008; Thulstrup, 2015) where both measure adaptability or adaptive capacity. Adaptive capacity is the ability to prepare for stresses and changes in response to outcomes caused by stresses (Engle & Bank, 2011; Huber et al., 2012). This bridging concept is mostly measured as a quality for a resilient system (Asmamaw et al., 2019; Cutter & Derakhshan, 2018; Cutter & Finch, 2008; Füssel, 2007; González et al., 2018; Hung et al., 2016; Links et al., 2018). However, some methods for assessing vulnerability have also addressed adaptive capacity (Mohammed et al., 2018b; Wei et al., 2017; Zukowski, 2014). Hence, to build a set of baseline resilience indicators, those to measure adaptive capacity can be extracted from the vulnerability assessment frameworks.

The third type of relationship between resilience and vulnerability can be found in the frameworks in which resilience is recognised as a dimension for measuring vulnerability and vice versa ([Figure 2.3.c](#)). Where resilience is measured as a dimension of vulnerability (G. Song et al., 2015; Toubes et al., 2017; Turner et al., 2003; D. Wang et al., 2017a; Wu et al., 2016) a set of indicators is presented to evaluate resilience. The indicators can be extracted for the purpose of generating a more comprehensive set of resilience indicators. In their work, Hu et al. (2018) developed a framework to measure resilience which includes a set of indicators related to the vulnerability in each social, economic, and ecological dimension of resilience, representing the fourth type of approach to connect the two concepts (Hu et al., 2018) ([Figure 2.3.d](#)). The vulnerability indicators should be excluded when extracting resilience ones.

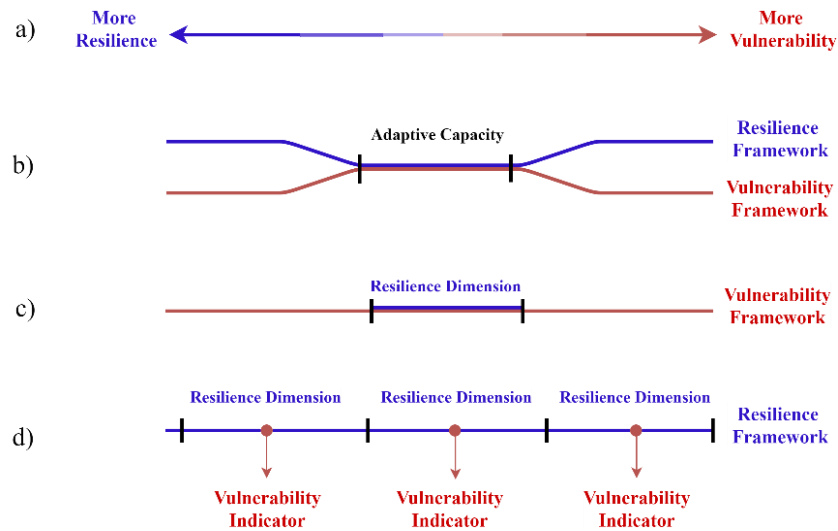


Fig. 2.3. Approaches that link resilience measurement with vulnerability based on the frameworks of indicators to measure resilience, vulnerability, or both. a) Resilience and vulnerability as opposite concepts, b) Resilience and vulnerability as overlapping concepts linked with adaptive capacity, c) Resilience as a dimension for vulnerability, and d) Vulnerability as a component of each resilience dimension.

Considering the relationship between resilience and vulnerability frameworks, indicators to measure resilience can be extracted from the vulnerability frameworks with the first three types of linking approaches with resilience. Chapter 4 presents the research that has been done on developing a framework of baseline resilience indicators. It also incorporates those extracted from vulnerability frameworks.

2.5 Chapter Summary

This chapter reviewed the concept of resilience, its measurement, and how it relates to sustainability and the SDGs. It is generally agreed that both sustainability and resilience are indications of the quality of life with a slight difference in the temporal scale and objectives being measured. Resilience is mainly understood as process-oriented which relates to a short space of time, while sustainability is mainly defined as outcome-oriented, and long-term effects are critical. The similarities and differences suggest that the integrated measurement of these two concepts could accelerate the achievement of sustainable development.

The SDGs integrate both resilience and sustainability measurement. However, the framework has been criticised for not having enough resilience indicators and its failure to integrate the measurement of resilience, which is a key component of sustainability. To examine the validity of the argument and to develop the basis for answering the first research question - To what extent do the SDGs measure resilience? – this chapter presented a review of resilience measurement methods and how they relate to the SDGs.

According to what argued in the chapter, resilience can be measured through quantitative, qualitative, and mixed-method approaches. While qualitative methods provide a deeper and bottom-up evaluation of resilience, they provide less robust results and this makes comparative studies difficult. The SDGs measure both resilience and sustainability based on a quantitative approach using objective indicators. Therefore, to answer the first research question and incorporate a more inclusive set of resilience indicators in the SDGs, objective indicators should be explored. The indicators exist in the vulnerability frameworks which are closely linked to resilience measurement. Chapter 4 presents a framework of baseline resilience indicators based on the above arguments.

CHAPTER 3

RESEARCH DESIGN AND METHODS

3 Research Design and Methods

3.1 Introduction

The aim of this chapter is to explain the research design and methods and how they help to answer the research questions. To avoid unnecessary complexity, the details concerning the data collection/generation/preparation and analysis processes are elaborated on in the following chapters. To articulate the approach for this research, the Creswell (2014) framework has been employed. This framework formulates the research approach that is quantitative, qualitative or mixed-method into three components: research methodology (philosophical worldview), research design, and research methods (Creswell, 2014).

The central aim of this research is to strengthen resilience measurement in the SDGs, which will serve as a framework for measuring and monitoring both sustainability and resilience. One objective of this research is therefore, to integrate a more comprehensive set of resilience indicators into the SDGs. Since the SDG framework uses objective indicators to measure sustainability, the same quantitative approach has been adopted in this study, so the suggested additional resilience indicators could be incorporated into the SDGs framework. The quantitative research method tests objective theories by examining the relationship among variables that can be measured (Creswell, 2014). Here, first a pool of quantitative indicators to measure resilience has been proposed, which has the potential to be incorporated into the SDGs. Later, to determine the indicators that contribute significantly to the local SDG Index in accordance with the local characteristics, the relationships between different combinations of dependent variables (the SDGs indicators and additional indicators from the proposed pool of resilience indicators) on the independent variable (the SDG Index), are analysed.

3.2 Research Methodology

Based on the defined approach and the nature of this research that is to study a causal relationship, Design Science Research Methodology (DSRM) is employed. DSRM, also called the postpositivist worldview, is very popular in quantitative research as it identifies causes that shape an outcome (Geerts, 2011; Creswell, 2014). This methodology has been previously utilised for Urban Informatics by Bilandzic and Venable (2011). They called it Participatory Action Design Research composed of five phases: 1. problem foundation, 2. action planning, 3. action taking, 4. impact evaluation, and 5. reflection and learning (Mark Bilandzic, 2011). Applying DSRM, this research will be conducted in three phases that are adapted from Matin et al.'s (2018) methodology, to conduct a systematic review of equitable resilience (Matin et al., 2018). They explored the definition of resilience through the grand level, which is the first phase.

Investigated resilience indicators in the middle level and reviewed resilience in practice at the ground level, which relies on practical samples.

In this research as explained in Chapter 1 ([Figure 1.2](#)), phase 1 (grand level) is the conceptualisation to develop shared understandings of the problem (resilience and sustainability), its dimensions, and scope. In the second phase (middle level) which is the development phase, a framework of baseline resilience indicators has been developed with the potential to be incorporated into the SDGs. The pool of indicators is fundamentally based on an analysis of the areas of resilience assessment that have been overlooked in the SDGs. Next, a methodological workflow has been designed to integrate resilience indicators to the SDGs at the local level. The final level (ground level) is where implementation and evaluation are done, so it is in effect the practical stage for assessing the developed workflow in a case study.

3.3 Research Design

This component defines the research direction or procedure according to the selected methodology. The research design for quantitative approaches might be experimental or non-experimental (Creswell, 2014). Experimental research tests whether a specific treatment leads to a certain outcome. On the other hand, non-experimental research, which is also called observational research, observes a subject without intervening. In this research, cause (different combinations of dependent variables that are the SDGs indicators and additional BRF indicators) and effect (dependent variable that is the local SDG Index) have already occurred and are being examined after the fact. Hence, since intervention is not part of the aim and scope of this research, non-experimental research designs apply here. As well, to examine the causal relationship, a correlational design is selected. Correlational design is one form of non-experimental research in which the correlational statistic is applied to describe and measure the association between variables without manipulation of an independent variable.

3.4 Research Methods

The third major element of the approach is the specific research methods that involve the forms of data collection, analysis, and interpretation. Methods that have been applied in each phase of this research are explained in more detail below.

3.5 Conceptualisation

In this research, a critical review of the literature has been done in three areas: 1. resilience dimensions and indicators, 2. resilience and vulnerability and indicators, and 3. resilience, sustainability, and SDGs. The aim of the first part is defining the key resilience dimensions, as well as objective indicators to measure them. In the second part, the vulnerability concept, which is linked to resilience, has been reviewed to reach

a comprehensive set of indicators to measure resilience. Finally, the association between resilience and sustainability concepts has been explored to understand how they relate to each other.

Data collection for the conceptualisation phase: data collection (see Chapter 4) has been done in four steps. The first step was to search for the relevant papers in two comprehensive academic search engine platforms (Scopus and Web of Science). In the next step, citation network analysis was done by VOSviewer to define the main fields in which resilience indicators have been investigated and delete irrelevant documents (van Eck & Waltman, 2017). The third step was to remove duplicates using Endnote software. Finally, the abstracts and full-texts of papers were checked to ensure that the sources refer to objective indicators that measure resilience.

Data analysis for the conceptualisation phase: following the extraction of the sources, to conceptualise resilience dimensions and indicators, a framework analysis has been applied (see details in Chapter 4). Framework analysis is an advanced method for analysing qualitative data (e.g. text) to identify patterns of meaning in seemingly unrelated material (Neuendorf, 2019) through the following steps: familiarisation, coding, identifying themes, charting, mapping, and interpretation (the developed chart is reported in [Appendix 1](#)) (Dudovskiy, 2016). Later, the same coding has been applied to resilience indicators extracted from vulnerability frameworks to develop a baseline resilience framework (BRF).

3.6 Development

In this phase, to answer the first and second questions the SDGs and BRF have been compared in order to identify the resilience aspects (variables) that are not included in the SDGs. Next, the additional indicators have been proposed to cover the overlooked areas to enhance the SDGs framework. Finally, a workflow has been proposed for integrating the proposed resilience indicators from BRF to the SDGs at the local level, which has been tested in the selected case study, Jakarta, Indonesia.

Data analysis for the development phase: to define the resilience variables that have been overlooked in SDGs, a semantic text similarity measurement has been done in three steps (see Chapter 6 for more details). In the first step (coding), both groups of indicators from BRF and the SDGs have been coded by applying the thematic coding method using NVivo software. This helps us to code phrases or sentences (here indicators) to describe aspects of the data (their connection with resilience variables, sub-domains, and dimensions) (Gibbs, 2007). Therefore, each of the SDGs and BRF indicators are considered as a unique code. Next in the clustering step, the matrices of coding have been developed based on the nearest neighbour method to find the connections between overlapping themes (shared variables) to form clusters (Guest, G., MacQueen, K. M., & Namey, 2012) ([Figure 3.1](#)). Finally, the results from the matrices have been analysed

utilising the Cosine similarity method, which served to define to what extent the SDGs indicators cover the resilience dimension's assessment (Muflikhah & Baharudin, 2009).

3.7 Implementation and Evaluation

Data Collection for Implementation: The data on informal settlements in Jakarta has been obtained from BAPANAS (Ministry of National Development Planning of the Republic of Indonesia). The census data, which is mainly available for formal settlements, has been obtained from several sources, including technical reports, Jakarta Open Data (<https://data.jakarta.go.id/>), Dukcapil [Civil Registrar], Diskominfo [Communication and Information], etc. Finally, the spatial data was collected from OpenStreetMap Jakarta, and DCKTRP (Agency for Development, Spatial Planning, and Housing).

Data generation and preparation: Following the data collection, data preparation was done and missing data was generated (see Chapter 7 for more details). One fundamental missing piece of data in Jakarta was for the location of informal settlements. This data has been generated using open data (OpenStreetMap and Landsat 8) by applying Machine Learning (ML) techniques - Random Forest (RF) algorithm. The same method has been applied to detect urban parks and green spaces. In addition to data generation, data preparation has been done to convert all the census, statistical, and survey information to spatial data (see Chapter 8 for more details). Also, in order to examine the data, all the data needed to come to a similar jurisdictional level. Here, aggregation and disaggregation of the data have been done to have all the data at sub-district level for all of the 286 sub-districts of Jakarta.

Data Analysis for Implementation: In this phase, implementation of the workflow for integrating resilience into the SDGs at the local level has been done in a case study through three steps: 1) Assessing the indicators from BRF and SDGs for data availability and application at the local level; 2) Aligning the indicators with the local context as required; and 3) Analysing the significance of the indicators in measuring resilience/sustainability at the local level applying the Exploratory Regression method. Exploratory regressions evaluate all possible combinations of the input candidate exploratory variables (independent variables - here SDGs and BRF indicators) and define those that best explain the dependent variables (here the SDG Index) (Esri, 2021). In this step, the most effective indicators for inclusion in the SDGs have been determined. This is an important step, as it will shortlist the indicators for time and budget efficiency. Later, the proposed 3-steps workflow is evaluated, through developing the local (Ordinary Least Square) and global (Geographical Weighted regression) models using the selected indicators. The results test the research hypothesis which is “the addition of resilience indicators will enhance the effectiveness of the SDGs in measuring resilience at the local level”. Even though it might seem reasonable to speculate

that any additional indicators might enhance the effectiveness of the SDGs in measuring resilience as more data is analysed, this may not necessarily be the case since not every indicator might contribute to the index.

3.8 Chapter Summary

This chapter describes the research design and briefly explains the chosen method. Firstly, the conceptual design has been described. Next, three steps of the research methodology including conceptualisation, development, and implementation and evaluation have been articulated. For each of these steps, applied methods for data collection and analysis were introduced. The method will now be described in more detail in the following chapters.

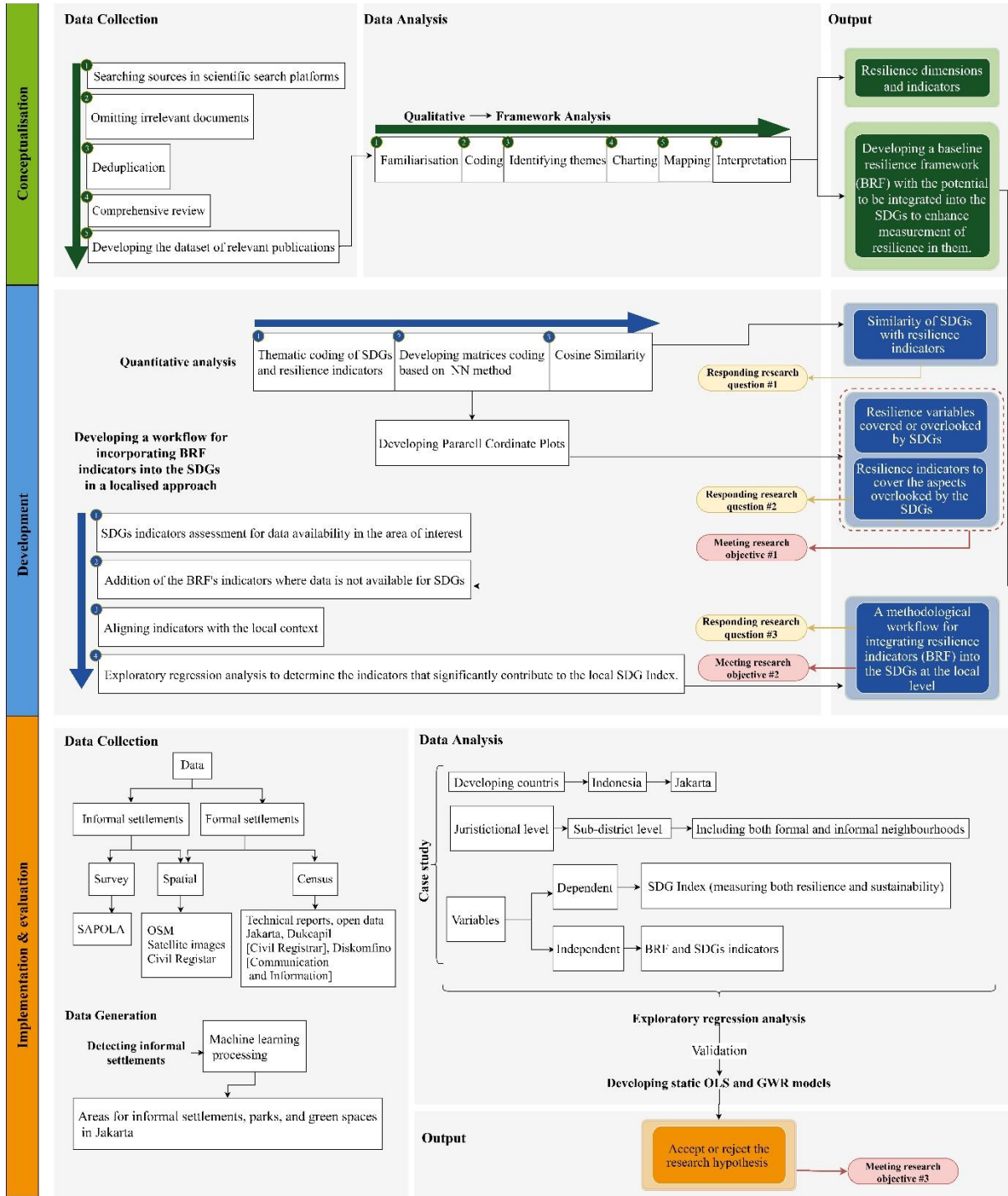


Fig. 3.1. Research methodology and applied methods.

CHAPTER 4

CONCEPTUALISATION AND QUANTIFICATION OF RESILIENC

4 Conceptualisation and Quantification of Resilience

4.1 Introduction

Resilience is a very broad concept. There have been many case studies, frameworks, tools, and models that attempt to measure it, but a widely accepted framework is still lacking. One major obstacle is inconsistency in the terminology and the existence of various dimensions addressed in different studies ([Table 4.1](#)). Community capital, social capital, community, community competence, social-cultural capital, and human capital are among those that sound very similar, or even address one specific issue. The most frequently addressed dimensions (FAD) for resilience noted in the literature are: social, economic, institutional, infrastructural, and environmental. However, many peripheral dimensions (PD) have been addressed in the literature and this leads to the following questions:

- 1) In what ways are diverse resilience dimensions similar or different?
- 2) How is it possible to reach consistent dimensions along with a common set of indicators to measure them?

This chapter seeks to answer the above questions. To answer the first question and define the similarities and differences of the existing resilience dimensions, FADs have been compared with PDs by developing a similarity matrix ([Table 4.2](#), [Figure 4.5](#)).

4.2 Data Collection Procedure

Search process: The search for the relevant reviews and articles has been done in the Scopus and Web of Science core collections (Indexes=SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI) ([Figure 4.1](#)). To identify all publications that contained relevant terms such as measuring or measurement, resilience, resiliency or resilient, and assess, assessing or assessment, a Boolean search for “resilien* AND (measure* OR assess*) AND (indicator OR variable)” in title, abstract, and keywords was done. The timespan has been limited to 1970-present (2019 in WOS and 2020 in Scopus) since the concept of resilience was introduced in the early 1970s (Holling, 1973). Irrelevant subject areas such as Medicine, Electrical Engineering, Psychology, etc., were excluded and the language limited to English.

Data extraction: Considering that resilience is a broad concept and applied in different fields, two data sets of 1744 publications from Scopus and 1604 publications from Web of Science were obtained based on the search conducted on 6 Nov. 2019. Once this was done a citation analysis was executed. This method prevents human error which may occur due to the large number of papers, and represents a network of relevant papers by analysing the relevance of publications (van Eck & Waltman, 2017). For this purpose,

bibliographic coupling relationships and co-citation relationships could be used, but the most accurate method is direct citation analysis (Klavans & Boyack, 2017).

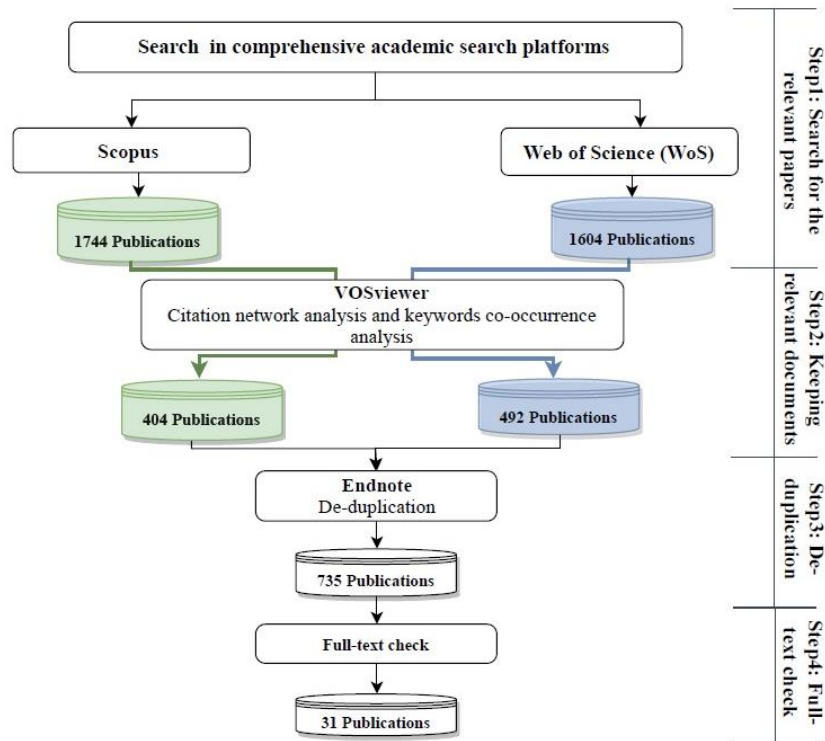


Fig. 4.1. Data collection and extraction process.

VOSviewer has been used to conduct citation analysis (Van Eck & Waltman, 2010, 2014). Here, sets of publications retrieved from WOS and Scopus were imported separately. Documents with even zero citations have been selected to keep and the documents with zero connection to the citation network have been removed. This analysis removes the publications with no link to any of the publication in the citation network which can be inferred as irrelevant to the topic; for instance, the resilience of the Zooplankton community in the field of biology ([Figure 4.2](#)).

By applying citation analysis, 1112 publications from the WOS list and 1340 documents from the Scopes list have been removed, and a total number of 896 papers retained for full-text checking. Then, the retrieved lists of the document were imported into the citation manager software "Endnote" to remove duplications. After de-duplication the initial data set of 735 publications was created. After running the full-text screen and removing the publications that did not mention any indicators to measure resilience, 38 publications relevant to objective indicators have been retained. [Table 4.1](#) summarises all the resilience dimensions addressed in the reviewed literature.

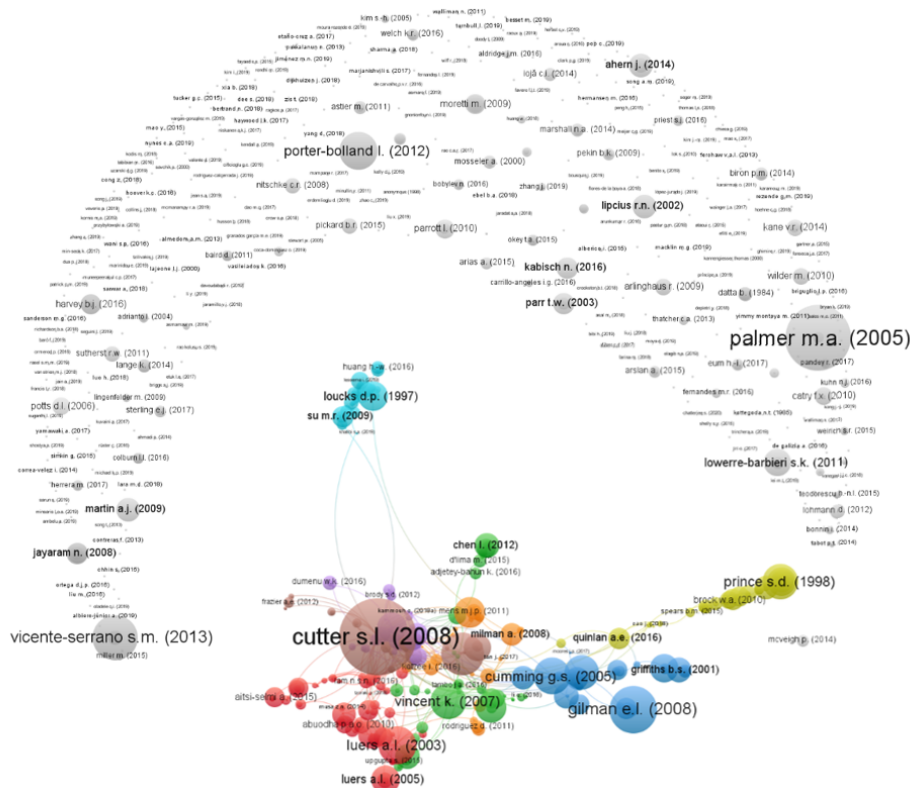


Fig. 4.2. Citation network analysis of the publications retrieved from Scopus. Citation network (Colour bubbles in the middle) is surrounded by publications with zero connection to it that were later excluded from the review.

Table 4.1. Resilience dimensions addressed in the reviewed literature.

Resilience dimension	Source	FAD
Social (S.)	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Cutter, 2016),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Kaye-Blake et al., 2019),(Kliskey et al., 2019),(Li, Lam, et al., 2016),(Hung et al., 2016),(Ainuddin & Routray, 2012),(L. Siebeneck et al., 2015), (Manyena et al., 2019),(Scherzer et al., 2019),(Kim & Park, 2018), (C. Zhang et al., 2016),(J. Song et al., 2018),(Yoon et al., 2016),(Fu & Wang, 2018),(Hu et al., 2018),(Mihunov et al., 2018),(J. Song et al., 2017)	+
Community capital	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Scherzer et al., 2019),(Kim & Park, 2018)	
Social capital (Social capacity)	(Cutter, 2016),(L. Siebeneck et al., 2015),(Fu & Wang, 2018)	
Population and demographics	(Cutter, 2016),(Li, Lam, et al., 2016),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)	
Community competence	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)	
Social-cultural capital	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)	
Human capital	(Yoon et al., 2016)	
Cultural	(Kaye-Blake et al., 2019)	

Resilience dimension	Source	FAD
Health	(Li, Lam, et al., 2016), (Mihunov et al., 2018)	
Socio economic	(Hung et al., 2016), (Abdrabo & Hassaan, 2015), (DasGupta & Shaw, 2015)	
Economic (Eco.)	(Cutter et al., 2014), (Cutter et al., 2010), (Moghadas et al., 2019), (Cutter, 2016), (Burton, 2015), (Singh-Peterson et al., 2014), (Hiete et al., 2012), (Kaye-Blake et al., 2019), (Li, Lam, et al., 2016), (Ainuddin & Routray, 2012), (L. Siebeneck et al., 2015), (Scherzer et al., 2019), (Kim & Park, 2018), (C. Zhang et al., 2016), (J. Song et al., 2018), (Yoon et al., 2016), (Fu & Wang, 2018), (Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019), (Hu et al., 2018), (Mihunov et al., 2018), (J. Song et al., 2017)	+
Institutional (Ens.)	(Cutter et al., 2014), (Cutter et al., 2010), (Moghadas et al., 2019), (Cutter, 2016), (Burton, 2015), (Singh-Peterson et al., 2014), (Hiete et al., 2012), (Kaye-Blake et al., 2019), (Ainuddin & Routray, 2012), (L. Siebeneck et al., 2015), (Scherzer et al., 2019), (Kim & Park, 2018), (C. Zhang et al., 2016), (Fu & Wang, 2018), (Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019), (DasGupta & Shaw, 2015)	+
Government	(Mihunov et al., 2018)	
Institutional and Infrastructural	(Hung et al., 2016)	
Infrastructural (Inf.)	(Cutter et al., 2014), (Cutter et al., 2010), (Moghadas et al., 2019), (Cutter, 2016), (Burton, 2015), (Singh-Peterson et al., 2014), (Hiete et al., 2012), (Manyena et al., 2019), (Scherzer et al., 2019), (Kim & Park, 2018), (C. Zhang et al., 2016), (J. Song et al., 2018), (Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019), (Mihunov et al., 2018), (J. Song et al., 2017)	+
Physical	(Kliskey et al., 2019), (Ainuddin & Routray, 2012), (Yoon et al., 2016), (Fu & Wang, 2018), (DasGupta & Shaw, 2015)	
Environmental (En.)	(Cutter et al., 2014), (Moghadas et al., 2019), (Burton, 2015), (Kaye-Blake et al., 2019), (Manyena et al., 2019), (Scherzer et al., 2019), (Kim & Park, 2018), (Yoon et al., 2016), (Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019), (Abdrabo & Hassaan, 2015), (Mihunov et al., 2018), (J. Song et al., 2017), (Mihunov et al., 2019)	+
Biophysical	(Hung et al., 2016)	
Ecological	(C. Zhang et al., 2016), (Delgado-Ramos & Guibrunet, 2017a), (Hu et al., 2018)	
Natural	(J. Song et al., 2018)	
Environmental capacity	(Yoon et al., 2016)	

4.3 Data Analysis Process

Following the extraction of the sources, a framework analysis has been applied to analyse the database. Framework analysis is an advanced method dedicated to qualitative data (e.g. text) through the following steps: familiarisation, coding, identifying themes, charting, mapping, and interpretation (Dudovskiy, 2016) ([Figure 4.3](#)). This method helps to identify patterns of meaning in seemingly unrelated material (Neuendorf, 2019).

In this research, coding has been done after familiarisation and immersion in different sets of indicators that served to measure resilience dimensions. Codes have been established for indicators related to each of the dimensions based on what they are measuring, called a variable. For example, “% Population finished secondary level of education” (Ainuddin & Routray, 2012; Burton, 2015; Cutter, 2016; Hung et al., 2016; Kliskey et al., 2019; Kotzee & Reyers, 2016; Li, Lam, et al., 2016; Yoon et al., 2016) and “Adult education

and training program per 1,000 persons” (Burton, 2015; Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019) both measure some features related to education level and quality. Therefore, they have been coded as “education level and quality” as one of the variables.

After coding all the indicators and defining the variables, themes have been generated by reviewing the variables and identifying patterns among them. For example, education level & quality, traditional knowledge, and public expenditure on education have all been identified as sub-categories of education and knowledge, which is one of the themes. These themes are referred to as sub-domains. Through the first three stages, all sub-domains and variables related to each dimension have been determined ([Figure 4.4](#)).

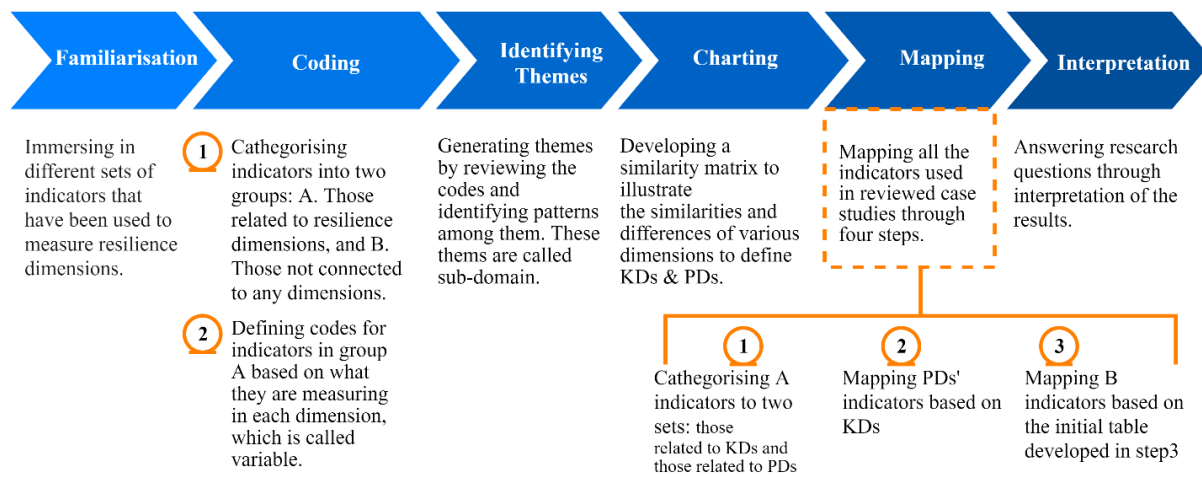


Fig. 4.3. Data analysis process.

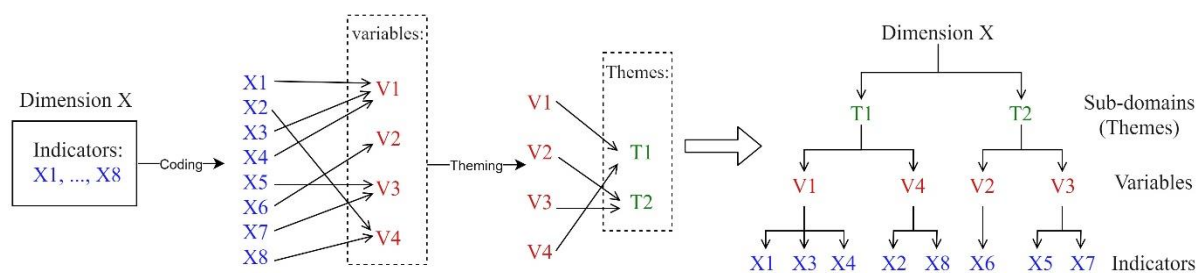


Fig. 4.4. Schematic overview of the coding process and identifying themes. Defining variables through the coding process and defining sub-domains from variables through theming.

In the next stage, a similarity matrix has been developed to illustrate the similarities and differences of various resilience dimensions based on the co-occurrence of sub-domains and the co-occurrence value. To develop the similarity matrix, the dimensions frequently addressed in the literature (FADs) were compared

with much less consistently addressed dimensions, called peripheral dimensions (PDs). Here, similarities have been defined based on the co-occurrence of sub-domains. The co-occurrence value has also been calculated as a confidence measure to justify the strength of the relationship between two sub-domains. Higher co-occurrence has been measured based on the number of similar variables related to the two similar sub-domains that defines whether the PDs can be considered as similar to the relevant FAD to resolve the existing terminology disagreement. Any relationships with 50% agreement or greater represent moderate confidence, and 75% or more represent high confidence (Paul, 2014). [Table 4.2](#) presents the developed similarity matrix that determines the key resilience dimensions, and the results are summarised in [Table 4.3](#). According to the similarity matrix ([Table 4.2](#) and [Table 4.3](#)) all the PDs have been covered by the FADs, meaning these five dimensions are the key resilience dimensions. In the following section, the similarity matrix conceptualises the resilience dimensions.

Table 4.2. Similarity matrix to compare frequently addressed dimensions (FADs) (on the top) with peripheral dimensions (PDs) (on the left). * Shows some co-occurrence exists. Colours shown in the 5 columns demonstrate the strength of co-occurrence of the subdomains of frequently addressed resilience dimensions (social, economic, institutional, infrastructural, and environmental) with those of peripheral dimensions. **Institutional.

	D	Social (S)							Economic (Eco.)				(Ins.)**		Infrastructural (Inf.)							Environmental (Env.)										
Dimintions (D)	Sub-Domains (SD)	Education & Knowledge (E&K)	Population & Demographics (P&D)	Community Strength (CSt.)	Health (He.)	Economic Capacity (Ec.C)	Social Protection (SP)	% Coverage of PDs by FAD	Household Capacity (HC)	Employment (E)	Income (I)	Business Activity & Production (BA&P)	Financial Services (FS)	% Coverage of PDs by FAD	Preparedness (P)	Recovery Response (RR)	% Coverage of PDs by FAD	Energy, Water & Sanitation (EW&S)	Housing (Ho.)	Health Infrastructure (HI)	Economic Infrastructure (EI)	Education (Ed.)	Community Services (CSe.)	Emergency Response (ER)	Transportation (T)	Communication (Co.)	% Coverage of PDs by FAD	Agriculture (A)	Ecosystem Functionality (EF)	Society Impact (SI)	Environmental Policies (EP)	% Coverage of PDs by FAD
Community Capital (Cca.)	CSt.		*																													
	SP						*																									
	He.			*																												
Social Capital (SC)	P&D	*																														
	E&K		*																													
	CSt.			*																												
	SP				*																											
Population and Demographics (P&D)	P&D	*																														
	He.			*																												
	E&K	*																														
	CSt.		*																													
	Ec.C				*																											
Community Competence	SP					*																										
	CSt.		*																													
	Ec.C				*																											
Social-Cultural Capital (SCC)	SP					*																										
	He			*																												
	P&D	*																														
	CSt.		*																													
	E&K	*																														
Health (He.)	He.		*																													

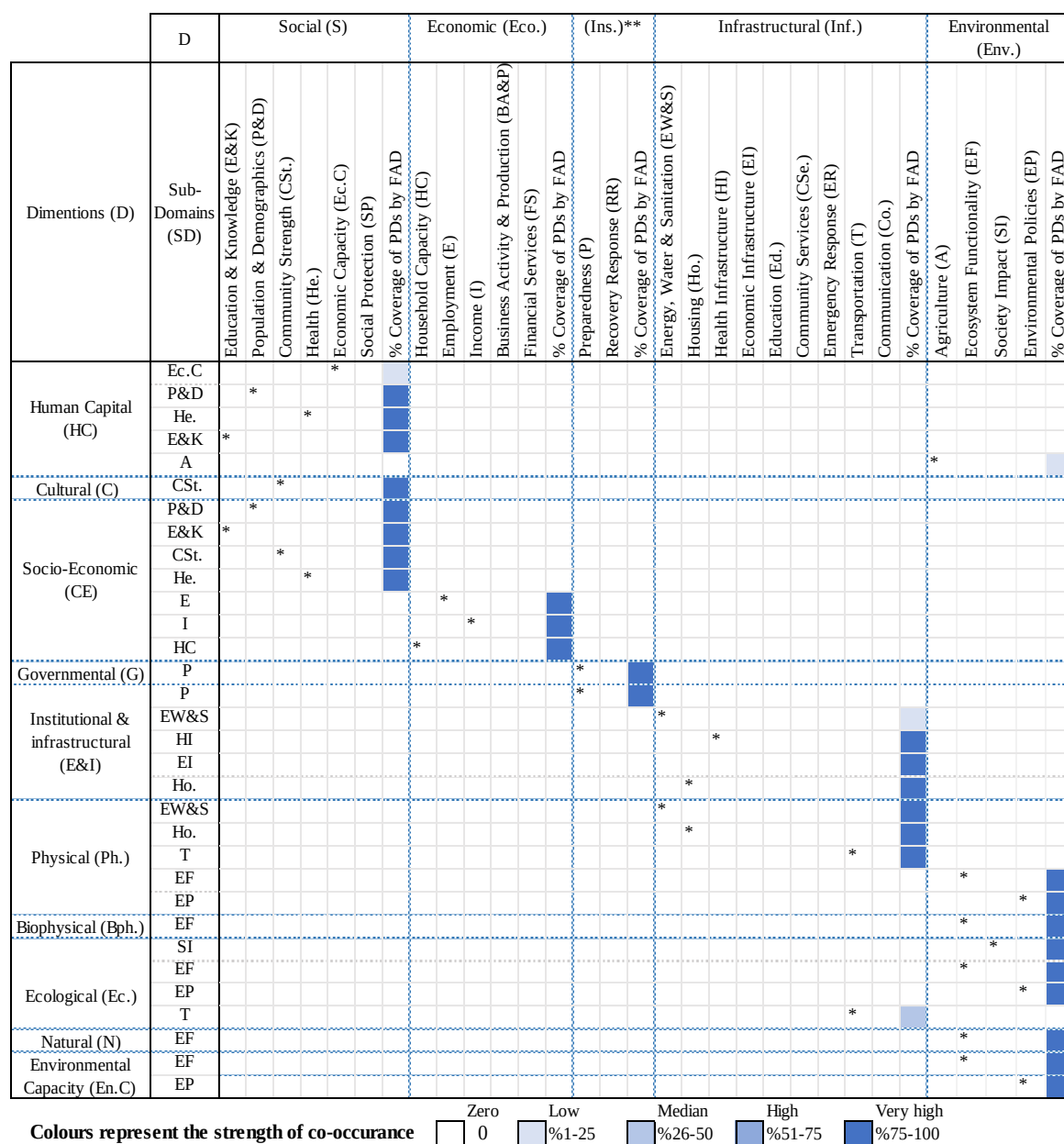


Table 4.3 Comparison of Frequently Addressed Dimensions (FADs) with Peripheral Dimensions (PDs). “✓” shows existing co-occurrence.

PDs	FADs					Common sub-domains
	S.	Eco.	Ins.	Inf.	En.	
Community capital	✓					Community Strength – Social Protection – Health
Social capital (Social capacity)	✓					Population & Demographics – Education & Knowledge – Community Strength – Social Protection
Population & demographics	✓					Population & Demographics – Health – Education & Knowledge – Community Strength – Economic Capacity
Community competence	✓					Community Strength – Social Protection
Social-cultural capital	✓					Population & Demographics – Health – Education & Knowledge – Community Strength – Economic Capacity – Social Protection
Health	✓					Health

PDs	FADs					Common sub-domains
	S.	Eco.	Ins.	Inf.	En.	
Human capital	✓					Health – Education & Knowledge – Economic Capacity – Social Protection – Agriculture
Cultural	✓					Community Strength
Socio economic	✓	✓				Population & Demographics – Health – Education & Knowledge – Community Strength – Employment – Income- Household Capacity
Government		✓				Preparedness
Institutional & Infrastructural			✓	✓		Preparedness – Energy, water & sanitation – Health Infrastructure - Economic – Infrastructure – Housing
Physical				✓	✓	Energy, water & sanitation – Transportation – Housing – Ecosystem Services & Impact – Environmental Policies
Biophysical					✓	Ecosystem Services & Impact
Ecological					✓	Society Impact – Ecosystem Services & Impact – Environmental Policies – Transportation
Natural					✓	Ecosystem Services & Impact
Environmental capacity					✓	Environmental Policies

4.4 Conceptualising Resilience Dimensions Based on the Results

After incorporating all aspects of peripheral dimensions in frequently addressed ones, the key resilience dimensions have been conceptualised as the following.

4.4.1 Economic Dimension

The economic dimension represents financial capacity at two levels of features/sub-domains: people (households and individuals) and the government.

The financial capacity of people represents income (I), employment (E), households' capacity (HC) or assets (e.g. vehicle, savings, house), as well as the availability of financial services (FS) to support them, such as any type of insurance.

The government's financial capacity represents business activity and production (BA&P), such as economic diversity and capacity, income (from business activities, production, tax, land), and expenditure on, for example, construction and mitigation (more information on economic features/sub-domains can be found in [Appendix 1](#)).

Socio-economic is the only PD that is partially related to this dimension. This PD considers people's financial capacity or circumstances, which is defined in the economic dimension, as well as the features related to people and the population, which are measured in the social dimension ([Figure 4.5](#)).

4.4.2 Institutional Dimension

The institutional dimension measures features/sub-domains concerning government performance and mitigation actions in line with preparation for, response to, and recovery from stresses.

Preparedness (P) highlights mitigation actions and achievements in all social, economic, infrastructural, environmental, and governmental aspects that are the responsibility of administrations when it comes to preparing for stress-related events. The social aspect, for example, describes populations' disaster knowledge and training prepared by the government or voting as an indication of social engagement in government activities. The economic aspect defines government budget allocation on preparedness, including insurance coverage and expenditure on mitigation strategies. The infrastructural aspect describes the availability of essential infrastructure to respond to any stress, such as shelters and evacuation routes. It also measures features of the existing infrastructure that define the level of resistance to any stress.

Recovery response (RR) covers protective actions by the government to help society and the environment to help victims recover from disasters (e.g. cash aid, home loan, and psychological support). More details on features/sub-domains of institutional dimensions are explained in [Appendix 1](#). The government PD relates to the financial capacity of people, measured in the institutional dimension ([Figure 4.5](#)).

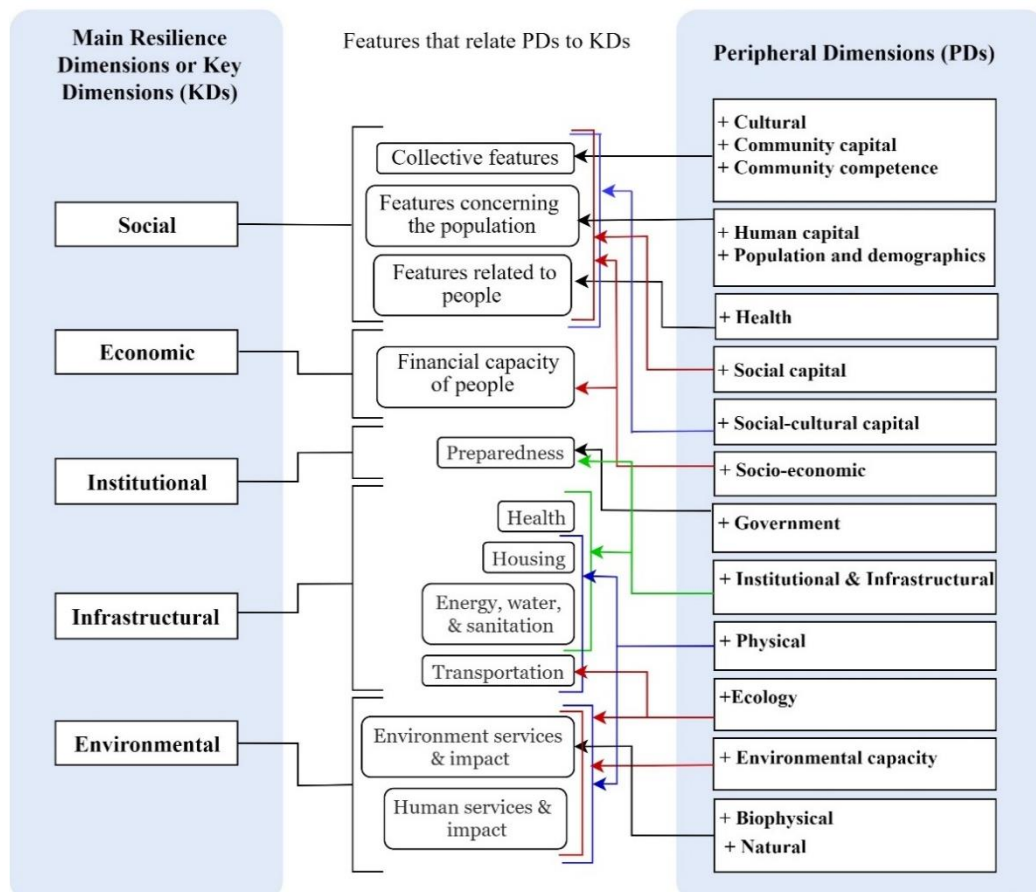


Fig. 4.5. Resilience dimensions. Dependent (peripheral) dimensions and their relationships with independent (key) dimensions. Each of the feature (middle column) include one or more resilience sub-domains (see sections 4.4.1-4.4.5 for more details).

4.4.3 Infrastructural Dimension

The infrastructural dimension deals with accessibility, quality, and functionality of different features/sub-domains of infrastructure (housing (Ho.), communication (Co.), transportation (T), energy, water, and sanitation (EW&S), health infrastructure (HI), economic infrastructure (EI), education (Ed.), emergency response (ER), and community services (CSe.)) in times of stress. This includes access to infrastructural services, including EW&S, housing, road networks, and telecommunications. Included here are the functionality of HI (e.g. number of hospital beds), communication (for warning and flow of information), and transportation (for evacuation) when shocks strike. This also measures the quality of the infrastructure, such as the quality and age of housing and road safety (see [Appendix 1](#) for more information on features/sub-domains).

The Institutional & infrastructural PD is considered a dimension dependent on both the infrastructural and institutional dimensions. It comprises some features of the institutional (disaster preparedness), and some of the infrastructural (housing, health, and energy, water, and sanitation related to infrastructural dimension) dimensions ([Figure 4.5](#)).

4.4.4 Environmental Dimension

The environmental dimension monitors features/sub-domains of: firstly, the environment services and impacts; and secondly, human services and impacts

The environment services and impacts include agricultural activities (A) and ecosystem's functionality (EF). Agriculture defines the ability of local farmers, horticulturalists, etc., to produce food considering the environmental factors, such as the availability of good quality soil and land, and the diversity of produce. To measure productivity, other factors such as income and farm assets are measured. EF describes availability, accessibility, and the quality of land, soil, air, water, and wildlife, as well as natural hazards.

Human services and impacts include environmental policies (EP), and social impacts on the environment. Environmental policies monitor the efficiency of using natural resources and energy, as well as recycling and waste management systems. Society impact measures the impact of humans on the environment, such as environmental violations and overpopulation (more information on each of the features/sub-domains can be found in [Appendix 1](#)).

The physical PD has a connection with both features of infrastructural (energy, water, and sanitation, housing, and transportation) and environmental (environment services and impacts, and human impact) dimensions. The ecological PD also has connections with both infrastructural (transportation) and environmental (environment services and impacts, and human impact) dimensions. Biophysical and natural

capital is another PD is connected to the environmental dimension through environment services and impacts. Environmental capacity is the last PD that relates to environmental resilience through both features of this dimension (human and environment services and impacts) ([Figure 4.5](#)).

Results from comparing FADs with PDs in the similarity matrix prove that despite addressing diverse resilience dimensions in different studies, all of them are measuring five common concepts, i.e. social, economic, institutional, infrastructural, and environmental resilience. These are the dimensions that have frequently been addressed in the literature ([Appendix 1](#)). The results also show that PDs are almost completely covered in FADs, as shown in [Figure 4.5](#). Based on this, the literature on FADs can serve to integrate all other research. Furthermore it can be stated that to comprehensively incorporate resilience measurement in different assessments and frameworks, including the SDGs, the key five dimensions should be measured. The presented definitions for these five dimensions provide a context in which future indicators can be added. In the next section, all the indicators presented in different studies to measure resilience will be integrated into a one framework that measures the key resilience dimensions.

4.5 Baseline Resilience Framework

After defining key resilience dimensions, to develop the Baseline Resilience Framework (BRF) all the indicators found in reviewed case studies were mapped against the key dimensions ([Appendix 1](#)). The mapping took three steps to complete. In the first step, indicators in the literature were collected and categorised into two groups: (i) indicators in the literature in which resilience dimensions are indicated (sources in table 4.1); and (ii) those presented in the research where a set of indicators is proposed without indicating resilience dimensions related to them (Asadzadeh et al., 2015; Green et al., 2017; Links et al., 2018; Tan et al., 2017; Toubes et al., 2017; Tumini et al., 2017; Wu et al., 2016). In the next step, the indicators in the first group have been divided into two sets: those related to key resilience dimensions and those related to PDs. In the third step, indicators related to PDs have been mapped based on key resilience dimensions to form the initial table of unified indicators. Finally, after the completion of the initial table, the indicators not related to any dimensions in the literature (the second group defined in the first step) have been mapped with resilience dimensions based on the variables they measure (that is defined through the coding process).

In the framework, every group of indicators that is connected to a variable measures some features of a community, city, etc., that may reduce (shown in [Appendix 1](#) as a negative impact) or increase (shown in Table 4.3 as + in the impact column) the level of resilience in that specific spatial scale. For instance, the first indicator in the table (ratio of the people with a college education to the people with education less than high school) measures education level which is a feature associated with social resilience. Higher

education level reflects a level of social and emotional behaviour that fosters support shown by members of a community during an extreme event and increases social resilience (Cahill et al., 2012). On the other hand, “% Population who are illiterate” is another indicator for measuring education level that has a negative impact on social resilience.

In addition to contributing the present knowledge on the concept and the measurement of resilience dimensions, the table presents a holistic view of the relationships among different dimensions, which is overlooked in one-dimensional research. For example, Delgado-Ramos and Guibrunet (2017) measure ecological resilience exclusively (Delgado-Ramos & Guibrunet, 2017b), while Tan et al. (2017) evaluate economic resilience (Tan et al., 2017). This is while some trade-offs exist between environmental and economic dimensions (e.g. more production and economic growth increases energy consumption and emissions, which in turn compromises environmental resilience) (French et al., 2018). To emphasise the relationships in developing the framework, indicators that were repeated in two or more dimensions were retained in all of them. There are some indicators to measure environmental resilience in the economic dimension such as “Energy use for residential, commercial and industrial land use”. Similarly, voting is an indication of engagement in the social dimension is included in the institutional dimension, as it is a social factor that also measures government performance. Such indicators are kept in all dimensions through the mapping process to prevent personal judgments, and understand how the dimensions are linked. In some cases small changes have been made to make the indicators usable for all.

Some indicators have been generalised and shown by * in the table. For instance, % Population in Storm Ready communities is an indicator of disaster mitigation, which has been developed in the U.S. according to the data available (see stormready.noaa.gov). Similarly, % Population in communities with Citizen Corps program has been developed based on data availability in another U.S. government agency (citizen.corps.gov) (Cutter et al., 2010, 2014). These indicators have been generalised as % Population with access to local disaster training.

Another alteration relates to the context-specific indicators, such as % Housing units not built before 1970 and after 1994 (Cutter et al., 2014), that has been generated based on the quality of housing in the United States, but is invalid as an international indicator. Another example is % Farms in federal conservation, which is a wetland conservation program in the US (Mihunov et al., 2019), or drinking water treatment technology, which has been defined and scored based on the local technologies (Kliskey et al., 2019). These indicators have been excluded but variables have been included in the table if applicable.

The next type of generalisation is related to the impact of the indicator on the overall evaluation of resilience, which is usually defined as positive or negative. A specific indicator might be used in diverse

forms to indicate a positive or negative outcome. For example, Moghadas et al. (2019) measure the percentage of the population with a special need, which undermines resilience measurement (Moghadas et al., 2019). On the other hand, Scherzer (2019) measures the percentage of the population without special needs, which has a positive impact on the overall index of resilience (Scherzer et al., 2019). Since both measure a similar concept, one of them (positive or negative) can be included in the table.

Lastly, to finalise the table, references that contain a similar set of indicators used or presented by the same author have been considered as one source. For instance, Cutter et al. (2010) (Cutter et al., 2010), Cutter et al. (2016) (Cutter et al., 2016), and Cutter and Derakhshan (2018) (Cutter & Derakhshan, 2018) have used a similar set of indicators. Indicators related to these references have been entered in the table, but only one of the references has been kept. This has been similarly applied for Kammouh et al. (2019), (Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019) and Kammouh et al. (2018) (Kammouh et al., 2018), as well as Li et al. (2016) (Li, Wang, et al., 2016) and (Xiaolu Li et al., 2016). However, both Cutter et al. (2010) (Cutter et al., 2010) and Cutter et al. (2014) (Cutter et al., 2014) have been included in the table since there are some differences between the two sets of indicators, unlike the high volume of similarity.

This framework, besides providing a comprehensive set of indicators to measure resilience holistically, resolves two main consequences of the proliferation of resilience dimensions. The proliferation is rooted in disagreement about the terminology and labelling a concept with several words, which results in overlooking some aspects of resilience measurement and exacerbating the data unavailability issue. For instance, for assessing environmental resilience, several indicators measure biophysical, ecological, natural, or environmental capacity. Without understanding the similarity of the terms, one study might only consider a small group of indicators presented in the literature under each of these labels, and disregard some areas that are part of other labels. This framework is based on the consideration of these similarities and gathered all the indicators under one dimension (in this sample: environmental). This comprehensive view also helps to overcome the data unavailability problem by presenting alternative indicators to measure each dimension, sub-domain, and variable. The framework proposes a pool of indicators that can be evaluated for possible addition to the SDGs.

4.6 Chapter Summary

Resilience is a very broad and complex concept but nonetheless a key component of sustainability. It has been included in the United Nations' 2030 Agenda for Sustainable Development. However, one criticism is that resilience indicators constitute a very small proportion of the SDGs indicator framework (4 out of 231 indicators). This chapter has argued that the initial challenge to comprehensively incorporate resilience

measurement in the SDGs is the lack of a common agreement about resilience. The problem is the existence of several overlapping definitions and dimensions. To address the issue, this chapter analysed similarities and differences among the resilience dimensions reported in the literature. So these dimensions frequently addressed in the literature (FADs) were compared with peripheral dimensions (PDs) by developing a similarity matrix. The results showed a strong co-occurrence of PDs' sub-domains with those of FADs'. Based on the results, FADs that are social, economic, institutional, infrastructural, and environmental in character can be considered the key resilience dimensions. However, they do not cover all aspects of PDs.

In the next step, after incorporating all aspects of PDs in FADs, the key resilience dimensions have been conceptualised. Accordingly, the social dimension is one of the five resilience dimensions that describes the features related to the population (population and demographics), people (education, health, and financial status), and communities (collective features, such as social engagement and protection). The economic dimension embodies the financial features of a society at two levels: the people (employment, income, etc.) and the government (business activity and economic diversity and capacity). The institutional dimension demonstrates the government's ability to prepare for, respond to, and recover from any shocks or dangerous events. The infrastructural dimension evaluates the availability of different types of infrastructure in times of shock. Finally, the environmental dimension monitors the environment/human services and impact as a factor of community resilience.

Later, the key resilience dimensions, as well as their description that elaborates on their sub-domains and variables, function as a context in which all resilience indicators from the reviewed literature have been merged ([Appendix 1](#)). The developed pool of 318 indicators can be considered for the incorporation of resilience measurement in the SDGs. The framework also contributes to the resilience literature by resolving a common confusion of what is measured by resilience and what its dimensions are. It also provides a pool of indicators to measure each dimension, sub-domain, and variable and in this way improve the accuracy of the resilience measurement.

Despite what is described in this chapter, some questions still need to be answered so that the resilience measurement in SDGs are properly integrated. A pool of three hundred and eighteen (318) indicators have been developed (BRF), while the SDGs comprises 231 indicators; are there any common indicators in these two sets? How do these two relate to each other? How can the indicators be used in a case study? The following chapters (particularly 6 and 7) respond these questions.

CHAPTER 5

RESILIENCE MEASUREMENT – THE SDGS VERSUS THE BASELINE RESILIENCE FRAMEWORK (BRF)

5 Resilience Measurement – The SDGs Versus the Baseline Resilience Framework (BRF)

5.1 Introduction

As discussed in Chapter 2 an integrated framework to measure both resilience and sustainability is very important to assess future developments. The SDGs, as a universally accepted framework to measure sustainability and resilience, could potentially be a united framework. This chapter aims to examine the similarities and differences of measuring resilience applying the SDGs and the Baseline Resilience Framework (BRF) to test the need for incorporating more resilience indicators into the SDGs. As a pilot study Infrastructure Resilience has been measured at the national level using indicators from the SDGs and the BRF. To conduct the comparison, infrastructure resilience indexes (IRI) and infrastructure resilience global scale country-level maps have been built through both approaches. Resilience refers to the capacity of a system to prepare for, withstand, and recover from shocks and extreme events (Siebeneck and Cova, 2012; Lam et al., 2016; Ahern, 2011). Accordingly, infrastructure resilience demonstrates the ability of the network of physical systems to remain functional under conditions of extreme stress (David R, 2003). The physical systems consist of energy, transport, telecommunications, provision of water, sanitation, and safe disposal of waste, and housing (Palei, 2015).

5.2 Theoretical approaches

Generally, there have been two approaches to address infrastructure resilience in urban planning practice and literature. Primarily, it has been studied as a dimension of resilience (Cutter et al., 2010; Cutter, 2016; Singh-Peterson et al, 2014; Hiete et al., 2012; Manyena et al., 2019; Kim and Park, 2018; Zhang et al., 2016; Song et al., 2018; Kammouh et al., 2019). Infrastructure resilience has also been examined in sustainability approaches, where resilience is considered a chief component of sustainability (Marchese et al., 2018; Roostaie et al, 2019). Furthermore it is viewed as the key to achieving sustainability in SDGs (The sustainable infrastructure imperative, 2016; The Economist Intelligence Unit, 2019). Different aspects of infrastructure have been addressed in all 17 goals and 72% of the targets (Thacker et al, 2019). For instance, Goals 2, 3, 4, 6, and 7 consider basic services such as food, water, energy, and education. Likewise, Goals 11-15 cover environmental infrastructures (Bhattacharya et al., 2016). Despite the existence of several indicators and targets related to infrastructure, one goal has been especially devised to measure infrastructure resilience and will be discussed in the next part.

5.3 A Global Scale Country-Level Comparison of Resilience Measurement by the SDGs and the BRF

5.3.1 Measuring Infrastructure Resilience Using the Baseline Resilience Framework

Resilience frameworks, tools, and models have used several indicators to measure IR. [Table 5.1](#) shows the indicators that have been used in two or more sources. The indicators measure infrastructure resilience in

eight different sectors, namely energy, water & sanitation, housing, health, community services, education, emergency response, transportation, and communication.

Table 5.1. Indicators to measure infrastructure resilience in BRF.

Sectors	Indicators	Impact	Source
Energy, water & sanitation	1. % Employed persons working in public utilities (e.g. transportation)	+	(Scherzer <i>et al.</i> , 2019; Mihunov <i>et al.</i> , 2018)
Housing	2. % Housing units that are not mobile homes	+	(Cutter <i>et al.</i> , 2014; Cutter <i>et al.</i> , 2010; Moghadas <i>et al.</i> , 2019; Kammouh <i>et al.</i> , 2019; Mihunov <i>et al.</i> , 2018; Burton, 2015; Singh-Peterson <i>et al.</i> , 2014; Hiete <i>et al.</i> , 2012)
	3. % Average housing age	-	(Cutter <i>et al.</i> , 2014; Cutter <i>et al.</i> , 2010; Moghadas <i>et al.</i> , 2019; Kammouh <i>et al.</i> , 2019; Burton, 2015; Hiete <i>et al.</i> , 2012)
	4. % Vacant units that are for rent	+	(Cutter <i>et al.</i> , 2014; Cutter <i>et al.</i> , 2010; Kammouh <i>et al.</i> , 2019; Burton, 2015; Singh-Peterson <i>et al.</i> , 2014; Hiete <i>et al.</i> , 2012)
	5. Hotels/motels per 1,000 persons	+	(Cutter <i>et al.</i> , 2014; Cutter <i>et al.</i> , 2010; Scherzer <i>et al.</i> , 2019; Moghadas <i>et al.</i> , 2019; Kammouh <i>et al.</i> , 2019; Song <i>et al.</i> , 2018; Burton, 2015; Singh-Peterson <i>et al.</i> , 2014; Hiete <i>et al.</i> , 2012)
Health	6. Hospital beds per 1,000 persons	+	(Cutter <i>et al.</i> , 2014; Cutter <i>et al.</i> , 2010; Moghadas <i>et al.</i> , 2019; Kammouh <i>et al.</i> , 2019; Singh-Peterson <i>et al.</i> , 2014; Hiete <i>et al.</i> , 2012)
Community services	7. % Area of community services (e.g. recreational facilities) per total area	+	(Kammouh <i>et al.</i> , 2019; Song <i>et al.</i> , 2017)
Education	8. Public schools per 10,000 persons/or per square mile	+	(Cutter <i>et al.</i> , 2014; Cutter <i>et al.</i> , 2010; Scherzer <i>et al.</i> , 2019; Moghadas <i>et al.</i> , 2019; Kammouh <i>et al.</i> , 2019; Burton, 2015; Singh-Peterson <i>et al.</i> , 2014; Hiete <i>et al.</i> , 2012)
Emergency response	9. No. of fire/ police/ambulance stations and shelters per 1,000 people	+	(Scherzer <i>et al.</i> , 2019; Moghadas <i>et al.</i> , 2019; Cutter, 2016; Burton, 2015)
	10. Mean distance in meters from denser settlement areas to the nearest /hospital/fire/police station	-	(Scherzer <i>et al.</i> , 2019; Song <i>et al.</i> , 2018; Song <i>et al.</i> , 2017)
Transportation	11. Rail miles per square mile area	+	(Cutter <i>et al.</i> , 2014; Kammouh <i>et al.</i> , 2019; Kim and Park, 2018; Burton, 2015)
	12. Principle arterial miles per square mile	+	(Cutter <i>et al.</i> , 2010; Scherzer <i>et al.</i> , 2019; Moghadas <i>et al.</i> , 2019; Kammouh <i>et al.</i> , 2019; Burton, 2015; Singh-Peterson <i>et al.</i> , 2014; Hiete <i>et al.</i> , 2012)
	13. Major road egress points per 10,000 persons	+	(Cutter <i>et al.</i> , 2014; Kammouh <i>et al.</i> , 2019; Song <i>et al.</i> , 2017)
	14. Roads network density	+	(Manyena <i>et al.</i> , 2019; Scherzer <i>et al.</i> , 2019; Zhang <i>et al.</i> , 2016)
Communication	15. % Population with access to broadband internet service	+	(Cutter <i>et al.</i> , 2014; Moghadas <i>et al.</i> , 2019; Kammouh <i>et al.</i> , 2019)
	16. Average no. of Internet, television, radio, telephone, and telecommunications broadcasters per household	+	(Kammouh <i>et al.</i> , 2019; Mihunov <i>et al.</i> , 2018)

5.3.2 Measuring Infrastructure Resilience Using the SDGs

The SDG 9 (Build resilient infrastructure, promote inclusive and sustainable industrialisation and foster innovation) assesses the level of resiliency in infrastructure using 7 indicators ([Table 5.2](#)) (*Transforming our world: the 2030 Agenda for Sustainable Development*, 2015). These indicators are presented to evaluate the achievement of 5 related targets covering regional infrastructure, application of environment-friendly technologies, improving scientific proficiencies, enhancing financial/technical support, and accessing the communication. In this research, infrastructure resilience is measured through these two approaches to examine the similarities, differences, and the possibilities of developing a joint framework.

5.3.3 The Comparative Study

To compare the SDGs and BRF approaches, infrastructure resilience has been calculated and mapped based on both. Here, maps have been produced for the global level in line with the SDGs framework. Three steps

have been followed to produce the map: 1. data collection to measure the indicators, 2. calculating the infrastructure resilience index, and 3. producing the map.

Table 5.2. SDG9 Indicators related to the achievement of resilient infrastructure.

Targets	Indicators
9.1 Develop regional and trans-border infrastructure	9.1.1 Proportion of the rural population who live within 2 km of an all-season road 9.1.2 Passenger and freight volumes, by mode of transport
9.4 Resource-use efficiency and adoption of clean technologies	9.4.1 CO ₂ emission per unit of value added
9.5 Scientific research, and upgrade the technological capabilities	9.5.1 Research and development expenditure as a proportion of GDP 9.5.2 Researchers (in full-time equivalent) per million inhabitants
9.a Enhance financial, technological and technical support	9.a.1 Total official international support (official development assistance plus other official flows) to infrastructure
9.c Access to information and communications	9.c.1 Proportion of population covered by a mobile network, by technology

Data Collection: Global-level data for calculating the indicators summarised in both [Table 5.1](#) and [Table 5.2](#) have been extracted from the databases published online by The World Bank (*The World Bank DataBank*, 2014). Data related to all countries have been collected for the year 2014, which is the most recent data as far as the indicators are concerned. Except for indicator 9.1.1, data related to all the selected SDGs indicators have been collected. Data for most of the resilience indicators ([Table 5.1](#)) are unavailable at the country level. However, available data for the indicators 1,6,11, 15, and 16 have been collected.

Index development and mapping: In this research, in order to compare the measurement of infrastructure resilience in SDG9 and the BRF, infrastructure resilience index (IRI) has been calculated based on the two approaches. IRI represents countries' scores of infrastructure resilience between the lowest (0) and the highest (1) level of resiliency. IRI is developed based on a two-step method that is commonly used to develop a resilience index (Avila-Foucat & Martínez, 2018b; Roy et al., 2019; Tambo, 2016b). Primarily, the indicators have been linearly transformed to a scale between 0 and 1 to define normalised indicators (*NI*) (Equation 1).

$$NI = \frac{IV-LV}{HV-LV} \quad (\text{Eq. 1})$$

Where: *LV*, *HV*, and *IV* are the lowest, the highest, and raw value of the indicator, respectively. Later the normalised indicators have been aggregated applying equal weighing (Equation 2).

$$IRI = \frac{1}{n} \sum_{i=1}^n NI_i \quad (\text{Eq.2})$$

Where: *IRI* is the index score, and *n* denotes the number of indicators that data is available for them.

[Table 5.3](#) shows the index development process for a sample group of countries based on the SDGs indicators (see [Appendix 2](#) for the complete data set). In [Table 5.3](#), N/A is placed where a specific indicator is not applicable for a country (i.e., official found flow for the U.S.) or wherever data is not available.

Table 5.3. Infrastructure Resilience Index (IRI) based on SDGs and BRF.

Countries	Data Type	Indicators						IRI
		9.1.2	9.4.1	9.5.1	9.5.2	9.a.1	9.c.1	
Argentina	IV	12121913	0.252522	0.59278	1202.028	4.68×10 ⁸	143.6158	0.163449
	NI	0.015893	0.167264	0.135092	0.162088	0.063783	0.436571	
Georgia	IV	196589	0.263254	0.1849	1070.877	3.4×10 ⁸	133.8377	0.134936
	NI	0.000258	0.174876	0.039642	0.1441	0.046403	0.404339	
Malaysia	IV	49673884	0.332015	1.26275	2029.607	10864840	150.4309	0.219459
	NI	0.065128	0.223641	0.291875	0.275599	0.001472	0.459036	
United States	IV	7.63×10 ⁸	0.31687	2.73389	4217.349	N/A	111.5562	0.551121
	NI	1	0.2129	0.636143	0.575671	N/A	0.330892	

After calculating the IRI based on the two approaches, world maps of infrastructure resilience have been produced using the Choropleth Mapping method in the GIS environment. To produce these maps, IRIs were classified into five categories to show the infrastructure resilience level from very low to very high, based on the Jenks Natural Breaks Optimisation method ([Figure 5.1](#)) (*The World Bank-DataBank*, 2014).

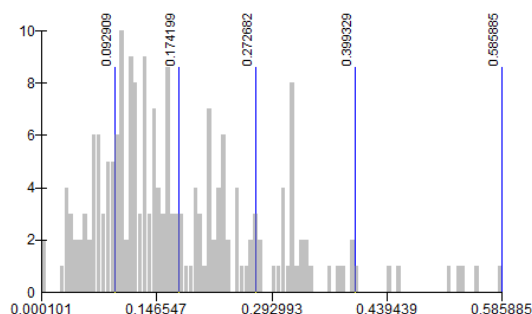


Figure 5.1 GIS classification of SDG IRI based on the Jenks Natural Breaks Optimisation method.

5.4 Comparing the Approaches

Results from infrastructure resilience measurement based on the BRF and the SDGs show a noticeable difference as can be seen in [Figure 5.2](#).

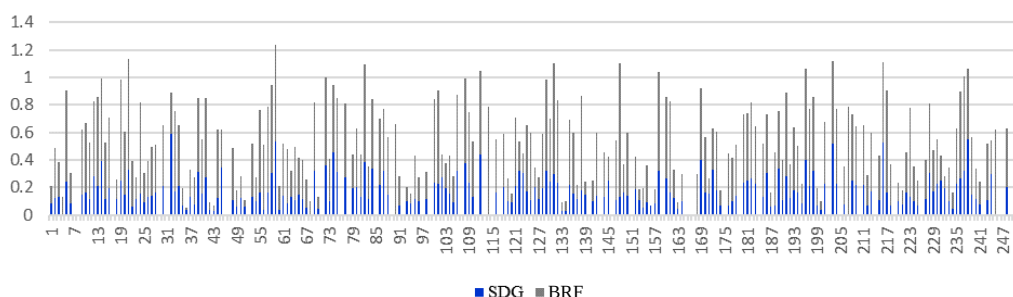


Figure 5.2. IRI calculated for countries based on the SDGs and the BRF. X axis represents countries (see [Appendix 2](#)).

Maps of the world's countries also demonstrates different levels of infrastructure resilience based on the BRF ([Figure 5.3](#)) and the SDGs ([Figure 5.4](#)). infrastructure resilience has been categorised into five levels on the maps, where the biggest numerical values show the highest level of IR. Australia, for instance, is shown as a country with a highly resilient infrastructure based on the SDGs, while it is categorised as a country with a moderate level of infrastructure resilience based on the BRF. Similarly, the level of infrastructure resilience in Mexico is very low based on the BRF, but moderate according to what the SDGs present.

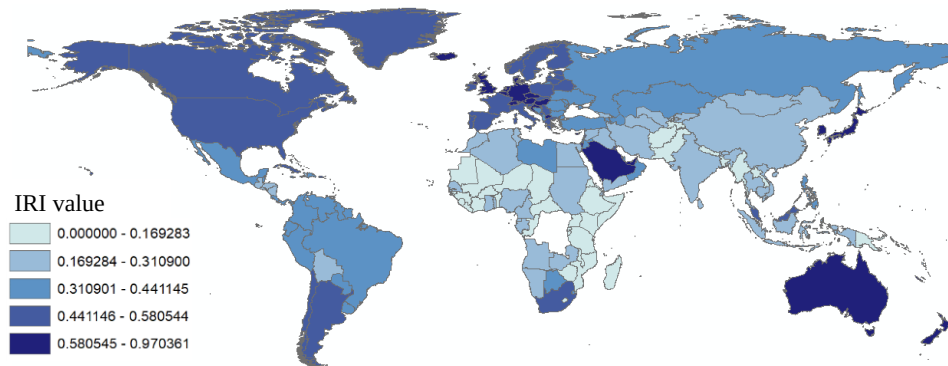


Figure 5.3. Mapping infrastructure resilience based on BRF. Countries are not coloured where data is not available.

The difference between the results from the two approaches suggests that perhaps none of the methods can provide a high level of confidence when applied separately. However, for this pilot study one goal has been considered in isolation, and the remaining question is whether more indicators from the SDGs measure aspects of infrastructure resilience that could be considered. This will be explored in Chapter 6.

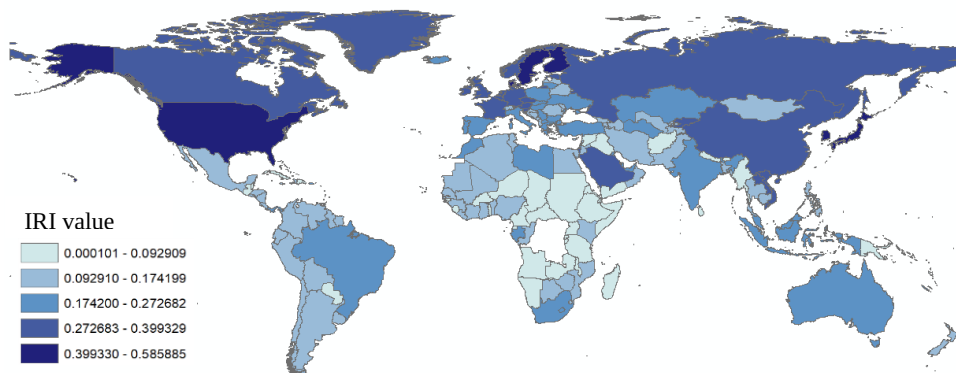


Figure 5.4. Mapping infrastructure resilience based on the SDGs. Countries are not coloured where data is not available.

5.5 A Common Framework to Measure Resilience

The SDGs, as a universally accepted framework, provide the opportunity for evaluating IR. However, the difference between the two maps and IRIs indicate that the SDGs indicators are less likely to be comprehensive enough to demonstrate a clear representation of IR. However, SDGs can be considered as a context for which the common framework can be built. Here, to examine this possibility, the two sets of indicators presented by the BRF and the SDGs have been compared.

Comparing the infrastructure resilience indicators in the BRF ([Table 5.1](#)), and SDG 9 ([Table 5.2](#)), it can be concluded that there is only one partially similar indicator among the two approaches. SDG indicator 9.c.1 and resilience indicator 16 both measure the mobile network coverage. Apart from this exception, the comparison shows here are many aspects of infrastructure resilience that are not addressed in SDG9. Some of these potential indicators are measuring common features introduced in SDG 9 targets, including education, transportation, and communication ([Figure 5.5](#)). These indicators (1, 8, 11-16 [Table 5.1](#)) can be introduced in SDG 9 to improve the accuracy of the measurement related to each target. Other features of resilient infrastructure, including housing, health, emergency response, and community services, can be incorporated in SDG9 to improve the accuracy of the measurement.

On the other hand, in this study, infrastructure resilience indicators of the SDGs have been extracted from only goal 9, while there might be some other indicators measuring IR. For instance, resilience indicator 7 is similar to SDG indicator 11.7.1 (average share of the built-up area of cities that is open space for public use for all, by sex, age, and persons with disabilities). Likewise, housing and community services have been addressed in SDGs in goal 11 (Make cities inclusive, safe, resilient, and sustainable). Target 11.1 considers safe housing, and target 11.7 evaluates the open space that is addressed as one of the community services in infrastructure resilience measurement methods. Therefore, the accuracy of the infrastructure resilience measurement or generally resilience measurement by the SDGs might not be accurate when goals are considered in isolation.

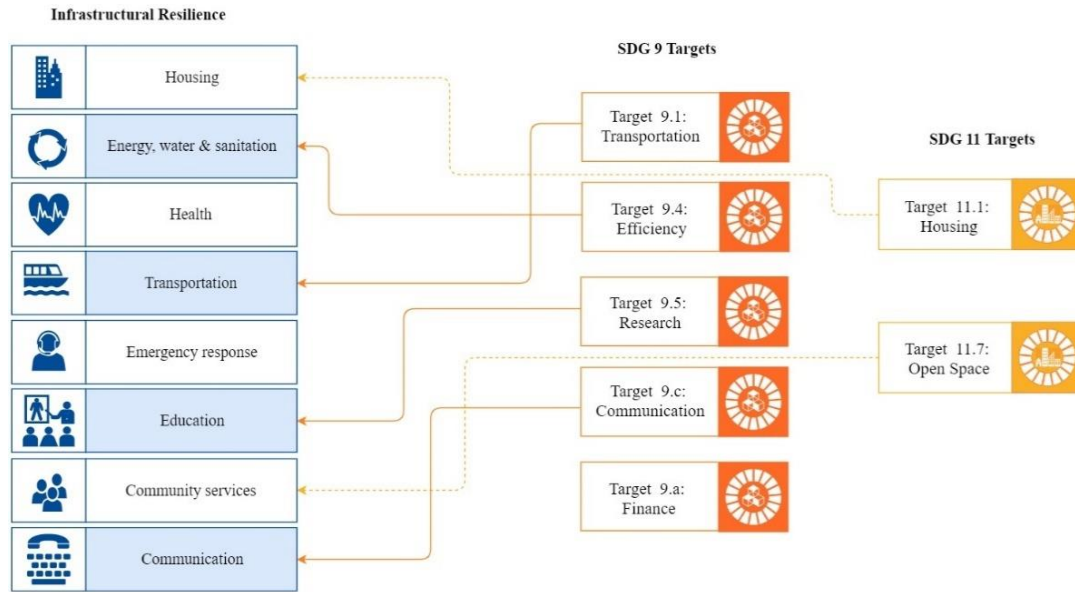


Figure 5.5. Common aspects of measuring infrastructure resilience using SDG and BRF.

5.5 Chapter Summary

This chapter explored the need to integrate resilience measurement into the SDGs. Since infrastructure is a key aspect of understanding future events, this dimension of resilience has been selected to conduct a pilot study that comparatively measures infrastructure resilience using the SDGs and the BRF at the national level throughout the world.

In the SDG, goal 9 is devoted to infrastructure resilience. Prior to and after the adoption of the 2030 Agenda on Sustainable Development in 2015, resilience frameworks measured infrastructure resilience using indicators. Measuring infrastructure resilience through two approaches generated some similarities and differences. The existing differences demonstrate the accuracy issue that occurs in both approaches. This might originate either in using a limited number of indicators in each method or data scarcity. On the other hand, similarities relate to the common aspects of infrastructure resilience that are measured in both methods, including transportation, education, communication, and energy, water, and sanitation. The differences and similarities suggest the necessity for examining the possibility of developing an integrated measurement whereby SDGs cover more aspects of resilience. Solving the data availability issue presents more potential indicators to measure each aspect of resilience, and is universally applied (a sample of the global application of the SDGs can be seen in section 1.1). However, some gaps should be covered, to begin with. In order to consider the SDGs as the context, goals should not be looked at in isolation. Yet, it is not clear which indicators from which of the goals address what aspects of resilience. Another problem relates to data unavailability, but this can be overcome by either adding alternative indicators from the BRF or using spatial data and techniques to generate the data. The following chapter answers some of the questions

by comparing the BRF with the SDGs, finding the areas of resilience assessment that have been covered or overlooked in the SDGs and proposing the resolutions.

CHAPTER 6

AN INTEGRATED FRAMEWORK TO MEASURE RESILIENCE AND SUSTAINABILITY

6 An Integrated Framework to Measure Resilience and Sustainability

6.1 Introduction

Chapter 5 described the importance for developing an integrated framework that measures resilience and sustainability in the SDGs. To do so, initially the first research question to be answered is “To what extent do the SDGs measure resilience?” To determine what aspects of resilience are covered or overlooked in the SDGs, this chapter compares the baseline resilience framework (BRF) with the SDGs for all five resilience dimensions.

6.2 Developing the Integrated Framework to Measure Resilience and Sustainability in the Context of the SDGs

To compare the SDGs indicators with the BRFs several text similarity methods can be applied from lexical matching methods to more complex semantic ones. However, text similarity metrics will generally fail in identifying semantic connections between text that originates from the similarity of the concepts rather than the words (Mihalcea et al., 2006). For instance, the SDGs indicator 5.4.1., “proportion of time spent on unpaid domestic and care work, by sex, age and location”, and one of the BRF indicators, “minimum wage rate per day” (L. Siebeneck et al., 2015) both address income level, which is linked to economic resilience. This semantic similarity, however, is hard to define using automatic text similarity methods.

Here, to enhance the accuracy of the defined semantic similarity, comparing the two frameworks has been done in three steps. In the first step (coding), both groups of indicators from the BRF and the SDGs have been coded applying the thematic coding method using NVivo software. This method enables us to code phrases or sentences (here indicators) to describe aspects of the data (their connection with resilience variables, sub-domains, and dimensions) (Gibbs, 2007). Therefore, each of the SDGs and BRF indicators are deemed to be a unique code. Next in the clustering step, the matrices of coding have been developed based on the nearest neighbour method to find the connections between overlapping themes (shared variables) to form clusters (Guest, G., MacQueen, K. M., & Namey, 2012) ([Figure 6.1](#)). Finally, the results from the matrices have been analysed through the Cosine similarity method to define to what extent the SDGs indicators assess the resilience dimensions (Muflikhah & Baharudin, 2009).

First Step: Coding

For the coding purpose, a code tree has been developed based on the connection of each of the BRF indicators with any of the resilience dimensions, sub-domains, and variables ([Figure 6.2](#)). This hierarchy has been developed in the BRF. Here, applying the same hierarchy for coding of the SDGs indicators makes it possible to determine the similarities between the two group of codes.

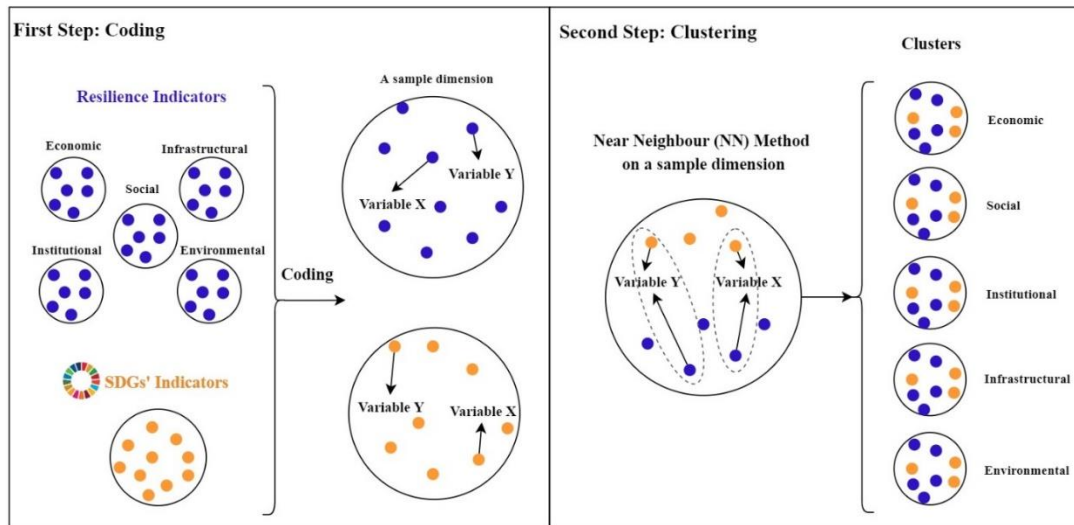


Fig. 6.1. Conceptual graph for the first two steps of the method for mapping SDGs indicators against resilience dimensions, sub-domains, and variables. First step: coding and connecting indicators of resilience (BRF) and the SDGs to variables. Second step: paring the indicators from the BRF with those from the SDGs that are connected to similar variables to develop clusters of indicators relevant to each resilience dimension.

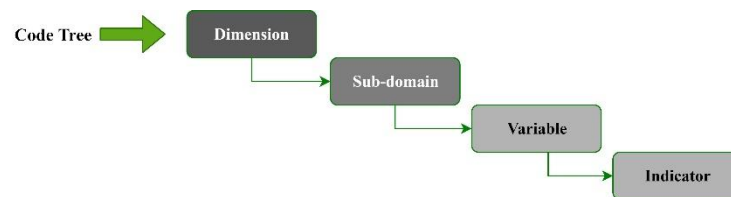


Fig. 6.2. Coding process for BRF indicators.

As stated in Chapter 4, there are five key dimensions for resilience: social, economic, institutional, infrastructural, and environmental. The social dimension relates to the features of population and demographics, people's health and knowledge, and communities' collective characteristics. The economic dimension addresses the financial aspects of a society. The institutional dimension demonstrates the government's organisational functionality in times of adverse change. The infrastructural dimension looks at the availability of infrastructure, and finally the environmental dimension denotes human-environment interactions.

In each dimension there are several sub-domains related to different features of the dimension. For example, the social dimension addresses demographic features, which are one of the social sub-domains. At the lower level there are some variables in every sub-domain that relate to different categories of features related to that sub-domain. For example, for the demographic sub-domain there are some variables such as population change and population size. The variables are measured by indicators that form the lowest level

of a code tree. Here, for coding the resilience indicators, this recently developed hierarchy of variable, sub-domains, and dimensions for resilience indicators has been followed ([Figure 6.3](#)).

After coding the BRF indicators (see [Appendix 3](#) in the supplementary material for the codebook), all 231 SDG indicators have been coded applying the same method and the set of codes established in the previous step ([Figure 6.2](#)). The similar coding connects each of the SDGs indicators to the resilience variables ([Figure 6.3](#)). To avoid any bias in the code definition, as mentioned before, each of the SDGs indicators (the entire sentence) have been considered as a code. Later the codes (indicators) have been connected to a variable based on the general aspect of resilience that they measure. For instance, in [Figure 6.3](#), the SDGs indicator 9.2.2 that measures some aspect of employment, is connected to workforce. Later, based on the similarity of the SDGs and BRF indicators for each variable, the coding matrices have been developed applying the nearest neighbour method. Nearest neighbour is a clustering technique that categorises the unknown data points (in this case, indicators) based on their nearest neighbour (here variables) whose class is already identified (Bhatia & Vandana, 2010).

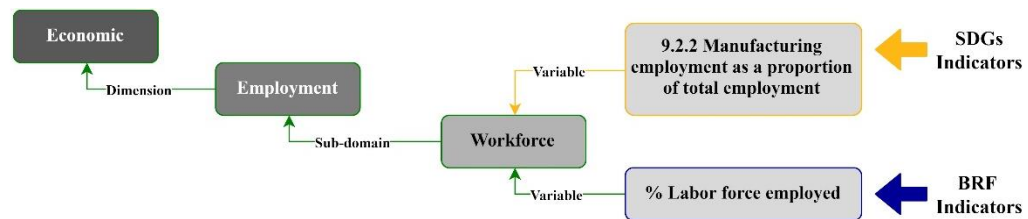


Fig. 6.3. A sample coding of the SDGs indicators by employing coding method, procedure, and developed code tree based on the baseline resilience framework (BRF).

During the coding process for the SDGs indicators, where an indicator has relationships with more than one variable, more codes have been defined for the indicator to reflect the SDGs coverage of all the relevant resilience sub-domains. For instance, the SDGs indicator 2.1.2 (“Prevalence of moderate or severe food insecurity in the population” (L. Siebeneck et al., 2015)) has been connected to two sub-domains of social resilience: “health” and “community strength” (see [Appendix 4](#) in the supplementary material).

Second Step: Clustering

Following the completion of the coding process, by connecting the SDGs and BRF indicators to similar variables, sub-domains, and dimensions, five indicator clusters have been formed. Each cluster is related to one of the resilience dimensions and incorporates two group of indicators, those from the SDGs and those from the BRF ([Figure 6.1](#)). Later, a matrix has been developed for each cluster to find the shared and unshared variables between the two groups of indicators ([Figure 6.4](#)).

The matrices have an arrangement of $V = \{v_1, \dots, v_n\}$ which serves as an array of variables in their columns (n columns), and $F = \{f_1, \dots, f_m\}$ is an array of frameworks in their rows (m rows). Consider $I_{No.}(f, v)$ denote the number of indicators that are available for $v \in V$ in $f \in F$. Since each row can be mathematically considered as a vector (Livesley, 1964), the i th framework can be represented as an n -dimensional vector:

$$\vec{f}_i = (I_{No.}(f_i, v_1), \dots, I_{No.}(f_i, v_n))$$

In this case, there are two frameworks (BRF and SDGs) and n variables related to each of the five clusters that form $2 \times n$ matrices for each cluster ([Figure 6.4](#)). As discussed, each matrix also forms two vectors; let us consider $\vec{R}$ for the vector that represents the BRF's row and $\vec{S}$ for the SDGs:

$$\vec{R} = (I_{No.}(r, v_1), \dots, I_{No.}(r, v_n)), \quad \vec{S} = (I_{No.}(s, v_1), \dots, I_{No.}(s, v_n))$$

Where r and s are, respectively, the BRF and the SDGs.

The developed vectors represent the number of indicators that the SDGs and the BRF have for each of the variables. However, to understand to what extent the SDGs cover resilience measurement, knowing whether they have any indicators to assess each of the resilience variables (yes or no, 1 or 0) is enough. Additionally, converting the decimal values to binary reduces the bias that may occur through the coding process. Consequently, the following function has been applied to $\vec{R}$ and $\vec{S}$ to convert decimal vectors to binary:

$$F(I_{No.}(f, v)) = \begin{cases} 1 & I_{No.}(f, v) \geq 1 \\ 0 & \text{Otherwise} \end{cases}$$

Therefore:

$$\vec{R}_b = (F(I_{No.}(r, v_1)), \dots, F(I_{No.}(r, v_n))), \quad \vec{S}_b = (F(I_{No.}(s, v_1)), \dots, F(I_{No.}(s, v_n)))$$

Due to $\vec{R}_b$ and $\vec{S}_b$ formed from binary data (have or not have an indicator for any variables) they can also represent sets as written below:

$$R_b = \{r \in F(I_{No.}(r, v_i)) \neq 0\}, \quad S_b = \{s \in F(I_{No.}(s, v_i)) \neq 0\}$$

Both forms of sets and vectors make it possible to apply a wide range of methods to calculate the similarity between the BRF and the SDGs.

Third Step: Evaluating the similarity of the SDGs and the BRF

In the third step, the small distance between $\vec{R}$ and $\vec{S}$ in each cluster has been calculated to measure the similarity between the BRF and the SDGs (Pang-Ning et al., 2005). Several methods have been devised to

measure the small distance, the most popular being the Overlap coefficient (Vijaymeena & Kavitha, 2016), the Jaccard similarity coefficient (Alqadah & Bhatnagar, 2010), and the Cosine similarity (Huang, 2008; Klawonn et al., 2013). Following these measurement methods, each has been tested based on the research objectives of this thesis to select the best matching approach ([Appendix 5](#) in the supplementary material). Here, Cosine has been selected to measure the similarity of frameworks where any relationships with 50% similarity or greater represent moderate similarity, while 75% or more represent a high level of similarity (Paul, 2014).

In this study, after evaluating the similarity of the frameworks, the aspects of resilience that have been addressed along with the relevant goals and indicators are documented in [Appendix 4](#) (refer to the supplementary material). Later this table has ranked the coverage of resilience dimensions by each of the goals since results from binary data do not represent the strength of the links between goals and resilience dimensions. Therefore, [Appendix 4](#) serves to visualise the similarity between the SDGs and resilience dimensions in the parallel coordinate plots (PCP) ([Figure 6.5](#)). After creating the PCPs, ranking the coverage of resilience dimensions by the SDGs has been conducted based on Weighted Standard Deviation (WSD) ([Figure 6.6](#)):

$$WSD = \sqrt{\frac{\sum_{i=1}^N w_i (x_i - \bar{x}_w)^2}{(N' - 1) \frac{\sum_{i=1}^N w_i}{N'}}}$$

Where x_i is the number of available indicators in each goal for resilience dimensions, w_i is the frequency of x_i , $\bar{x}_w$ is the weighted mean, N is the number of x_i , and N' is the number of non-zero weight. Based on WSD, goals will be categorised in classes based on having low to very high coverage for a resilience dimension.

6.3 The SDGs Coverage of Resilience Indicators

According to the similarity of the variables that each of the SDGs and BRF indicators measure, coding matrices have been created. The matrices are developed based on having the framework as the rows and variables as the columns, in order to evaluate the variables that are shared by the two frameworks in each cluster ([Figures 6.4](#)).

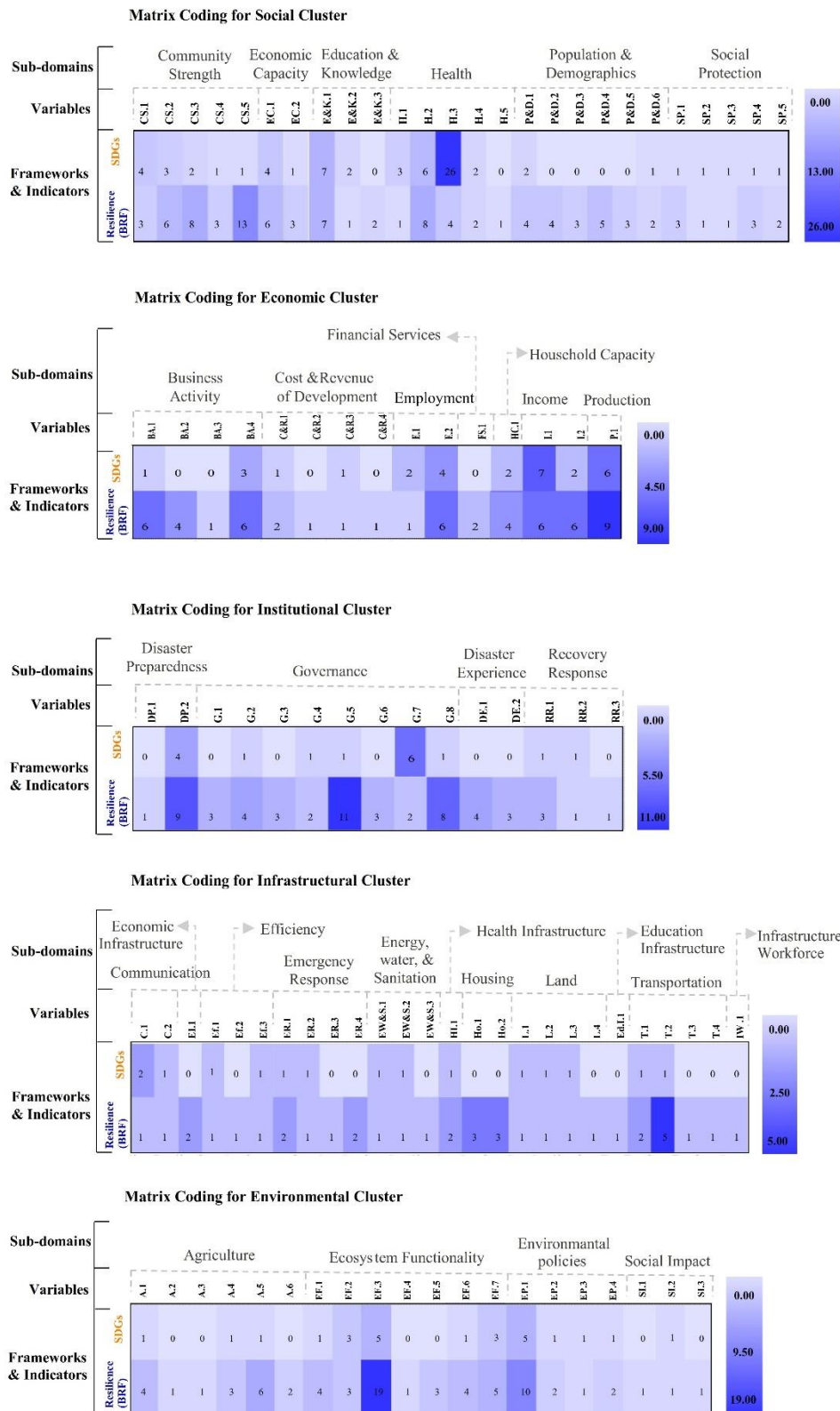


Fig. 6.4. Matrix coding for five clusters developed after the coding process. Numerical values in colour tiles represent the number of available indicators for each variable (recall the acronyms from [Table 4.2](#)).

Each matrix coding represents the number of indicators that each of the BRF and SDGs have for all the resilience variables, sub-domains, and dimensions. For example, the matrix coding for social dimensions shows that BRF and the SDGs encompass 3 and 4 indicators, respectively, to measure communication (CS.1). This is a variable for community strength and a sub-domain of social resilience.

Given that some of the indicators have been repeated in different dimensions, in a matrix coding for one resilience dimension, one or two variables might represent some features of the other dimensions. For instance, the matrix coding for the infrastructural cluster integrates some variables for the “Health Infrastructure” sub-domain (HI) that are similar to the “Health” sub-domain (H) in the social cluster. This is because the same indicator, “Hospital beds per 1,000 people”, indicates the provision of health services in both social and infrastructural dimensions (see [Appendix 3](#) in the supplementary material).

In the next step, after converting the count data to binary, Cosine similarity has been calculated for each cluster. As an example, Cosine similarity for the economic cluster has been calculated as follows:

$$\begin{aligned}\vec{R} &= [6, 4, 1, 6, 2, 1, 1, 1, 1, 6, 2, 4, 6, 6, 9] & \& \quad \vec{S} = [1, 0, 0, 3, 0, 0, 1, 0, 2, 4, 0, 0, 7, 2, 6] \\ \vec{R}_b &= [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1] & \& \quad \vec{S}_b = [1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1] \\ \text{Cosine}(\vec{R}_b, \vec{S}_b) &= \frac{\vec{R}_b \cdot \vec{S}_b}{|\vec{R}_b| |\vec{S}_b|} = \frac{\sum_{i=1}^N r_i \times s_i}{\sqrt{\sum_{i=1}^N r_i^2} \sqrt{\sum_{i=1}^N s_i^2}} \\ &= \frac{1 \times 1 + 1 \times 0 + 1 \times 0 + 1 \times 1 + 1 \times 1 + 1 \times 0 + 1 \times 1 + 1 \times 0 + 1 \times 1 + 1 \times 1 + 1 \times 0 + 1 \times 0 + 1 \times 1 + 1 \times 1 + 1 \times 1}{\sqrt{15 \times 1^2} \sqrt{9 \times 1^2 + 6 \times 0^2}} \\ &\times 100 = 81.65\end{aligned}$$

The calculated similarity based on the binary data shows the percentage of the variables for each of the resilience dimensions that the SDGs have at least one indicator for ([Table 6.1](#)). After defining the similarity of the BRF and the SDGs, Parallel Coordinate Plots (PCPs) have been developed for each resilience dimension ([Figure 6.5](#)). [Table 6.1](#) shows the rate of resilience variables for all of these dimensions that can be measured by the SDGs regardless of how accurate the measurement is. The percentages show that the SDGs have at least one indicator for each of the resilience variables (0 or 1). PCPs, on the other hand, demonstrate which goals address each dimension as well as the areas of strengths and weaknesses of the coverage.

Table 6.1. Cosine similarity between the SDGs framework and the BRF for each of the resilience dimensions.

Dimension (cluster)	Social	Economic	Institutional	Infrastructural	Environmental
Cosine similarity	87.71%	81.65%	73.03%	73.38%	80.62%

PCPs exhibit the relationship between the SDGs (middle line) and resilience dimensions (lower line) based on the number of indicators (top row) that each of the SDGs has for each resilience dimension. For instance, social PCP shows that the highest similarity between social resilience and the SDGs relates to goal 3 with 22 indicators, which is the highest number of indicators for this dimension. On the other hand, the lowest similarity relates to goals 6, 8, 10, 13, 15, 16, and 17, with only one indicator addressing social resilience. Furthermore, from the social PCP the goals that encompass zero indicators to measure social resilience can be inferred. These goals have no connection with social resilience which are goals 7, 12, and 14.

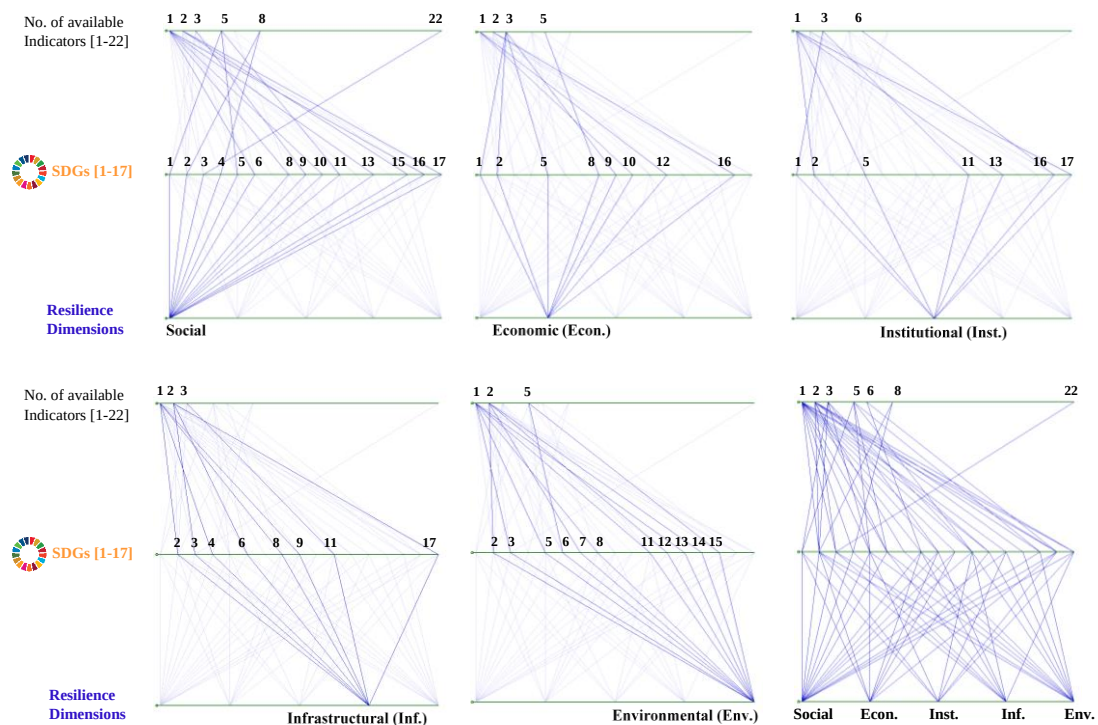


Fig. 6.5. Parallel coordinate plots (PCP) for each of the five resilience dimensions. Plots represent the number of indicators that 17 Sustainable Development Goals have for measuring each resilience dimension (e.g. the first plot on the top left shows there are five indicators in Goal 1 that address social resilience).

From PCPs, the goals can be ranked in terms of their similarities with resilience dimensions ([Figure 6.6](#)). For instance, concerning social resilience, from [Table 6.1](#) it is evident that the SDGs cover the measurement of 87.71% of the variables. As discussed earlier, the value of 75% or more represents a high level of similarity (Paul, 2014). Subsequently, it can be inferred that the SDGs have a high coverage of social resilience. However, this overall percentage of similarity does not provide more information on the goals that have the highest or lowest coverage.

Here, according to the data from PCPs by applying WSD, the goals have been categorised in four classes based on their coverage of resilience dimensions ([Figure 6.6](#)). Based on WSD, the SDGs that incorporate 3 indicators or less for a dimension are considered to be goals with low coverage for resilience measurement. Goals with 4-6 indicators have medium coverage, goals with 7-10 indicators have high coverage, and finally goals with more than 10 indicators have very high coverage for resilience dimensions. For instance, [Figure 6.6](#) shows that for the social dimension, goal 3 has a very high coverage, while goals 6, 8, 10, 13, and 15-17 exhibit a low coverage. This result serves to rank the relevance of the SDGs with resilience dimensions. For instance, the most relevant goal to social resilience is goal 3.

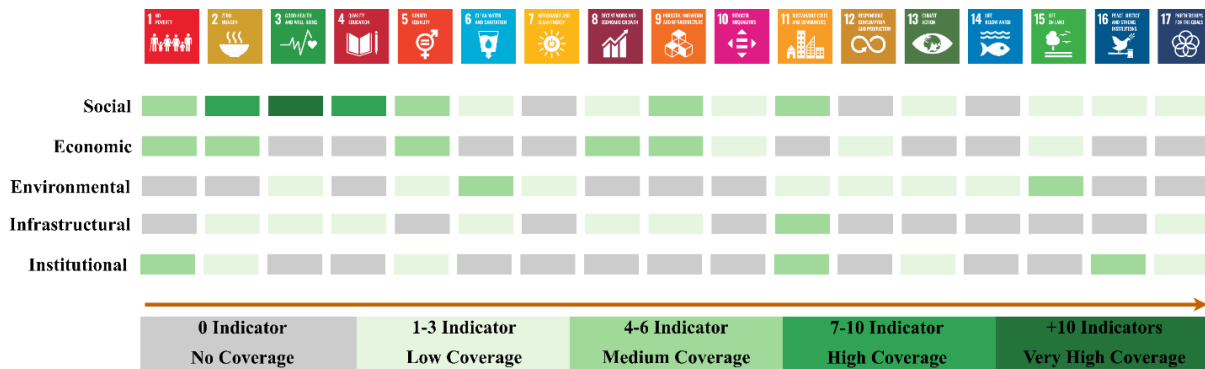


Fig. 6.6. Categorisation of the SDGs based on their coverage of resilience dimensions.

6.4 Enhancing the SDGs: Embedding Resilience Indicators

Based on the results from Cosine similarity ([Table 6.1](#)), the least similarity between the SDGs and BRP relates to institutional and infrastructural resilience, with at least 73.03% and 73.38% similarity, respectively. As the similarity of 75% or more is considered high (Paul, 2014), the calculated Cosine similarity shows that the SDGs indicators have a high level of similarity with those measuring resilience (from the comprehensive resilience framework). However, the value of less than 100% indicates there are some aspects of resilience (some variables) that have been overlooked in the SDGs.

The similarity measurement is based on the availability of at least one indicator for each of the resilience variables. This shows whether the SDGs have any indicators for each of the variable. The next step to understand to what extent the SDGs incorporate resilience measurement is to analyse how many indicators SDGs have for each variable in the five resilience dimensions. In [Figure 6.6](#), the SDGs have been rated from low to very high based on the number of indicators that they encompass to cover each resilience dimension. For instance, the results from the coverage ranking suggest that in the case of employing the SDGs to measure social resilience, the key goal to take into consideration is goal 3, while the least relevant ones are goals 6, 8, 10, 13, 15, 16, and 17.

The final part of the analysis, after defining the aspects of resilience that are covered in the SDGs, is to explore the overlooked areas and possible resolutions. Below, the results from the three parts of the analysis are discussed for each dimension.

6.4.1 Social resilience

The highest similarity of resilience by the SDGs relates to the social dimension with 87.71% similarity with the BRF ([Table 6.1](#)). Social resilience indicators have been incorporated into 14 goals among 17 SDGs, including goals 1-6, 8-11, 13, and 15-17 ([Figure 6.6](#) and [Appendix 4](#) in the supplementary material). Although there is at least one indicator in the SDGs to cover many of the variables relating to social resilience, some variables are still not covered by this framework. These variables are mainly associated with the population and demographics sub-domain (P&D) ([Figure 6.7](#)).

P&D measures the features related to the population that can affect resiliency, from population change to household density. Some of these features have been indirectly addressed in the SDGs. For instance, the population growth rate has been used to calculate indicator 11.3.1 (“Ratio of land consumption rate to population growth rate”). Likewise, the ratio of men to women or total population has been used in several indicators such as 1.2.1 (“Proportion of population living below the national poverty line, by sex and age”) and 1.2.2 (“Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions”). Although the data for most of the indicators related to population proposed in [Appendix 3](#) has been available and used to calculate the SDGs indicators, the direct impact of these factors on resilience has been overlooked in the SDGs.

In addition to P&D, traditional knowledge that keeps a community functioning based on local experience, and also social welfare capacities that address the availability of shelter to vulnerable groups, have been disregarded ([Figure 6.7](#) and [Appendix 3](#) in the supplementary material). Incorporating these two aspects in the SDGs framework can enhance the accuracy of assessing resilience.

Unlike social resilience, the SDGs are the least similar to BRF for infrastructural and institutional resilience ([Table 6.1](#)). This is despite the importance of these dimensions being recognised in both the 2030 Agenda and generally among academia. The SDGs acknowledge the prominence of infrastructural resilience by devoting nine goals specifically to addressing infrastructure resilience. Likewise, the critical role of the institutional dimension, which relates to the rules governing the operation of the whole system, is recognised for maintaining functionality in dealing with challenges and shocks (Herrfahrdt-Pähle & Pahl-Wostl, 2012).

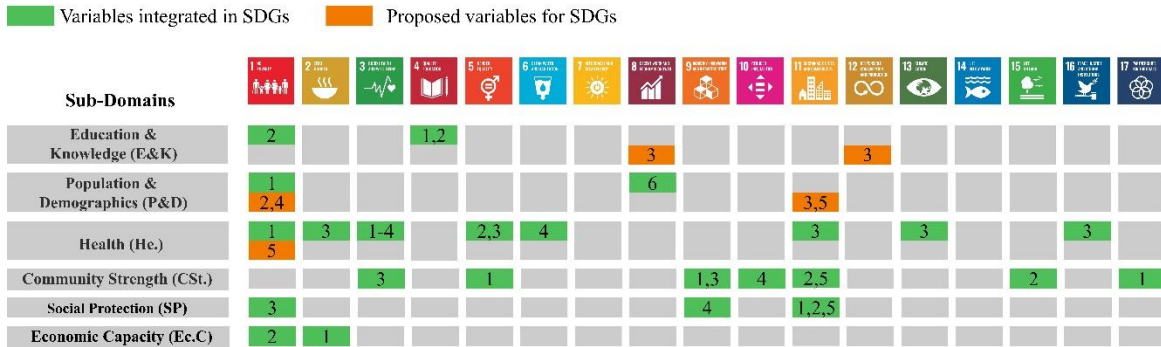


Fig. 6.7. The SDGs coverage for variables of social dimension. Numbers represent the code for variables of each sub-domain (E&K: 1. Education level & quality, 2. Public expenditure on education, 3. Traditional knowledge- P&D: 1. Equality, 2. Household features, 3. Population change, 4. Population structure, 5. Urbanisation and density, 6. Workforce- He.: 1. Expenditure on health, 2. Health services, 3. Health status, 4. Sanitation, 5. Social welfare capacity- CSt.: 1. Communication, 2. Land, 3. Mobility, 4. Place attachment, 5. Social engagement- SP: 1. Community disaster preparedness, 2. Cultural heritage, 3. Expenditure, 4. Innovation, 5. Organisation- Ec.C: 1. Food capacity, 2. Household economy)

6.4.2 Infrastructural resilience

The SDGs cover several aspects of the infrastructural resilience in nine goals: 1-3, 6-8, 9, 11, and 17 (Figure 6.6 and Appendix 4 in the supplementary material). However, this framework does not cover resilience features related to the housing (Ho) (e.g. housing quality), which is very critical when a disaster strikes, as well as the availability of workforce in the sector of infrastructure (IW) (e.g. transport engineers), and economic infrastructure (EI) aspects. Other crucial aspects that have been disregarded relate to the safety and accessibility of transportation, efficiency in water consumption, commercial infrastructure to support economic resilience, availability of schools for education resilience, and urbanisation density (Figure 6.8 and Appendix 3 in the supplementary material). This is while all of these components are vital to retain the functionality of a system as a whole.

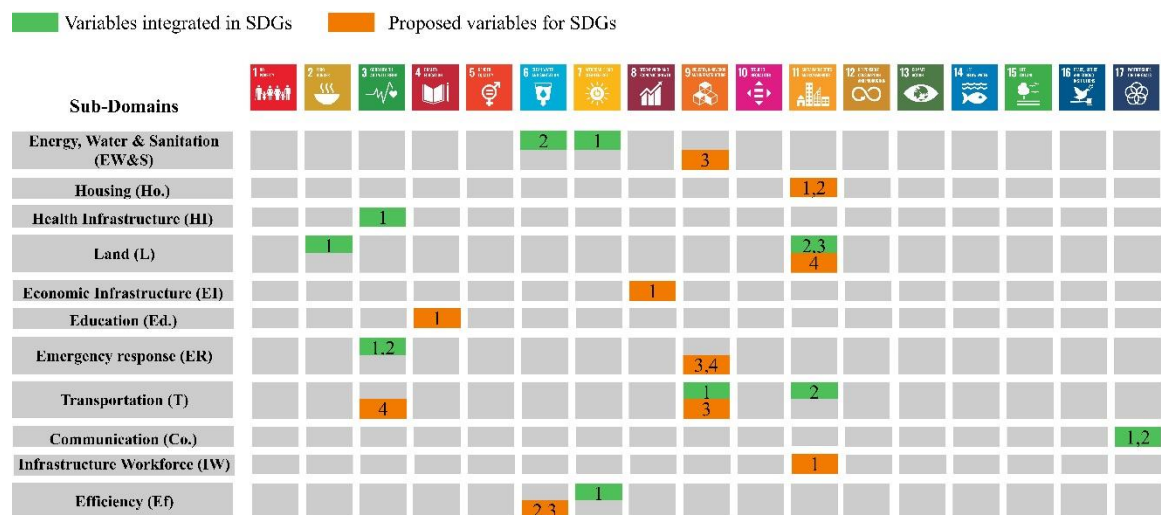


Fig. 6.8. The SDGs coverage for variables of infrastructural dimension. Numbers represent the code for variables of each sub-domain (EW&S: 1. Electricity, 2. Plumbing and sewage, 3. Public establishment- Ho.: 1. Housing features, 2. Temporary housing

availability- HI: 1. Health services- L: 1. Agriculture, 2. Informal settlements, 3. Social engagement, 4. Urbanisation and density- EI: 1. Commercial establishment- Ed.: 1. School restoration potential- ER:1. Emergency stations and shelters, 2. Emergency workforce capacity, 3. Infrastructure, 4. Transportation access- T: 1. Evacuation potential, 2. Accessibility, 3. Industrial re-supply potential, 4. Road safety- Co.: 1. High speed internet, 2. Telecommunication- WI: 1. Public utility sector- Ef: 1. Electricity, 2. Gas, 3. Water)

6.4.3 Institutional resilience

In this study, the indicators to measure institutional resilience are noted in 7 SDGs: 1-2, 5, 11, 13, and 16-17 (Figure 6.6 and Appendix 4 in the supplementary material). In terms of institutional resilience, the SDGs do not cover the assessment of disaster experience (DE), performance of local governments and their role in nation-wide decisions, national financial support to recover from shocks, and the role of government in developing resilience (Figure 6.9 and Appendix 3 in the supplementary material) that can be incorporated into this framework in future improvements.

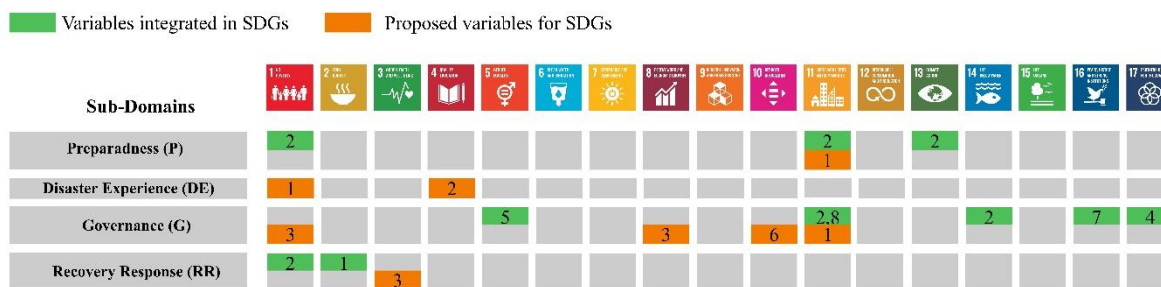


Fig. 6.9. The SDGs coverage for variables of institutional dimension. Numbers represent the code for variables of each sub-domain (P: 1. Accessibility, 2. Mitigation- DE: 1. Disaster aid experience, 2. Disaster knowledge - G: 1. Development, 2. Environmental, 3. Financial, 4. Income and expenditure, 5. Infrastructure, 6. Performance regime, 7. Social, 8. Urban improvement- RR: 1. Ecosystem support, 2. Financial support, 3. Psychosocial support)

6.4.4 Economic resilience

For the economic dimension, there is 81.65% similarity between the SDGs and the BRF (Table 6.1). Overall, the SDGs have addressed this dimension in goals 1, 2, 5, 7-10, 12, and 16 (Figure 6.6 and Appendix 4 in the supplementary material). Economic diversity, commercial activities, and availability of insurance (as part of financial services-FS) are key features of a resilient economy but they have not been incorporated into the SDGs. Similarly, the costs of urbanisation and economic development, such as road construction expenses as a factor with a negative impact on economic resilience, have been overlooked within the SDGs (Figure 6.10 and Appendix 3 in the supplementary material).

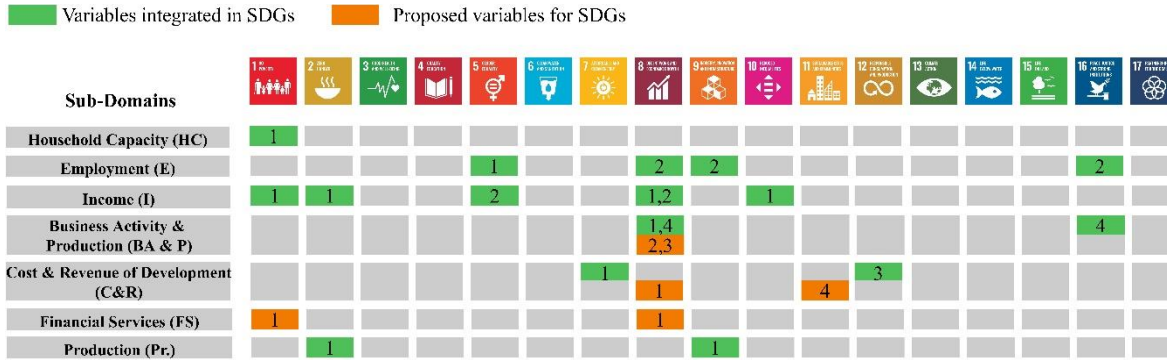


Fig. 6.10. The SDGs coverage for variables of economic dimension. Numbers represent the code for variables of each sub-domain (HC: 1. Household assets- E: 1. Equality, 2. Workforce- I: 1. Equality, 2. Income features- BA&P: 1. Business features, 2. Commercial activities, 3. Economy diversity, 4. Income and expenditure- C&R: 1. Energy/water, 2. Land, 3. Renewable energy, 4. Urbanisation and density- FS: 1. Insurance- Pr.:1. Production type and features.)

6.4.5 Environmental resilience

Finally, the SDGs have 80.62% similarity with the BRF for the environmental dimension (Table 6.1). This dimension has been addressed in eleven goals, specifically 2-3, 5-8, and 11-15 (Figure 6.6 and Appendix 4 in the supplementary material). However, some aspects related to agricultural resilience, including farms' access to the internet, being self-organised_ availability of fertile land in safe zones with minimum exposure to natural hazards, and crop diversity, cannot be assessed in the SDGs. Frequency of natural disasters, environmental violation, and population density are other factors that threat environmental resilience that have not been measured in SDGs (Figure 6.11 and Appendix 3 in the supplementary material).

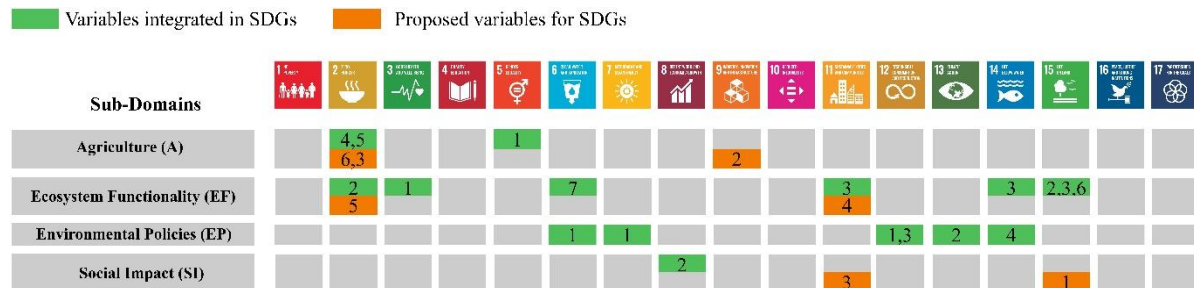


Fig. 6.11. The SDGs coverage for variables of environmental dimension. Numbers represent the code for variables of each sub-domain (A: 1. Assets, 2. Connectivity, 3. Diversity, 4. Income, 5. Local food suppliers, 6. Being self-organised - EF: 1. Air, 2. Biodiversity, 3. Land & Sea, 4. Natural disasters, 5. Safe zones, 6. Soil, 7. Water- EP: 1. Efficiency, 2. Emission, 3. Recycling, 4. Swage & waste- SI: 1. Crime, 2. Gross production, 3. Population.)

In addition to the indicators for the overlooked but high priority variables that could be considered in future amendments to the SDGs, this study proposes more indicators to enhance the accuracy of resilience measurement in the goals with little similarity to BRF. The indicators can also be used as an alternative to the current SDGs indicators to help overcome the data availability issue. These suggested additional

indicators, as well as the most relevant goals to them, are highlighted in [Appendix 3](#) in the supplementary material.

The results also suggest that it is not only the BRF that can be used to improve the SDGs. For some of the resilience subdomains, some indicators from the SDGs can be introduced to the BRF. Matrices in [Figures 6.4](#) show the areas in which either the BRF or the SDGs have more indicators. For example, for the social resilience CS1, E&K2, H1, and H3 are the areas in which the SDGs have more indicators. Similarly, economic resilience, E1 and I1, and for the infrastructural resilience C1 are the other areas where again SDGs have more indicators for their measurement. Generally, in the case of using the BRF to measure resilience, in addition to these specific areas, all SDGs indicators that are also measuring resilience could be added to the BRF (list of the 119 SDGs indicators to measure resilience can be found in [Appendix 4](#) in the supplementary material).

6.5 Chapter Summary

The SDGs have been criticised for failure to incorporate more measurements of resilience, which is one of the key components of sustainable development. Unlike the critiques, the results of this study show that the SDGs indicators have at least 73% similarity with the baseline resilience framework (BRF) (see [Appendix 3](#) in the supplementary material), in terms of the variables they measure. This number (73%) that shows the similarity between the SDGs and the BRF in terms of measuring infrastructural and institutional resilience grows to 80.62% for environmental, 87.71% for economic, and reaches 82.38% for social resilience. Based on the results, the measurement of most of the resilience sub-domains has been incorporated in the SDGs through all 17 goals and in 119 unique indicators ([Table 6.1](#) and [Appendix 3](#) in the supplementary material).

The high similarity between the SDGs and the BRF confirms that the SDGs have incorporated resilience measurement. However, the efficiency of the framework to measure resilience differs slightly from one dimension to another based on the different levels of similarities between this framework and the BRF. The greatest similarity of the SDGs and the BRF relates to social, economic, and environmental dimensions. This might due to the framework's focus on three main pillars of sustainable development: social, economic, and environmental features. On the other hand, the SDGs and the BRF have the least similarity as far as infrastructural and institutional dimensions are concerned.

The similarity assessment suggests that incorporating the overlooked variables of infrastructural and institutional dimensions has the highest priority in future SDGs improvements so that resilience can be comprehensively assessed. The next priority is to address all the variables of the other resilience dimensions (social, economic, and environmental) that have not been integrated into the SDGs.

This chapter also explored all the aspects of resilience that should be assessed (all variables) and demonstrated which ones have been covered in the SDGs and those that are overlooked (Figures 6.7-6.11). Based on this analysis, firstly a group of indicators has been defined from the BRF that can cover aspects of resilience overlooked by the SDGs, or as an alternative to replacing current SDGs indicators in case of data unavailability (see [Appendix 3](#) in the supplementary material). Although there are many indicators from the BRF that can be introduced to the SDGs, the results do suggest a two-way relationship between the SDGs and the BRF, where the SDGs can also help with improving the BRF. The five matrices in [Figure 6.4](#) illustrate the areas in which the SDGs have more indicators to measure resilience in comparison to the BRF.

Generally, the explored coverage of each of the resilience dimensions by the SDGs contributes to the future refinement of this framework by indicating the strengths and weaknesses of the SDGs with regard to resilience measurement. Apart from making a contribution to enhancing the SDGs, and generally the momentum that has since 2000 accompanied the MDGs, the results from this study contribute to expediting a smooth application of the current SDGs framework. The ranking of the BRF coverage by the SDGs ([Figure 6.6](#)) provides a guideline for authorities who apply the SDGs in their assessments. This will help them to recognise the goals that are most relevant to their needs. For instance, in the case of using the SDGs as a framework to measure environmental resilience and sustainable development, the ranking suggests that goals 6 and 15 are the most relevant. These goals incorporate the largest number of indicators to measure environmental resilience. However, there are other goals among the SDGs that have fewer indicators for environmental resilience, namely goals 3, 5, 7, and 11-14.

Since the indicators to measure five dimensions of resilience are scattered in different goals, several aspects of resilience might have been overlooked in those studies that undertake measurement based on one or only a few goals. Therefore, for the SDGs to effectively assess resilience, goals should not be considered in isolation. This chapter is a guideline to enhance the measurement of resilience by the SDGs. However, how the long list of the suggested resilience indicators can be limited to a few most practical and needed indicators and how the enhanced SDGs can be applied to the local scales, are the questions that need to be answered in Chapter 8.

CHAPTER 7

JAKARTA CASE STUDY

PART 1: DATA GENERATION

7 Jakarta Case Study Part 1: Data Generation

7.1 Introduction

As indicated in Chapter 1, one of the problems hindering the viability of the SDGs is the paucity of statistical and census data, particularly in informal settlements. These are some of the world's most vulnerable communities, for which the assessment of resilience is very critical. Therefore, to propose a workflow for incorporating resilience into the SDGs and the localisation of the SDGs (elaborated in Chapter 8), this study selected for the case study Jakarta, the capital of Indonesia, as it has many informal settlements. Data availability is also a critical issue for Jakarta as an up-to-date map of its informal settlements was not available (the most recent land-use map was produced in 2015). Therefore, to resolve the data availability issue, this case study started with informal settlements detection presented in this chapter. For the purpose of this research, the available data also needed some preparation. The second part of the case study that starts with data preparation (transforming the collected statistical data to spatial data) and using all the spatial data for analysis is presented in the next chapter.

Jakarta, the capital city since Indonesian gained independence in 1945 (Garr, 1986), is located on the island of Java. Indonesia is the world's fourth most populous country (Counihan, 2017) ([Figure 7.1](#)). With a population of more than 10 million as of 2020, Jakarta is the most populated city in Indonesia and the world's 10th most populated metropolitan area (Statistics Indonesia- Badan Pusat Statistik (BPS), 2020).

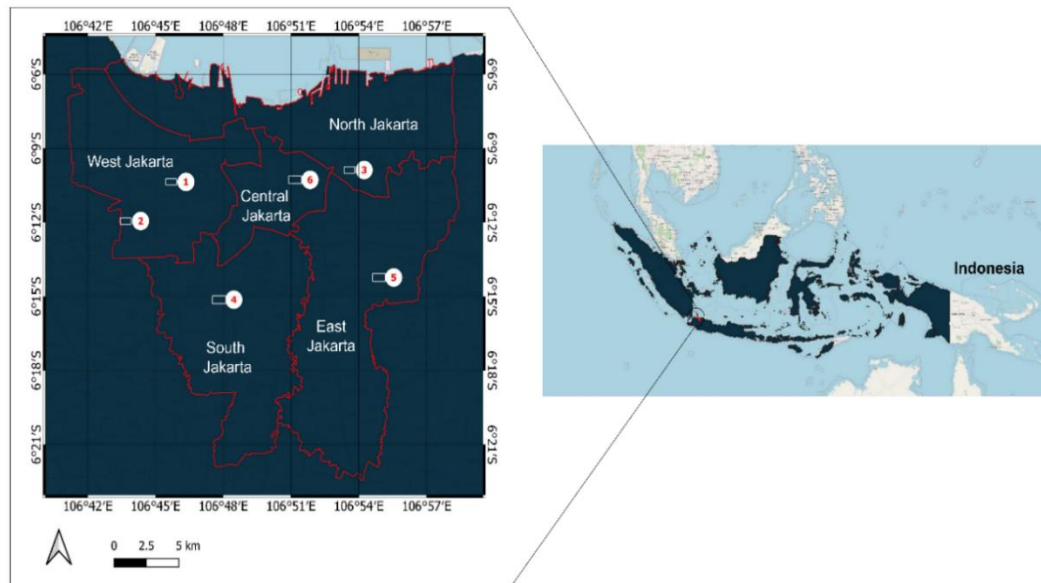


Fig. 7.1. Study areas: Jakarta, Indonesia. Small rectangles numbered from 1-6 represent 2.4 km² sample areas for the visualisation and the magnification of the results from data generation presented in the following sections.

Jakarta's particular importance, apart from its population, comes from its strategic role as the economic hub of Indonesia and it is where the financial and business sectors operate (Rukmana, 2008). Based on Indonesia's Central Bureau of Statistics reports (2005), Indonesia's GDP from the financial and business sector in 2005 amounted to 146.3 trillion rupiahs, 62.1% of which was generated in Jakarta. Despite the social and economic importance of Jakarta, this city is dangerously exposed to flooding disasters and the most vulnerable areas are its informal settlements (kampung) (The World Bank, 2011).

7.2 Informal Settlements in Jakarta

Informal settlements – otherwise known as slums – emerge as unplanned, illegal, and irregularly structured built-up areas with a distinct physical pattern of road networks and building sub-divisions within the city limits. They generally do not have access to basic infrastructure and municipal services (McLaren, Coleman and Mayunga, 2005). Informal settlements might form as a consequence of rural-urban migration, which is called “inserting”. This type of living arrangement mainly grows in peri-urban areas (city fringes) and refers to the development that occurs on vacant lands (Dovey & King, 2011). Another type of settlement that is treated as being informal concerns the autochthonous villages that are surrounded by built-up areas as urbanisation expands. This type of informal settlement creation is called “settling”, which means living on unregistered lands as a village (Counihan, 2017) (Figure 7.2). During the urbanisation process, these villages are typically considered to be self-governing settlements. They end up becoming isolated and characterised by a lack of much needed metropolitan services and infrastructure.



Fig. 7.2. Settling type of informal settlements in Jakarta (Source: satellite image from Google Earth Engine).

The Asia-Pacific region is home to the world's largest concentrations of urban slum populations and people living below the poverty line. Collectively, these settlements pose a major challenge to realising sustainable development (UN-Habitat, 2015). Asia has the largest population of both types of informal settlements' inhabitants with over 80% of slum dwellers in southern and eastern countries. Since the 1970s governments have implemented policies to limit the spread of informal settlements in these countries

(Sweeting, 2017). Indonesia currently has 29 million informal settlement inhabitants who lack access to urban services (The World Bank, 2016). Since 1969, beginning with Jakarta, the largest city and the economic centre of Indonesia (Alzamil, 2018), upgrading the infrastructure in informal settlements has been undertaken under the Kampung Improvement Program (KIP). Informal settlements in Jakarta that are also referred to as “kampung” are of the settling type. They are urban villages in which millions of people live and work but are deprived of civic services (Garr, 1986).

Kampung areas, and informal settlements in general, are vulnerable to disasters due to poorly constructed houses and unsuccessful integration into an urban life style (Rumbach & Shirgaokar, 2017). As is the case in most areas of urban deprivation, Kampung areas are characterised by communities lacking access to services when emergencies arise (UN-Habitat, 2014). The recent COVID-19 pandemic crisis, for example, has exposed the inequality and vulnerability of the urban poor due to the challenges of tracking and controlling the virus, access to healthcare services, transportation infrastructure, and water and sanitation (UN-Habitat, 2020). Considering the large number of people living in informal settlements and the high level of risk and vulnerability they are subjected to, monitoring these settlements is necessary if disasters are to be recovered from (Hofmann et al., 2008), and the COVID-19 pandemic is no exception.

The first step for upgrading Jakarta’s informal settlements is mapping these deprived areas. Here, the role of remote sensing is central to enable monitoring and planning of informal settlements in order to improve the lives of their inhabitants, aligned with the global efforts to reach sustainable development and get on track to achieve SDGs by 2030 (Mayunga et al., 2007). Generally, remote sensing and specifically satellite imagery has been widely used as an alternative source of data to monitor urban areas. In recent decades, the use of satellite imagery has been increasingly investigated to estimate urban population and density (Dittakan et al., 2013; Hillson et al., 2019; Lu et al., 2010; Ogrosky, 1975; L. Wang et al., 2020), mapping land cover and land-use in urban areas (Carleer & Wolff, 2006; Gamba et al., 2007; Movia et al., 2016; Novack et al., 2003; Ouyang et al., 2011; Voorde et al., 2007), and also for tracking changes in the urban landscape (Lv et al., 2020; Volpi et al., 2013; Y. Zhang et al., 2018). Remote sensing has also been used to detect informal settlements in urban areas, which is the first step to improving the lives of the most vulnerable communities (Fallatah et al., 2020; Weir et al., 2019).

7.3 Remote Sensing Data for Detecting Informal Settlements

According to the UN, settlements can be defined as informal if they have at least one of the three following criteria: a) lack of security of tenure; b) deprivation of basic services and infrastructure; and c) housing that does not meet current planning and building regulations (UN-Habitat, 2013a). The first feature relates to

the legal aspect of informal settlements, while the last two features consider the physical structures and can be examined using remote sensing data. For instance, the lack of quality roads that constitute a basic infrastructure can be observed in the satellite images.

Several efforts have been made to use remote sensing technologies and data, such as active sensors (Wurm et al., 2017) and satellite images, to detect informal settlements based on their physical features (Du et al., 2015; Dubovyk et al., 2011; Hofmann et al., 2008; Mayunga et al., 2007; Owen & Wong, 2013). However, in almost all the efforts made so far to detect and map informal settlements, Very High Resolution (VHR) and High Resolution (HR) satellite imagery has been employed. One of the weaknesses of VHR/HR is that it is a very expensive source of data and might not be available due to budget/funding shortages, especially in developing countries. Besides, despite the high cost and high accuracy of the informal settlements detection by VHR/HR, misclassification of formal areas as informal occurs in the results (Prabhu et al., 2021). The limitation associated with VHR/HR triggered researchers' growing interest to use open data sources to detect informal settlements.

7.4 Open Data for Detecting Informal Settlements

Open data sources that have been used to detect informal settlements can be categorised into two groups: (1) open and freely available to public census and statistical data that are collected by governments and non-profit organisations through surveys; and (2) open spatial data including freely available Medium Resolution satellite images (MR) and OpenStreetMap (OSM). The second group is mainly used to detect informal settlements based on their physical features. Soman et al. (2020) recently conducted street block analysis in 120 low and middle income countries to detect informal settlements based on the lack of public street access (Soman et al., 2020). The method relies on OSM data that can have varying levels of accuracy in different countries. Mahabir et al. (2020) mixed the data from OSM and MR with open census and statistical data to identify the most suitable indicators, such as the level of vegetation, road type, etc., to detect informal settlements in Kenya.

However, informal settlement detection in this study has been conducted based on both physical and socioeconomic features that require a high volume of data. Gram-Hansen et al. (2019) used Sentinel-2 to detect informal settlements. However, they did resort to VHR to enhance the accuracy of detection. On the other hand, Verma et al. (2019) compared the performance of the transfer learning model for detecting informal settlements on MR and VHR at the city scale. Their results showed unexpectedly high performance of MR in the detection of informal settlements and suggested further studies on ensemble methods in machine learning to enhance the classification accuracy. Here, the possibility of using open data,

including MR and OSM, as a cost-effective and open-to-all approach to detect informal settlements at the city scale is investigated.

7.5 Satellite Image Classification for Informal Settlement Detection

Apart from visual interpretation, image classification is the most applied method for mapping the physical features of informal settlements using satellite imagery. Satellite image classification refers to the process of categorising the pixels of images to meaningful classes (Karlsson, 2003). There are generally two approaches for classification: Pixel-Based Classification (PBC) and Object-Based Classification (OBC). PBC analyses the spectral properties of every pixel within an area of interest, without considering contextual information, such as shape (Makinde et al., 2016). This approach does not produce accurate results when analysing VHR (Toll, 1984; Xia, 2007), which is due to the high spectral variability in VHR imagery. Greatly improving the quality and resolution of satellite images, OBC was introduced in the 1970s as an alternative way to classify VHR. OBC analyses objects rather than pixels by extracting homogeneous regions and incorporating contextual information (Ouyang et al., 2011) ([Figure 7.3](#)).

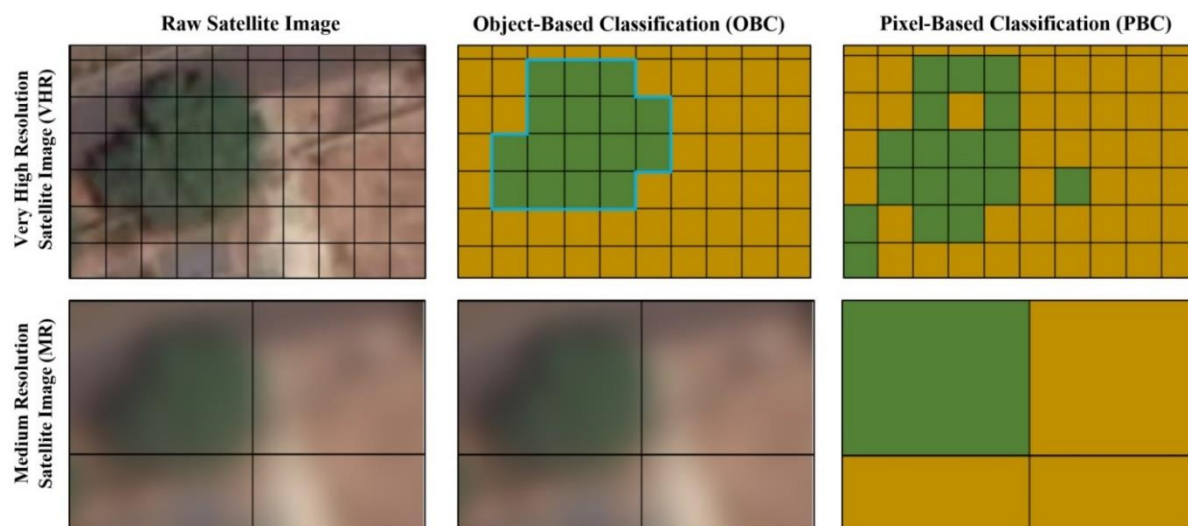


Fig. 7.3. Schematic comparison of Pixel-Based Classification (PBC) and Object-Based Classification (OBC). Top Row: on VHR, OBC more accurately detects vegetation, while PBC comprises a mix of pixels. Bottom Row: Spatial resolution and size of the pixels define either OBC or PBC can be more effective. Regarding MR, OBC is inefficient as a pixel contains more than one object, while PBC still detects vegetation (Source for the background satellite image: Google Earth Engine).

It is generally thought that OBC produces more accurate results than PBC. However, high accuracy can be achieved when classifying VHR (Blaschke, 2010; Hofmann et al., 2008; Mayunga et al., 2007). In a comparative study on the accuracy of the classification of High Resolution satellite imagery (HR) by OBC and PBC, Duro et al. (2012) suggest that both classifiers perform well when applying similar machine learning algorithms (Duro et al., 2012). However, OBC has proved to be inefficient in analysing medium and low resolution satellite images, while PBC performs quite well (Blaschke, 2010; Makinde et al., 2016).

This is because, as shown in [Figure 7.2](#), when reducing the resolution, every pixel might encompass more than one class (e.g. build-up and vegetation).

In several studies OBC has been used to detect informal settlements through HR/VHR classification based on defining a group of image-based proxies to differentiate land-use classes (Fallatah et al., 2020; Hernandez & Shi, 2018; Hofmann et al., 2008; Rangelova et al., 2019). On the other hand, PBC, which effectively classifies MR, has rarely been applied to detect informal settlements. Jain (2007) has explored the application of PBC for this purpose. However, the analysis has been conducted on IKONOS data which is a type of VHR (Jain, 2007). Similarly, Kit et al. (2012) applied PBC on QuickBird VHR data (Kit et al., 2012). Here, as indicated earlier, PBC using machine learning techniques can enable highly accurate informal settlement detection on MR.

7.5.1 Pixel-Based Classification (PBC) Using Machine Learning Techniques

Several methods have been proposed to classify satellite images. These methods range from parametric (based on any assumptions about data distribution) algorithms such as maximum likelihood (Nilsson, 1965) to non-parametric machine learning algorithms, including Decision Tree (DT) (Brodley & Friedl, 1997; Pal & Mather, 2003), Support Vector Machine (SVM) (V. Rodriguez-Galiano et al., 2015), k-Nearest Neighbours (kNN), and Artificial Neural Networks (ANN) (Rumelhart et al., 1986), as well as a combination of other classifiers that are referred to as ensemble classifiers, such as Random Forest (RF) (Breiman, 1996). Among the classification methods, nonparametric machine learning algorithms are more accurate, particularly for large-scale mapping. The algorithms demonstrate a high capacity in learning a large number of functional forms regarding the training data. This is due to not making any assumption about the data and underlying function (V. F. Rodriguez-Galiano et al., 2012).

Several studies have been conducted to compare non-parametric machine learning algorithms in terms of accuracy and effectiveness. Generally, with the exception of DT, which is found to be a less effective classifier with the tendency to overfit in, and having high sensitivity to the training data (Breiman, 2001), all other classifiers are similar in terms of accuracy (Dixon & Candade, 2008; Noi & Kappas, 2017; Pal, 2005). However, RF has several advantages over the rest (V. F. Rodriguez-Galiano et al., 2012; Teluguntla et al., 2018) that make it a better choice for land-use classification and more particularly informal settlement detection.

In comparison to other non-parametric algorithms, the RF algorithm is more robust due to minimal supervision and fewer user-defined parameters, less sensitivity to the training data, and faster analysis processing (Dixon & Candade, 2008; Ming et al., 2016; Noi & Kappas, 2017; V. F. Rodriguez-Galiano et

al., 2012; V. F. Rodriguez-Galiano & Chica-Rivas, 2014; Teluguntla et al., 2018). For instance, ANN is sensitive to the number of hidden nodes; kernel parameters affect the accuracy in SVM; and accuracy in kNN depends on the ideal value of k , which is difficult to set (Dixon & Candade, 2008; Noi & Kappas, 2017). In addition, results from a study by Rodriguez-Galiano et al. (2012) show that RF delivers more variety among different land-use/land cover classes than traditional classification approaches, such as a simple decision tree (V. F. Rodriguez-Galiano & Chica-Rivas, 2014). The differentiation among similar land-use classes is of great importance in the case of informal settlement detection. This is because categorising similar land-use classes, such as formal and informal built-up areas is less manageable than the noticeably distinct ones (e.g. built-up zones and green spaces).

RF proposed by Breiman (2001) is a classifier comprising a collection of (K) independent random tree-structured classifiers (or decision trees) $\{h(X, \theta_n), N = 1, 2, 3, \dots K\}$, where X is the input data and $\{\theta_n\}$ denotes a family of identical and independently distributed random vectors (Breiman, 2001). To classify a pixel, RF will assign the pixel to the land cover class that receives the most votes from all the trees in the ensemble (Hermosilla et al., 2018) (Figure 7.4).

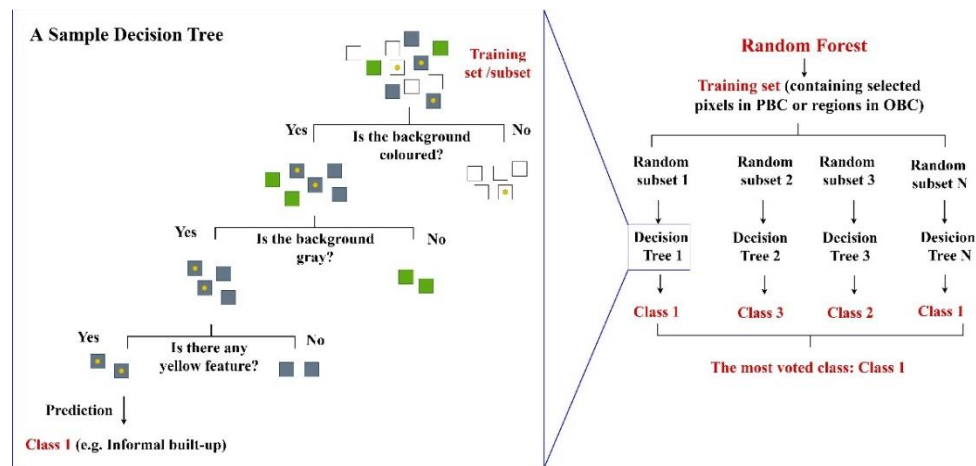


Fig. 7.4. Random forest algorithm's schematic function in image classification. The classifier consists of a collection of individual trees. Each tree independently offers a class prediction. The class with the most votes becomes the model prediction for image classification.

7.5.2 Methods for Developing the Training Set and the Application of Open Data

The most traditional method for developing the training set is *in situ* data collection. This method, in addition to being considered time-consuming, is also cost-prohibitive for large areas (B. Zhou et al., 2020). One commonly used replacement for this approach is the available databases as the training input, including existing land classification maps or the survey data. In a recent study by Campos-Taberner et al. (2020), the classification samples originate from *in situ* surveys provided by the regional government of Valencia

in Spain (Campos-Taberner et al., 2020). Similarly, Zhu et al. (2016), used the Land Cover Trends (LCT) data produced through the U.S. Geological Survey (2015) as the training sample (Zhu et al., 2016). Although this method relies on highly trusted training input and is a good replacement for *in situ* data collection, the data might not be available for all areas and purposes.

A new era of increasingly available open data provides the opportunity to find a more accessible replacement data source for developing the training set. Here, determining how to benefit from the freely accessible data is crucial. Building the training set based on visually interpreting higher spatial resolution images available in open access platforms, such as Google Earth (<https://www.google.com/earth/>) and Bing (<https://www.bing.com/maps>), is one of the common uses of open data (Pontarollo & Mendieta Muñoz, 2020). However, the visual interpretation method relies on expert comprehension and might be compromised by human error.

As a recent approach, Volunteered Geographic Information (VGI) has been used for developing the training set (Goodchild, 2007; Yuan et al., 2018). One of the most popular VGI initiatives is OSM. OSM is a collaborative project to develop open spatial data worldwide that provides data layers in editable formats, such as shapefile, for further analysis and exploration (“OpenStreetMap,” 2020). In each city, different data layers might be available on the OSM website (<https://www.openstreetmap.org/>), such as roads, trails, buildings, etc., which is one of the limitations of using OSM. In addition, its accuracy has widely been questioned as OSM offers a collaborative and editable data source. In response, some case studies have shown that the accuracy of OSM is comparable to those of authoritative sources (Haklay, 2010; Jokar Arsanjani et al., 2013). However, in general, OSM suffers from the heterogeneity in inaccuracy from one location to another and among different data layers (Estima & Painho, 2015). Therefore, if this type of data is to be relied on, it is essential to validate the data.

Literature indicates that OSM has been used in the machine learning supervised land-use and land cover classification (Forget et al., 2018; Jokar Arsanjani et al., 2013). Forget et al. (2018), used OSM to detect built-up areas in sub-Saharan African cities on Landsat images (Forget et al., 2018). Nevertheless, in this practice, OSM has not been implemented to classify different types of built-up areas such as formal and informal with low intra-class differences. Jokar et al. (2013) used OSM to classify diverse built-up areas, such as low density, medium density, and high-density urban fabrics. (Jokar Arsanjani et al., 2013). However, they apply the classification on Rapid-Eye images with spatial resolution of 6.25 m which is much higher than the resolution of Landsat 8.

Since different types of built-up areas such as formal and informal settlements or infrastructure (e.g. road network) appear to be very similar in MR, this study is initially aiming to examine the usage of OSM for this sensitive classification. In the next step, the accuracy of the informal settlement detection with and without OSM will be compared to outline which approach is more efficient. The results from this study will contribute to detecting informal settlements, particularly in developing countries by using free and accessible open data. Since informal settlements detection is the first step for monitoring and upgrading urban life in informal or slum-like areas, this study will help city planners and policy-makers to develop more sustainable and liveable cities and communities.

7.6 Satellite Image Classification for Data Generation in Jakarta

To generate data for land-use in Jakarta and particularly detection of informal settlements, Landsat 8 images are obtained that are freely available to the public. Landsat 8 images are multi-spectral data with 11 spectral bands, five of which (bands 1-4 and 8) are visible. The satellite offers seasonal mapping of the entire globe at a spatial resolution of 30 meters for most of the bands (U.S. Geological Survey, 2016). Landsat 8 images for the study area taken on 24/5/2020 are downloaded from the Copernicus Open Access Hub (<https://scihub.copernicus.eu/>). The acquired images were cloud-free as May is the start of the dry season in Indonesia.

In this research, for classification of land-use and land cover, seven bands including visible, near infrared, and shortwave infrared band are used. The bands include: band 1-coastal aerosol, band 2-blue, band 3-green, band 4-red, band 5-near infrared (NIR), and bands 6 & 7-shortwave infrared (SWIR), all with a resolution of 30 meters. Omitted bands with irrelevant applications include band-8 which is a panchromatic band with a resolution of 15 m. It is used for sharpening and visualisation purposes, as well as the thermal and atmospheric bands (9-11) (Loyd, 2013). For training purposes, the most recent informal settlement map in Jakarta created in 2015 ([Figure 7.5](#)) (The World Bank, 2015) is used. Also, the OSM data for Jakarta is obtained from OpenStreetMap Indonesia (<https://openstreetmap.id/en/dki-jakarta/>). For Jakarta, the street, governmental boundaries, and building blocks were available layers at the time of data collection. Later, both survey data and OSM layers are used for land-use classification and the detection of informal settlements in Jakarta on medium resolution satellite images (Landsat 8).

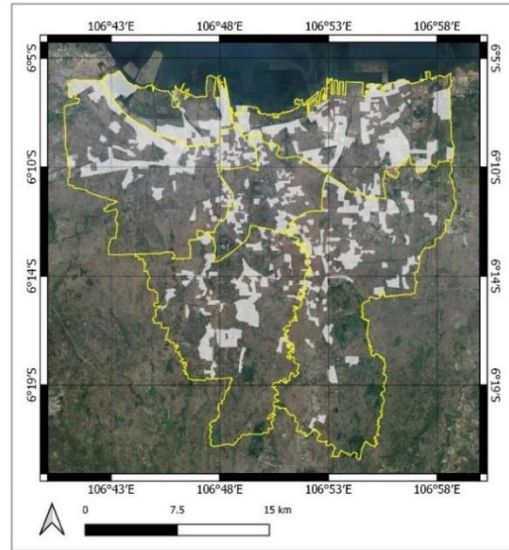


Fig. 7.5. Informal settlements of Jakarta (2015) (Source: adapted from The World Bank, 2015).

For the classification of Landsat 8, the Random Forest (RF) algorithm is utilised. As indicated in section 7.5.1, the RF algorithm is robust and it requires few defined parameters; highly accurate results can be achieved through the default parameters (Duro et al., 2012; H. K. Zhang & Roy, 2017). However, the number of trees (ntree) and the number of variables (mtry) are the parameters that have been set. The ntree is 100 in the default setting and the mtry is the square root of the total number of bands in the image data. In this study, testing a range of values for the two parameters concluded that ntree of 200 and mtry of 2 gives the highest accuracy.

Despite the advantages of RF over other non-parametric algorithms (e.g. kNN, SVM, and ANN, the algorithm), it can still produce overfit. To cope with the possible overfitting issue and enhancing the accuracy, choice of training method is more important than the algorithm (Abdi, 2020; Foody & Arora, 1997). Hence, in this research, two complementary training approaches have been applied and the results compared. Another factor to reduce overfitting is the sample size. The training sample should be relatively large enough (concerning the area of interest). It is recommended that to reach high accuracy the training sample should cover approximately 0.25% of the total study area (Noi & Kappas, 2017) that has been followed in this study. Despite the considerations, overfitting might still happen that will be discussed, and possible solutions are proposed in section 7.5.

Through the first approach, two methods have been implemented for developing the training set. First is the traditional method of using available databases, such as survey data and available maps (Campos-Taberner et al., 2020), while the second involves the visual interpretation method using freely available VHR Google Map Imagery (Pontarollo & Mendieta Muñoz, 2020). Here, in the latter approach, the

application of OSM, as a complementary source of data, for developing the training set has been tested (Figure 7.6).

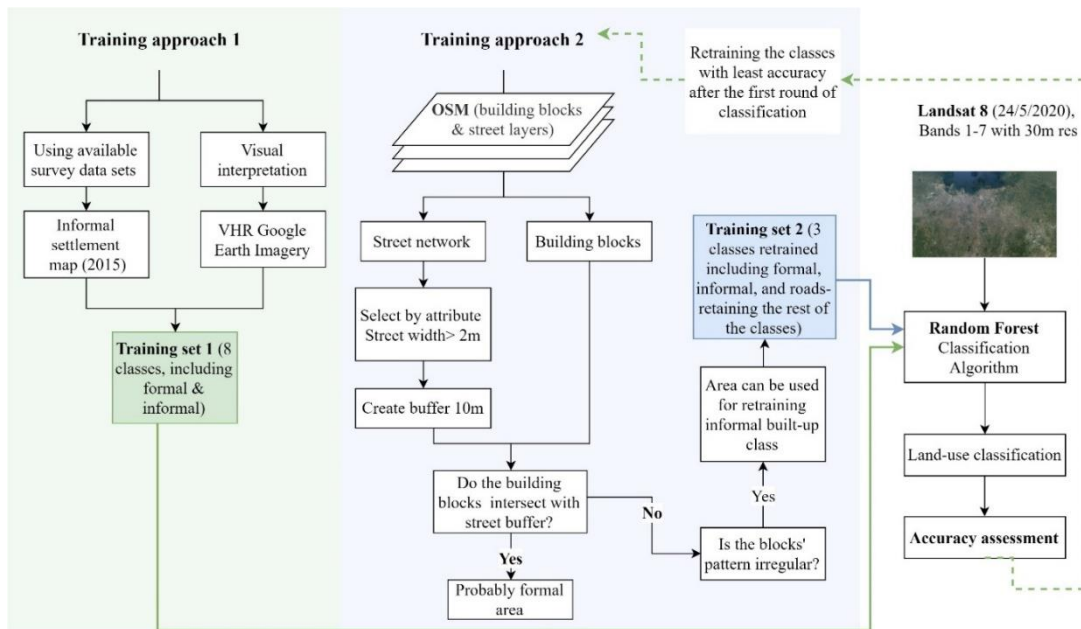


Fig. 7.6. Overview of the procedure followed to detect informal settlements using medium resolution satellite images (MR), OpenStreetMap (OSM) and random forest machine learning algorithm (RF).

First approach for training: Initially, the 2015 informal settlements map for Jakarta (The World Bank, 2015) was the reference to develop the training set. Although the map is not very recent, based on a review of the slum upgrade programs in Jakarta, changes in the settlements have been mainly practical rather than physical. This includes the provision of basic infrastructure such as sanitation rather than relocating the settlements, reconstructing the houses, and changing street patterns (Pangeran & Akbar, 2020). Considering the insubstantial reduction in the extent and location of informal settlements since 2015, the 2015 map is still useful for this study. However, possible alterations should be considered while selecting the training point to minimise training errors. For this purpose, VHR from Google Earth 2020 for Jakarta has been used as a base map on which a transparent layer of informal settlements polygons (2015) has been overlaid. VHR Google Earth has been used to visually interpret the differences between the informal settlements in 2015 and the same areas in 2020. In a few cases, the areas mapped as informal settlements in 2015 retained the regular pattern of building blocks and streets in the 2020 Google Earth image. These areas which might be upgraded or rehabilitated have been excluded when developing the training sets.

After selecting 120 training points for informal built-up areas, to obtain the highest level of accuracy, seven other classes of land-use, each containing a similar number of samples, were developed using the

same visual interpretation method relying on VHR Google Earth layer as the base map. The higher number of classes increases the depth of the decision tree and leads to higher accuracy (Breiman, 2001). Overall, a training sample of 960 points in eight classes was developed ([Table 7.1](#)).

Table 7.1. Proposed classes for the classification of Landsat 8 in Jakarta.

Training Classes	Description
Formal Build-up	Standard size building blocks with ample open space and vegetation in between.
Informal Build-up	Substandard housing with limited open space and vegetation in between.
Bare Soil	Undeveloped areas with no dominant vegetation cover.
Low Vegetation	Areas covered by low vegetation, such as grass.
Road	Street network and areas covered by asphalt.
High Vegetation	Areas dominated by trees.
Water	Areas covered by water such as lakes, canals, and pools.
Cloud Mask	Areas of satellite image that are covered by cloud.

Second approach for training: In the next approach for training, OSM layers of building blocks and roads have been used to develop the training set for the “formal build-up”, “informal build-up”, and “road” classes. Due to uncertainty about the OSM accuracy, using the detailed data attributes of OSM, such as the type of material used in building blocks, can be very challenging. Here, OSM has been used only to extract the physical patterns of built-up areas and the road network which, according to a recent survey, is one of the most complete and reliable data layers (Barrington-Leigh & Millard-Ball, 2017) is the only used attribute. Here, the selected training points using OSM layers have been double-checked using high resolution Google Map imagery. The application of OSM layers for developing the training set in order to detect informal settlements depends on the context and physical characteristics of the area of interest. Hence, the first step would be defining the physical features of informal settlements in the study area. Later, it can be decided which OSM layers can best reflect the features.

In Indonesia, car ownership is not common among kampung inhabitants due to their ever-present financial difficulties. Therefore, streets in kampung areas are very narrow and mainly suitable for pedestrians or motorcycles (Hidayati et al., 2020). In a study of informal settlements in Jakarta, Alzamil (2018) describes the internal roads as “very narrow, winding, and non-paved” in which emergency vehicles cannot commute (Alzamil, 2018). In a similar study, Hidayati et al. (2020) have shown that streets with a width of 2 meters or less is quite normal for an informal settlement (Hidayati et al., 2020) ([Figure 7.7](#)). Such roads might also be found inside formal built-up areas. Here the urban fabric of informal settlements has been considered as the second indication. The fabric can be analysed by the geometry of housing and alleyways (Suhartini & Jones, 2020). Geometric order in the urban fabric refers to the regular and hierarchal street patterns as well as the consistent building placement and block patterns (Rubinowicz, 2000). Conversely, informal settlements are generally described as irregular forms shaped by residents who do not

follow any planning process (Alzamil, 2018), with diverse housing patterns comprising different block sizes and shapes (P. Jones, 2019).

Suhartini and Jones (2020), in a study of informal settlements in Indonesia, argue that the outcome of this self-organisation of the space is a disorder or self-made urban order that is organic with a variety of housing sizes and styles within a settlement (Suhartini & Jones, 2020). Similarly, Alzamil (2018) describes the fabric of informal settlements in Indonesia as a wavering distribution of blocks that are irregular and tend to be semi-rectangular, linear, or semi-square (Alzamil, 2018).

Based on the review of studies conducted on physical features of informal settlements in Jakarta, key features can be described as: a) narrow streets with 2-meter width or less, and b) lack of uniform size and pattern of buildings. After defining the key physical features of informal settlements in Jakarta, the available OSM layers have been reviewed to select those that can best reflect these two features. For Jakarta, the road layer in OSM provides the data for road hierarchy in which roads with a smaller than 2-meter width can be chosen. For reflecting the housing features and fabric of the settlements, building block layers serve as the secondary data layer for developing the training set.

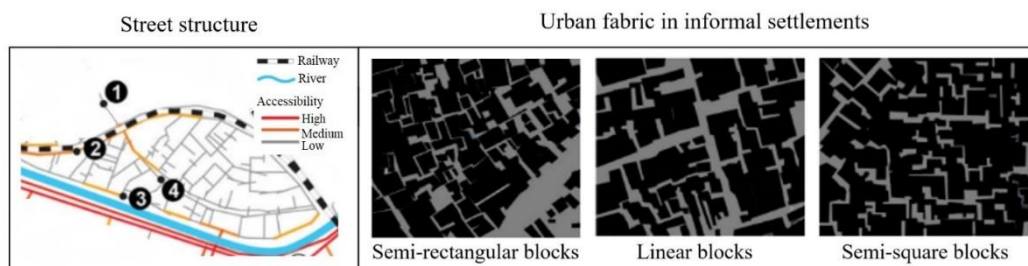


Fig. 7.7. Left: Street structure in informal settlements in Jakarta. Numbers 1-4 represent the entry points to the informal settlement with no vehicle access (Source: Hidayati, Yamu, and Tan 2020). Right: Urban fabric types in informal settlements (Source: Alzamil 2018).

For sampling informal built-up areas using OSM, shapefiles of the building blocks layer and street layer from OSM were imported into QGIS. To perform the sampling based on the physical characteristics of the informal settlements, the selection by attribute function was initially conducted on the street layer to pick wide streets (streets width > 2). Later, a buffer zone was created with the distance of 5 meters since the largest street width measured in Jakarta was 9.8 meters. Next, the building at the intersection of the wide streets' buffer has been chosen as the formal block. Finally, the selection has been inversed to pick the informal building block ([Figure 7.8](#)).

After selecting the informal building blocks based on lack of access to wide streets, they have been visually checked for the second criterion. Here, the regularity and geometry of areas that have been selected as informal were visually checked and the errors were manually resolved. For instance, some building blocks with a regular structure were selected as informal since width attribute was not defined for them. These blocks have been manually removed from the informal area selection. After finalising the layer for informal areas, it has been used as the secondary data layer for training.

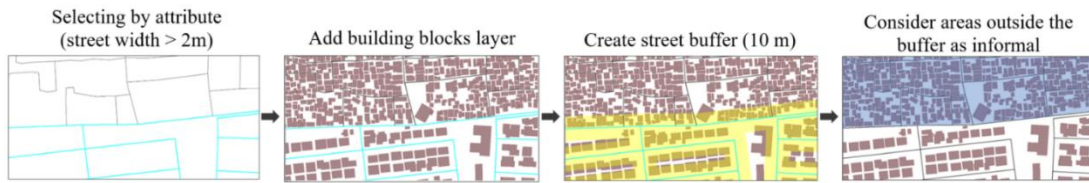


Fig. 7.8. Steps for using OpenStreetMap (OSM) for developing the training set for the informal built-up class. The blue areas represent the building with no access to a street or access to narrow streets that have been used to select pixels for informal settlements (Source: Author, Source for data layers: OpenStreetMap).

In the second round of developing the training set, after analysing the OSM layers as explained earlier, 120 samples for “road”, “formal build-up” and “informal build-up” classes were redefined. The samples are retained for other classes from the first round.

To validate the results, due to the literature (Gram-Hansen et al., 2019; M.-X. Wang et al., 2020) and the consideration of the data size, 80% of each class were randomly selected and set as training data and the remaining 20% constructed the test set. To evaluate the performance a confusion matrix was developed and it comprised true positive (TP), true negative (TN), false positive (FP), and false negative (FN) that are later used to calculate accuracy and precision (Lu et al., 2004):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

After the classification is finalised, post-processing has been done and the obtained map from both rounds of classification filtered for better visualisation (Khorram et al., 2013). Here, a median filter with a 5-pixel by 5-pixel window kernel was applied to the classified images to reduce noise and filter isolated pixels.

7.6.1 Land-Uses Classification and Informal Settlement Detection in Jakarta

In this section, the results from the first and second rounds of the classification along with accuracy

assessment results will be presented. [Figure 7.9](#) represents the first round of land-use and land cover classification using supervised RF on Landsat 8. Validation results for the proposed machine learning classification results can be found in Table 7.2.

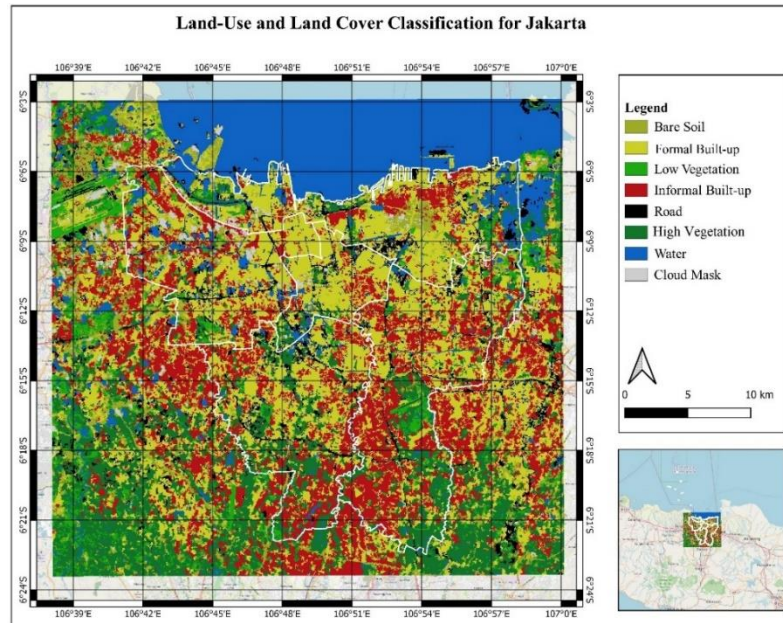


Fig. 7.9. First round of land-use and land cover classification on Landsat 8.

The land-use classification in [Figure 7.9](#) represents a very close combination of formal and informal settlements in Jakarta. However, formal built-up areas are mostly located in the north and central parts of the city, while informal settlements are mainly detected in west, east, and south ([Figure 7.9](#)). The validation results in [Table 7.2](#) show that the lowest level of precision and accuracy relates to formal settlements. Based on the table, informal built-up areas and roads have been mainly misclassified as formal built-up. This outcome suggests that the accuracy and precision of the classification might be improved by upgrading the training process for these three layers.

In the next step, the second-round training set has been developed by retraining the roads, informal built-up, and formal built-up classes using OSM layers. The resulting map from the second round of land-use classification is presented in [Figure 7.10](#). The map highlights a significant change in the detected formal and informal areas where the former areas are mainly concentrated in south and east Jakarta. In the second round of classification, informal settlements are mainly detected in the west, central, and eastern areas of the city ([Figure 7.11](#)).

Table 7.2: Confusion Matrix of RF for the first round of classification. Least accuracy and precision relate to formal built-up in which mainly roads and informal built-up have been wrongly classified as formal.

Classes	Classes								Precision	Accuracy
	Bare Soil	Formal Built-up	Low Vegetation	Informal Built-up	Roads	High Vegetation	Water	Cloud Mask		
Bare Soil	75	5	9	0	3	0	2	1	0.76	0.93
Formal Built-up	1	60	2	16	9	4	0	3	0.58	0.88
Low Vegetation	9	2	76	0	2	1	5	0	0.75	0.93
Informal Built-up	6	14	4	62	8	1	0	0	0.72	0.91
Roads	1	14	0	7	59	5	8	1	0.60	0.88
High Vegetation	2	3	7	0	4	78	1	0	0.86	0.95
Water	0	3	2	1	9	2	77	1	0.81	0.94
Cloud Mask	4	3	1	0	4	0	2	81	0.93	0.97

The validation results for the second round of classification calculated by the RF machine learning algorithm are presented in [Table 7.3](#). Based on the table, the accuracy and precision for all three retrained classes have risen. The enhancement is particularly noticeable in the formal built-up class with the increase in precision from 0.58 to 0.79 and the increase in accuracy from 0.88 to 0.94.

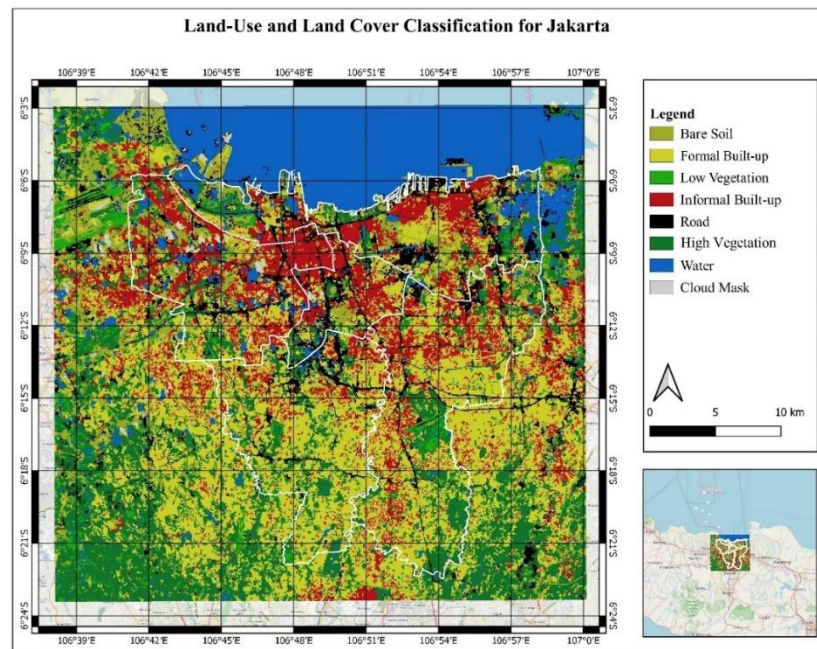


Fig. 7.10. Second round of land-use and land cover classification on Landsat 8 using OSM for developing the training set.

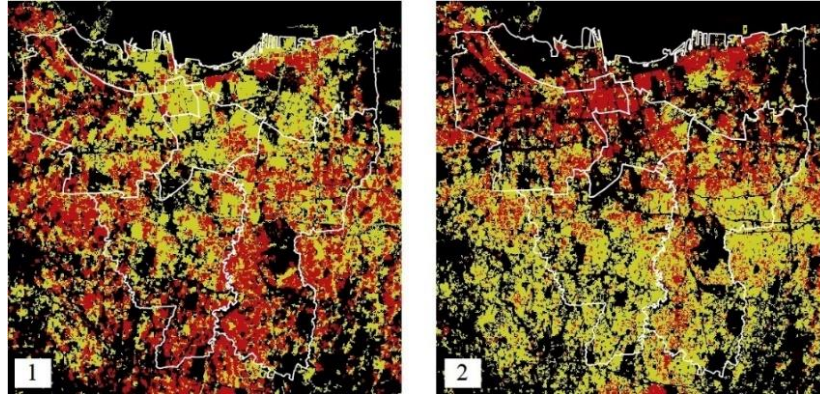


Fig. 7.11. Informal (in red) and formal (in yellow) settlements detected in Jakarta. 1. Classification by RF machine learning algorithm through the traditional method of training. 2. Classification by RF which takes advantage of OSM for developing the training set.

Table 7.3. Confusion Matrix of RF for the second round of classification.

Classes	Classes								Precision	Accuracy
	Bare Soil	Formal Built-up	Low Vegetation	Informal Built-up	Roads	High Vegetation	Water	Cloud Mask		
Bare Soil	87	2	5	0	0	0	0	1	0.86	0.97
Formal Built-up	2	76	2	9	6	0	0	0	0.79	0.94
Low Vegetation	6	0	86	0	1	1	1	0	0.86	0.97
Informal Built-up	1	8	3	81	1	1	0	0	0.88	0.93
Roads	1	8	0	2	77	2	4	1	0.81	0.95
High Vegetation	1	1	4	0	3	85	1	0	0.93	0.98
Water	1	1	0	0	6	2	84	1	0.92	0.97
Cloud Mask	2	0	0	0	1	0	1	91	0.97	0.99

The confusion matrix for the first round of classification ([Table 7.2](#)) shows that the least accuracy and precision relates to the formal built-up class. Here, mainly roads and informal built-up pixels have been wrongly detected as being formal. In the second round of classification, resampling has been undertaken for the problematic classes, including roads, formal built-up and informal built-up. Results from the second round of classification confirmed a particularly high level of accuracy classification for these three layers ([Table 7.3](#)). For instance, the accuracy and precision for the class of “roads” has increased, respectively, from 0.88 and 0.60 ([Table 7.2](#)) to 0.95 and 0.81 ([Table 7.3](#)). This significant boost in both accuracy and precision is also evident in the classified maps, as roads in the second round of classification are more continuous and represent less noise ([Figure 7.12](#)).

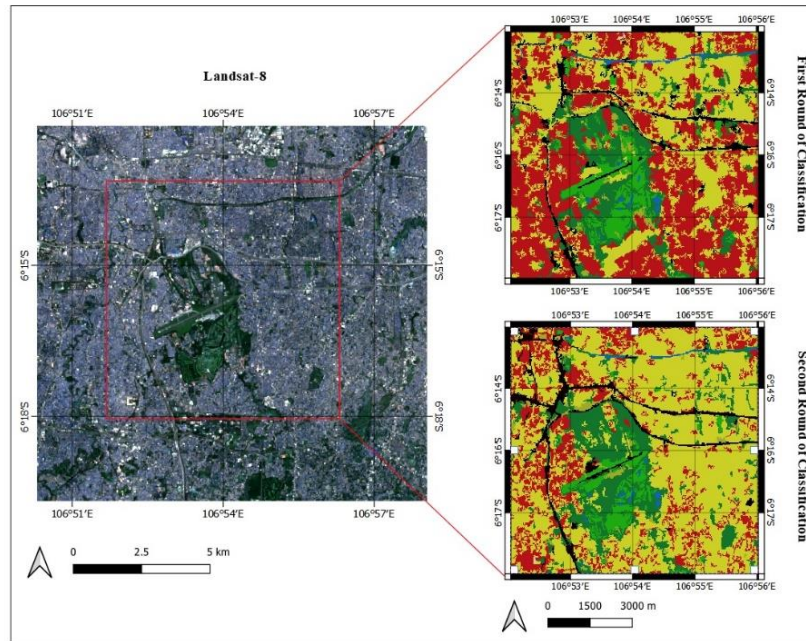


Fig. 7.12. Comparison between the roads detected in the first and second round of classification (roads are mapped as black lines). Roads in the first round of classification are not continuous and represent some noise. Unlike the first-round results, street lines in the second round are mainly unbroken and demonstrate a high level of precision that is represented in [Table 7.3](#).

The enhancement has been achieved by reducing visual interpretation errors. In the case of Jakarta, the OSM layer for roads contains the data attribute for the street width. This feature enables the use of the hierarchy of the roads network to pick samples for the roads with higher width in which the central point most likely contains a homogeneous pixel. However, it is very difficult and time-consuming to consider the width of streets during the sampling process through the visual interpretation. As a result, narrow streets might be chosen in which the selected pixels include the tones of other classes such as vegetation or built-up.

OSM data layers also enhanced the classification of formal and informal built-up areas in the second round of classification. As can be seen in [Figure 7.11](#), informal settlements detected in the first round of classification are more dispersed and mainly located in the south of Jakarta. Conversely, the informal settlements detected in the second round by using OSM are more clustered and focused in the northern areas. The 2015 informal settlement map in Jakarta (The World Bank, 2015) (see [Figure 7.5](#)) also supports the accuracy of the results mapping the most informal settlements in the northern areas. Nevertheless, one limitation of this method is its dependence on the availability of the OSM layers and comprehensiveness of the data attributes for the area of interest (Estima & Painho, 2015).

According to the results from the second round of classification, urban areas with small building blocks and narrow streets in between were effectively detected and mapped as informal settlements (Number 1-3, 5, and 6, [Figure 7.13](#)). The detected areas fit in the simple definition for slums or informal settlements that are “heavily populated urban areas characterised by substandard housing” (UN-Habitat, 2007). However, in some poorly developed or deprived areas, both formal and informal settlements might be similar in terms of structural features, such as the size of building blocks and the width of streets. In this case, OSM does not enhance the satellite image classification. Conversely, it might compromise the classification result if the training data is only developed based on the structural features guided by OSM. This is because additional factors should also be considered when developing the training set. For instance, formal settlements might have been built with stronger materials that create different colour compositions on the satellite image. By ignoring the housing quality and rooftop material in the training step, all the settlements might be selected as the training points for one class.

Although this can be considered as a limitation of applying OSM, it can be dealt with by experts who conduct a precise visual interpretation. This finding supports two points regarding the detection of informal settlements through satellite image classification: firstly, the importance of the rigorous sampling that has also been emphasised in previous research (Abdi, 2020) by considering all the physical and structural features; and secondly, the potential of using OSM to enhance the diligence of sampling when clear structural differences exist between formal and informal settlements.

In Jakarta, in some areas, the structures of formal and informal settlements are significantly different. These areas are well categorised in the second round of classification. In [Figure 7.13](#), samples number 1, 2, 4, and 5 represent how the clusters of red pixels (informal settlements) match with visually noticeable irregular built-up areas in VHR Google Earth Image. This suggests that, despite the medium spatial resolution of Landsat 8, the RF algorithm with the help of OSM can effectively detect the informal settlements.

Conversely, in the case of the complex mixture of formal and informal settlements in the urban fabric (Number 6, [Figure 7.13](#)), accurate detection of the informal settlements is not achieved. This is because the two classes are intricately interwoven and they do not produce recognisable colour composites on Landsat 8. As well, in some areas (Number 3, [Figure 7.13](#)) the formal built-up has been selected as informal. From the visual comparison of informal areas detected in FR classification and the pattern of built-up areas in VHR Google Earth Image, it can be inferred that this might be due to the similarity between the colour composite of the pixels in both settlements.

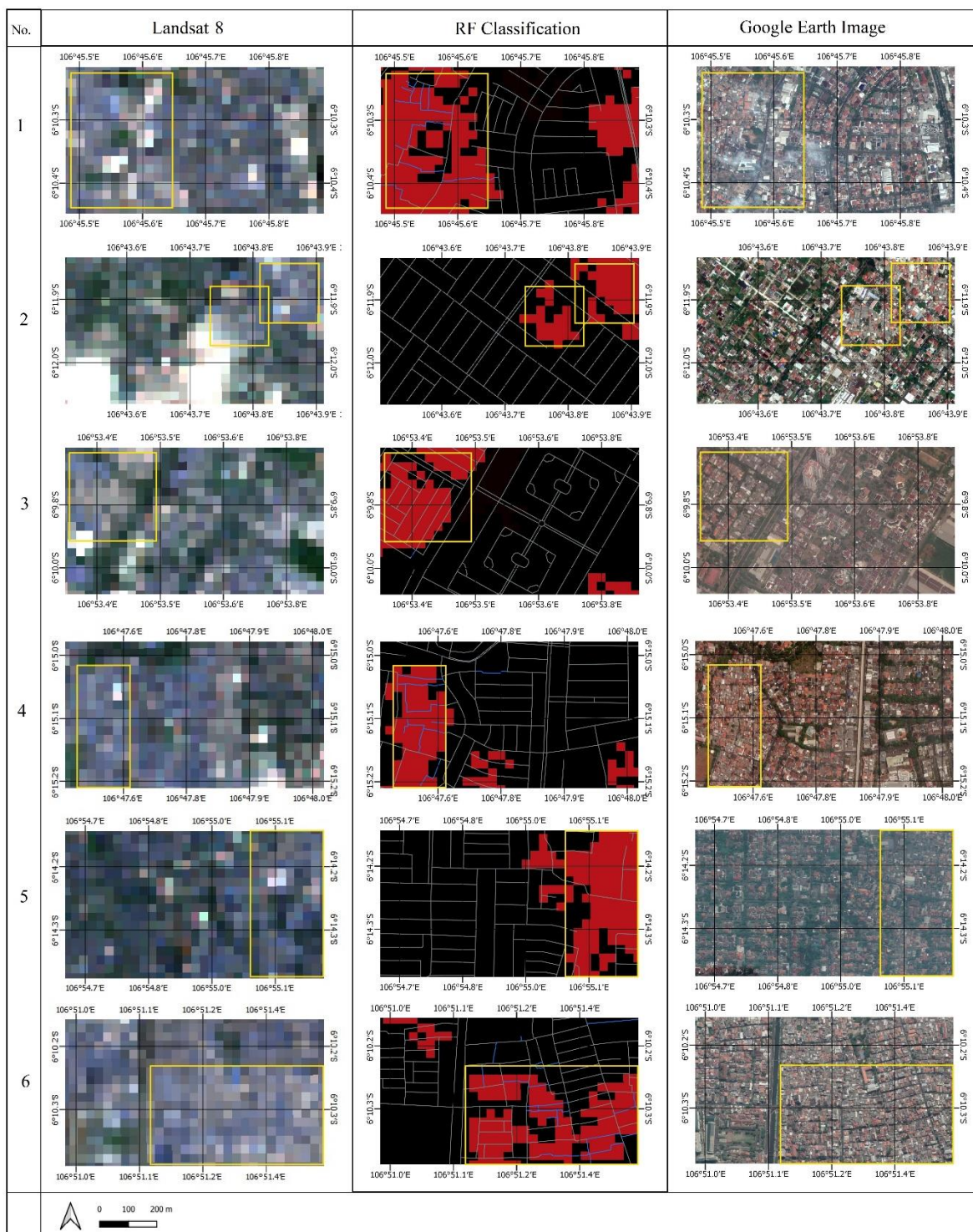


Fig. 7.13. Sample areas (No. 1-6) for magnification of the informal settlement detection by RF.

In Jakarta's informal settlements, roofs are mainly built of grey shaded material (The World Bank, 2015). Home blocks are very close to each other without noticeable trees or vegetation (UN-Habitat,

2013a). These physical features produce a specific colour composite on Landsat 8 pixels that is more blue and grey. Conversely, the colour composite is more green and brown in the formal built-up areas due to the availability of more green space and type of roofing material (Figure 7.14). The formal areas detected wrongly as informal in RF classification demonstrate similar features with a grey shade for roofs and no vegetation (Number 3, Figure 7.13). This similarity, which can be observed in high density urban areas, can be misleading for the algorithm, particularly when classifying medium resolution satellite imagery.

Generally, while OSM can boost the detection of structurally distinctive informal settlements, it might deteriorate the classification results if additional physical features, such as the rooftop materials, are ignored during the training time. Apart from the misclassification and overfitting issues in some areas, the resulting map is also noisy with several dispersed points selected as informal settlements. This is due to the relatively lower level of precision in comparison to accuracy. Accuracy refers to the level of trueness or bias, which indicates how close the average value of the results is to the true value. On the other hand, precision shows the noise that ends up as a random component (Lu et al., 2004). Given the concept and application of accuracy and precision, several isolated pixels detected in both round 1 and 2 of classification can be omitted. Furthermore, the clusters can be a better representative for informal settlements.

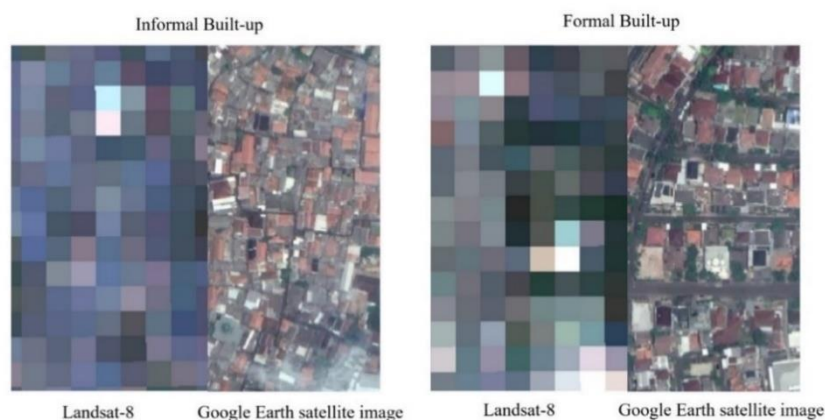


Fig. 7.14. Colour composite of Landsat 8 pixels in formal vs. informal built-up.

This result suggests that although RF has proven to be effective in the differentiation between similar classes (V. F. Rodriguez-Galiano & Chica-Rivas, 2014), misclassification can also be observed when applying the algorithm on MR to divide built-up areas into formal or informal settlements. The presented method enhanced the accuracy of the informal settlements when applying RF on Landsat 8. However, due to the diversity of the physical characteristics of the informal settlements, one method will not be applicable to all areas. Applying the presented method will be limited to the areas where formal and informal settlements encompass distinctive structure, pattern, and physical features, such as roof materials. In this

study, the training points were developed based on available data sources (2015 Jakarta's informal settlements map) which should be replaced with visual interoperation in cases where there is no current evidence. Visual interpretation is a process that takes time, especially for larger-scale contexts such as a country. This limits the application of the proposed method to relatively small-scale scenarios, such as a city.

7.6.2 Mapping of informal settlements in Jakarta

After detecting the area for informal settlements, the most recent map of informal settlements (2015) has been updated based on the findings. Through the updating process (Figure 7.15), initially the intersection between the detected informal settlements (Figure 7.11) with the 2015 map of informal settlements in Jakarta was obtained.

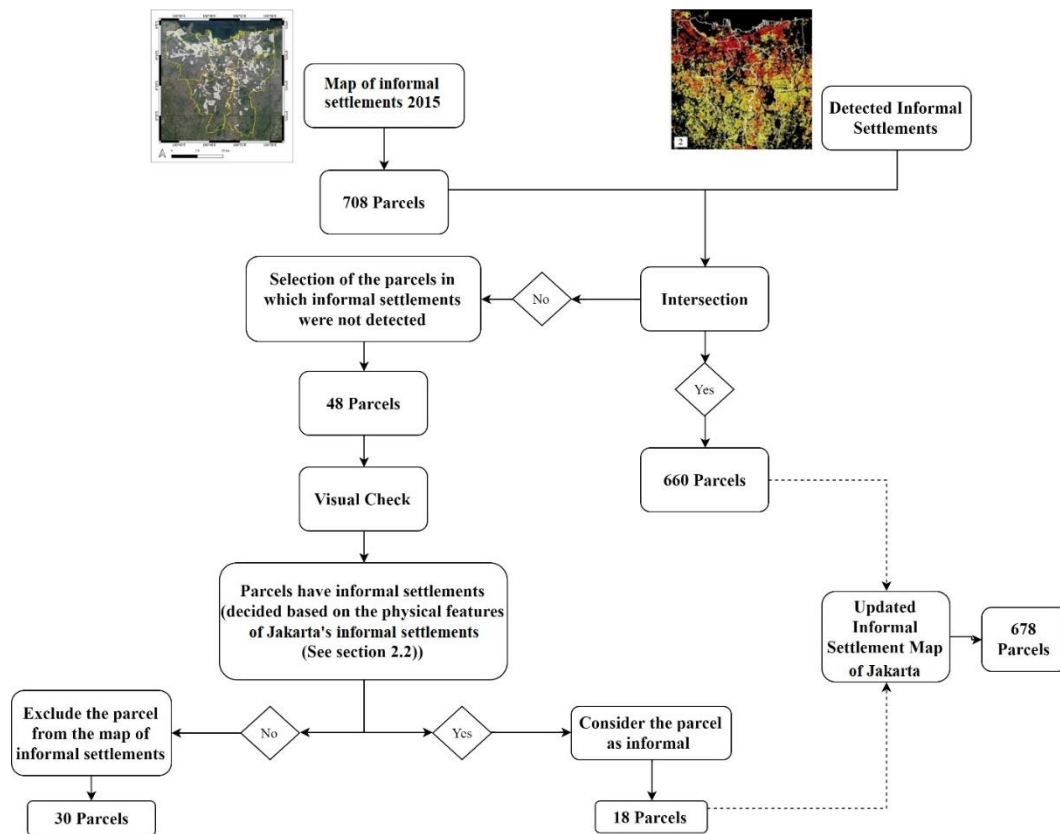


Fig. 7.15. Process for updating the map for the 2015 informal settlements based on the informal settlement detection.

Based on the results, from 780 informal settlements parcels of the 2015 map, 660 parcels had intersection with the detected areas. 48 parcels were mapped as informal in 2015 that, according to the results, no informal settlements were detected in them. The 48 parcels were visually interpreted with reference to 2020

VHR Google Earth Image. 30 parcels were defined as not being informal due to the physical characteristics of the building blocks and streets ([Figure 7.16](#)). This can be inferred as the correct detection. Therefore, RF successfully detected the formal and informal areas for 690 out of 678 parcels. [Figure 7.17](#) represents the updated map for Jakarta's informal settlement in 2020.



Fig. 7.16. Sample for Excluded Parcels from Informal Settlement Map.

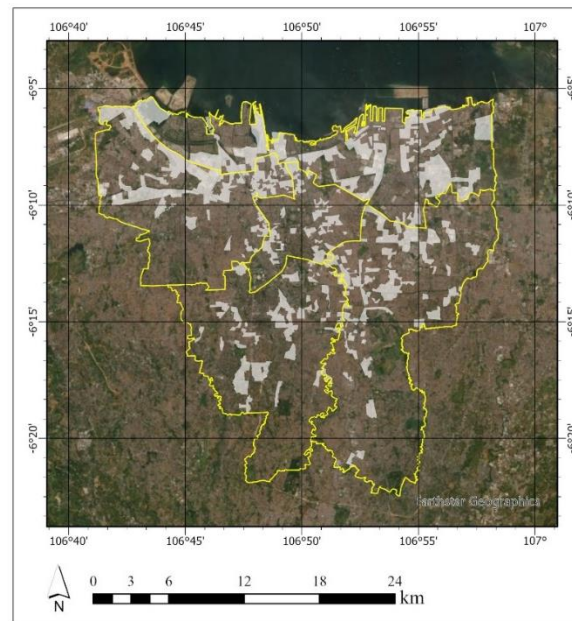


Fig. 7.17. Updated map of informal settlements in Jakarta (based on image classification-2021).

7.6.3 Mapping parks and farmlands in Jakarta

One of the data layers that was missing in Jakarta was the area of parks that can be used for temporary public shelters in times of disaster. Through the land-use classification processes, parks might be classified

as two different classes: high vegetation and low vegetation. In Jakarta, farmlands are mainly classified as low vegetations. Where farmlands are located, minor mixture of high vegetation class appears. Conversely, where only high vegetations are detected without low vegetation in between, the area is mainly urban jungle or street tree lines (Figure 7.18). In this research, all of the detected vegetation parcels have been visually checked and compared with Google Map VHR to finalise the target parcels.

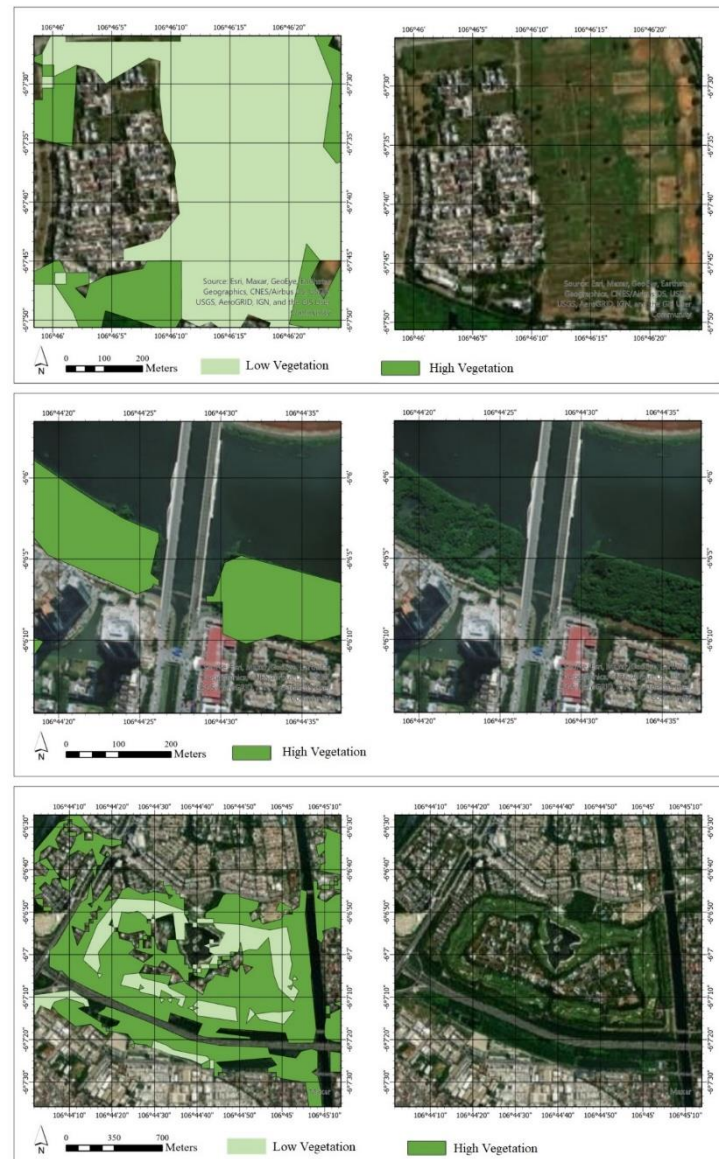


Fig. 7.18. Left: areas classified as low and high vegetation on Landsat 8, right: the same area on VHR Google Map images.

7.7 Chapter summary

It is estimated that informal settlements accommodate 25% of the world's urban population (UN-Habitat, 2013b). This remarkable percentage is the most vulnerable and least recognised in planning and

management practices (Rumbach & Shirgaokar, 2017; UN-Habitat, 2014). Informal settlements have also received limited acknowledgment in the global efforts to reach the Sustainable Development Goals (SDGs), despite its main slogan saying 'leave no one behind'. This is due to the lack of statistical and census data about the settlements and the willingness of authorities to end such conditions. The first step to address this is to detect informal settlements within urban areas, yet monitoring and upgrading them is one of the biggest challenges. Although high resolution remotely sensed data and particularly satellite images provide the opportunity to detect informal settlements, the drawback is still the lack of access as a cost-prohibitive data source. In the current study, the application of random forest algorithm (RF) for the detection of informal settlement on freely available Landsat 8 has been tested through two complementary approaches for developing the training set. In the primary approach, the training samples were developed applying two methods: using available databases (the most current map for informal settlements); and visual interpretation method using VHR. In the secondary or complementary approach, OpenStreetMap (OSM) helped build the sample set for the classes with the least accuracy and precision in the first round of classification.

Comparing the results from the first and second rounds of classification showed that OSM can be used as a complementary data layer to enhance the rigour of developing the training set, as well as making the detection of informal settlements more accurate. However, the results showed that OSM is helpful when distinctive structural features exist between formal and informal settlements (e.g. different building size or street width). Consequently, the method does not enhance the classification in the areas where formal and informal settlements are structurally similar. Additionally, in case the training relies only on OSM, some physical features such as rooftop materials that create unique colour composites might be overlooked. So, in this sense visual interpretation is unavoidable.

The final limitation of applying OSM relates to the validation issue of the open data and availability of data with the required data attributes. Based on the aim of classification, required data might not be available through the OSM of the area of interest. In addition, OSM as a Volunteered Geographic Information (VGI) is less reliable in comparison to the data provided by authorities, such as maps created by government agencies. Nevertheless, the opportunities that OSM provides has made it a competitive source of data. Furthermore, several methods exist that can be used to validate OSM, such as the ground check: comparing with the available data from other sources such as government prepared maps or Google maps for the physical features.

As well as the limitation of using OSM, the results reveal another impediment that exists in the detection of informal settlements on Landsat 8, which is overfitting and misclassification of formal areas as informal,

or vice versa. This is due to Jakarta's informal and formal areas' colour composite on Landsat 8 being very similar. This might happen due to the same type of roof materials employed in both classes, the mixture of formal and informal blocks in some urban areas, or closeness of the building blocks or lack of green spaces in the formal settlements which is mainly a physical attribute of the informal urban fabric.

Overall, the findings confirm that applying the proposed workflow is a cost-effective way to detect informal settlements. However, considering the impediments and the necessity for visual checks, the application of this method best suits areas not bigger than a city where: 1) informal and formal settlements are structurally very different and easy to spot; 2) major differentiations exist in roof materials of the settlements; and 3) formal and informal settlements are generally not well linked, if at all.

CHAPTER 8

JAKARTA CASE STUDY PART 2: INTEGRATING RESILIENCE INTO THE SDGs AT THE LOCAL LEVEL

8 Jakarta Case Study Part 2: Integrating Resilience into the SDGs at the Local Level

8.1 Introduction

In Chapter 6 indicators from the BRF to integrate a more inclusive system for measuring resilience into the SDGs have been proposed. Although this is a good strategy, a methodological workflow is yet to be developed to add the proposed indicators and test the effectiveness of the enhanced SDGs in measuring resilience at the local level. To cover these discrepancies, this chapter: 1) proposes a workflow for incorporating baseline resilience indicators into the SDGs at the local level; and 2) evaluates the hypothesis, whether adding baseline resilience indicators will enhance the effectiveness of the SDGs in measuring resilience at the local level.

8.2 SDGs' Localisation

According to the United Nations Development Program (UNDP), the SDGs' localisation can be defined as “translating the aspirations of the goals and targets into implementable plans and programmes on ground” (UNDP, 2019). However, it is not clear how local parties can formulate and implement the global framework (Fenton & Gustafsson, 2017). Representatives of academia and industry have tried to define how this process of localisation can be achieved (Allan et al., 2021). One accepted approach is to conceptually align existing and future strategies, plans, and actions with the SDGs as followed by some Swedish municipalities (Krantz & Gustafsson, 2021). Despite being a good start, the approach does not provide any resolutions or workflow to enable the SDGs' localisation. Rather, it conceptually considers the ambitions of goals when setting strategies. Krellenberg et al. (2019), looking at four cities (Hamburg, Magdeburg, Milwaukee, and St. Petersburg), criticise the approach setting the sustainability plans while no indicators have been developed locally to make such SDGs implementation feasible (Krellenberg et al., 2019).

Another approach is to select specific indicators and apply them in local strategic planning. Souza Santos and Kahn Ribeiro (2015) suggest the importance of sectoral variables, such as CO₂ emissions as a transportation indicator, to govern local commitments in line with achieving the SDGs. Taking Rio de Janeiro as an example, they stress the importance of applying the SDGs indicators as long as they are relevant to local practice (Santos & Ribeiro, 2015). Although referring to the SDGs indicators shows commitment to sustainability, the idea could lead to isolated decision-making. With the first and second approaches there is the concern of cherry-picking the goals based on sectors' or local governments' priorities and disregarding the subtle connections among different aspects of sustainability and SDGs (Stafford-smith et al., 2017).

A third approach stresses the essence of the prioritisation, selection, or alignment of indicators to line up with local development strategies. The idea is to set up a series of targets and indicators that are context-specific while corresponding to national measures developed for realising SDGs (Fox & Macleod, 2021; Krellenberg et al., 2019; Lucci, 2015). However, this approach has not been properly applied in practice due to the lack of a proper methodological workflow. As such, this study proposes a methodological workflow in line with the third approach.

8.3 Innovative Workflow for SDGs' Localisation

To achieve the aim of this study- strengthen resilience measurement in the SDGs, to be used as a framework for measuring and monitoring both sustainability and resilience, as well as developing a methodological workflow that functions well at the local level-, a three-step methodological workflow has been developed: 1) Indicators' assessment, 2) Indicators' alignment with the local context, and 3) Analysing indicators' significance in measuring resilience/sustainability at the local level ([Figure 8.1](#)).

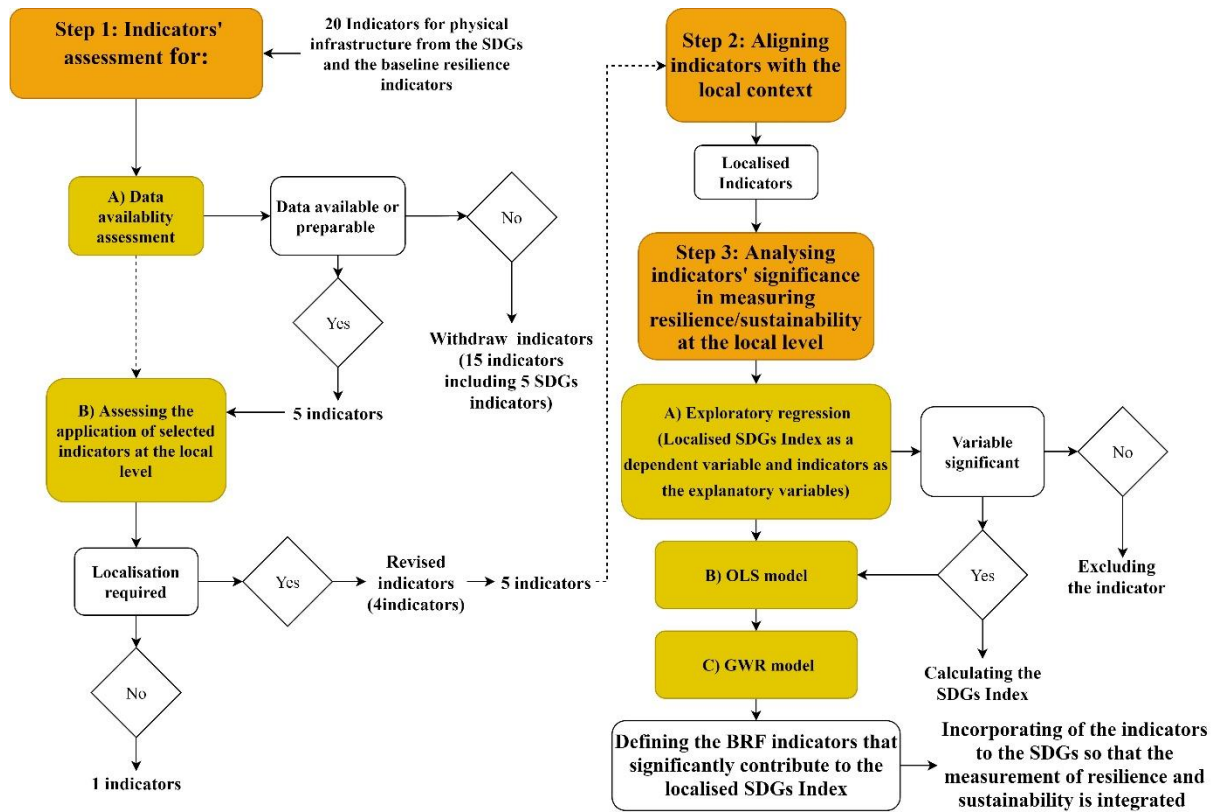


Fig. 8.1. Proposed workflow for incorporating resilience indicator into the SDGs through a local approach.

Step 1 (Indicators' assessment): The proposed workflow starts with data availability assessment, where all the formerly proposed baseline resilience indicators from BRF are evaluated for the required data at the

local scale being accessible. This step reduces the impact of data paucity on the final assessment of resilience through the SDGs. For the purpose of this study, of the five resilience dimensions elaborated in Chapter 4, infrastructure has been selected for integration into the SDGs, as it is the key to achieving the SDGs (Casier, 2015). Infrastructural resilience is generally divided into social and physical infrastructure. Social infrastructure includes physical facilities and spaces where the community can access social services. These include health-related services, education and training, social housing programs, police, courts and other justice and public safety provisions, as well as arts, culture, and recreational facilities. Social infrastructure therefore addresses health, economic, workforce and education infrastructures, efficiency (consumption of water, energy, etc.), and emergency response. Physical infrastructure, on the other hand, incorporates land (L), housing (Ho.), transportation (T), Communication (Co.), and utilities including energy, water, & sanitation (EW&S) (see [Appendix 3](#) for more details).

Here as a proof of concept, incorporation of the physical infrastructure indicators into the SDGs will be examined. In the first step, the pool of indicators for assessing the resilience of physical infrastructure (listed under the physical infrastructure components reported in [Appendix 3](#)) have been evaluated for data accessibility. Indicators for which data is available ([Table 8.1](#)) were selected to be added to the SDGs indicators that evaluate physical infrastructure ([Figure 8.2](#)). Despite the availability of data for some of the indicators, the data might require aggregation or disaggregation. Following this data preparation the next step would be checking for application at the local level and aligning the indicators as required for the local context.

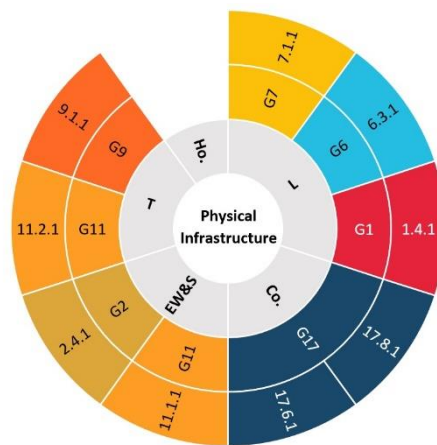


Fig. 8.2. SDGs Addressing the Resilience of Physical Infrastructure, including land (L), housing (Ho.), transportation (T), Communication (Co.), and energy, water, & sanitation (EW&S).

Step 2 (Indicators' Alignment): Through the second step, indicators have been aligned to the local context. For instance, convenience of access to public transport (walkable distance) that is evaluated by a

fixed number (500 meters) in the SDGs (indicator 11.2.1) cannot be accurate for different locations where weather conditions will vary. Therefore, the local climate features have been considered for this indicator. After aligning the indicators where required, the spatial layers for each of the localised indicators have been created.

Step 3 (Measuring Resilience and Sustainability in the Context of the SDGs): After creating the spatial data for all selected indicators at the sub-districts level ([Figure 8.3](#)), the SDG Index for physical infrastructure resilience and sustainability in Jakarta has been calculated based on both SDGs' and additional resilience indicators in each of the 286 sub-districts. The index is calculated applying the SDGs' method and this means calculating the average of the score for each indicator after normalising all values between 0-1.

In the next step, an exploratory regression has been applied on the indicators as the exploratory variables and the Index as the dependent variable. The exploratory regression evaluates all possible combinations of the input candidate explanatory variables, and defines those that best explain the dependent variable (Esri, 2021). Here, by defining the existence and strength of any linear correlations of the exploratory variables and the Index, the indicators that significantly contribute to the local SDGs Index are determined (Braun & Oswald, 2011).

Exploratory regression, in fact, shows the correlation between the calculated SDG Index with the value of each indicator. As a tangible example, imagine a classroom with 262 students (here, sub-district parcels). Consider their Grade Point Average (GPA) (here the Index) comes from 6 units (here the value of each of the 6 indicators for the parcel). In this case, the exploratory regression will define whether there are units that have linear correlation with the GPA. If the result shows that for a given semester math has a positive linear correlation with the GPA with 80% confidence, that means, having only the math results, the GPA can be estimated with 80% confidence. In this research, the high confidence linear correlation shows that the specific SDGs or BRF indicator are a good indication of the level of resilience/sustainability in Jakarta - the significance of the indicator for measuring resilience/sustainability at the local level. This means if in a sub-district data is only available for the indicator exhibiting a high level of significance, its resilience/sustainability (the local SDG Index) can still be estimated. After selecting the indicators, they have been measured for each of the 286 sub-districts to calculate the local SDG Index.

Validation: After selecting the most effective indicators, Ordinary Least Squares (OLS) and Geographical Weighted Regression (GWR) models were devised for testing the hypothesis: "the addition of the resilience indicators will enhance the effectiveness of the SDGs in measuring resilience at the local level". Assuming spatial stationarity of the data, OLS indicates that the dependent and independent

variables have global relationships (constant relationships over space), regardless of distance. However, in some cases the association between the variables might be affected by distance. GWR on the other hand, based on the distance between observed points, reveals the spatial association between variables (Koh et al., 2020). Although GWR provides more information about the variables association, OLS should always be run before moving to the GWR model because it does not have the strong diagnostics (e.g. p-value) that OLS does.

By developing these models, the observed local SDGs Index (calculated after the step three) will be estimated using different sets of indicators according to the scenario. If the estimation of the local SDGs Indexes in OLS and GWR model that are developed based on the additional BRF indicators are close to the observation (based on the accepted values for standard residual), it can be inferred that adding the indicators could enhance the effectiveness of the SDGs in measuring resilience at the local level. Therefore, the hypothesis of this research is supported.

The models are arranged based on four scenarios creating dummy variables for each added indicator (Hardy, 1993). The regression model for all scenarios will be written as follows:

$$Index = \beta_0 + \beta_{NoHo}X_{NoHo} + \beta_{NoSh}X_{NoSh} + \beta_{AFOr}X_{AFOr} + \beta_{ATra}X_{ATra} + \beta_{ARoa}X_{ARoa}$$

$$\text{Scenario 1: } \beta_{NoHo} = 0 \text{ \& } \beta_{NoSh}, \beta_{AFOr}, \beta_{ATra}, \beta_{ARoa} \neq 0$$

$$\text{Scenario 2: } \beta_{NoSh} = 0 \text{ \& } \beta_{NoHo}, \beta_{AFOr}, \beta_{ATra}, \beta_{ARoa} \neq 0$$

$$\text{Scenario 3: } \beta_{NoHo} = 0 \text{ \& } \beta_{NoSh} = 0 \text{ \& } \beta_{AFOr}, \beta_{ATra}, \beta_{ARoa} \neq 0$$

$$\text{Scenario 4: } \beta_{NoHo}, \beta_{NoSh}, \beta_{AFOr}, \beta_{ATra}, \beta_{ARoa} \neq 0$$

$$\text{Test Scenario: } \beta_{NoHo} \neq 0 \text{ \& } \beta_{NoSh} \neq 0 \text{ \& } \beta_{AFOr}, \beta_{ATra}, \beta_{ARoa} = 0$$

Where each of the $\beta_{NoHo}, \beta_{NoSh}$ are the baseline resilience indicators and $\beta_{AFOr}, \beta_{ATra}, \beta_{ARoa}$ are the SDGs indicators (See [Table 8.2](#)).

In the first scenario, one of the baseline resilience indicators will be omitted from modelling while the rest will be presented. In the second scenario, the next resilience indicators will be omitted and the first one along with the SDGs' will remain in developing the models. In the third scenario both the baseline resilience indicators will be omitted, and finally in the fourth scenario none of the indicators will be removed. The test scenario in which the SDGs indicators are removed will show whether the omission of any indicators will affect the accuracy of the model estimation at the same level.

8.4 Testing the Developed Workflow for Integrating Resilience Indicators into the SDGs in Jakarta

In this section, results have been presented based on the three main steps of the developed workflow. Starting from the results obtained from assessing indicators for data availability and local application, the

selected indicators are aligned according to the local context, and finally the significance of the proposed indicators is investigated.

8.4.1 Indicators' Assessment for Data Availability and Application in Local Level

As discussed in the method section, the indicators to measure physical infrastructure resilience have been extracted from both the SDG and baseline resilience frameworks that are listed in [Table 8.1](#).

Among nine SDGs indicators that measure physical infrastructure ([Figure 8.2](#)) data was available for three that demonstrates the essence of a solution to cope with data scarcity. Here, the pool of baseline resilience indicators from the BRF can help. From the pool, ten indicators measure physical infrastructure's resilience, among which the data is available for two in Jakarta. However, the data was not ready to use and in order to measure the indicators the data processing and preparation is necessary and, in many cases, to be aligned with the indicators ([Table 8.1](#)). Following data preparation, spatial data has been built by creating a map for each indicator ([Figure 8.3](#)).

Table 8.1. Results from the assessment of the SDG and resilience (BRF) indicators of physical infrastructure for data availability and local application.

Original Indicators	Source		Indicators' Assessment and alignment		
	BRF indicators	SDGs (Indicator No.)	Data preparation required	Indicator's localisation required	Localised indicator
1 Proportion of urban population living in slums, informal settlements (indication of inadequate housing).		✓ (11.1.1)	✓	✓	Area of formal settlements to the residential area.
2 No. of hotels/motels per 10,000 persons (indication of shelter availability).	✓		✓		
3 Distance to nearest public shelter.	✓			✓	a) No. of indoor shelters per 10,000 persons. b) Area of public open spaces to the residential area.
4 Proportion of population that has convenient access to public transport (500 m).		✓ (11.2.1)	✓	✓	Area with convenient access to public transport (450 m) to the residential area.
5 Proportion of the rural population who live within 2 km of an all-season road (indication of access to an area for emergency response).		✓ (9.1.1)	✓	✓	Area with access to quality roads to the residential area.

8.4.2 Indicators' Alignment to the Local Context

According to the data availability and the characteristics of the local context, indicators 1, 3 and 5 require alignment ([Table 8.1](#)). For indicator 1 (SDGs indicator 11.1.1: proportion of urban population living in slums, informal settlements, or inadequate housing), the population data survey 2018 has been used.

However, the data does not include an attribute for the share of population living in the formal and informal settlements. To disaggregate the data into formal and informal, the data sets on population of the informal settlements based on the 2015 survey (The World Bank, 2015) have been used. However, the population data was not complete for all settlements. As a solution, the 2015 informal settlement map for Jakarta has been checked for the sub-districts that were completely occupied by informal settlements. The population of those sub-districts could be used as a reference to estimate the population in other sub-districts. However, only three parcels were completely occupied with informal settlements so this was not enough for calculating the informal population in all other sub-districts. Therefore, for the indicator to be locally measurable, it should be revised according to the data availability and local context. Here indicator 1 has been revised to “Area of informal settlements to the residential area” in each sub-district. For the calculation of this indicator, the area of informal settlements within each sub-district has been divided by the area of each sub-district and a map illustrating the spatial data has been created ([Figure 8.3](#)).

For indicator 3 (distance to nearest public shelter) the first step in collecting the data was to detect the location of public shelters in Jakarta. In Jakarta public buildings, schools, religious buildings, and public parks mostly serve as public shelters (Kusumo et al., 2017). Here, utilising the VGI from Jakarta OSM, the map for public shelters was created based on the building blocks layer that includes the attributes for building type. The selected building types include church, mosque, community group offices, malls, schools, and social facilities that have served as indoor shelters. The original indicator (distance to nearest shelter) measures a relative level for resilience (the further the lower resilience), while in this study the indicators should be calculated for each sub-district where more than a shelter might exist. Therefore, the indicator is localised as “No. of indoor shelters per 10,000 persons”. On the other hand, in Jakarta, parks and open green spaces are considered as potential shelter sites. For parks, since neighbourhood parks are very different from urban forests, the area attribute could be a better indication for the availability of shelters. Therefore, another indicator is added: “Area of public open spaces to, the residential area”. Here, parks have been considered as public open spaces ([Figure 8.3](#)).

For indicator 4 (SDGs indicator 11.2.1: Proportion of population that has convenient access to public transport), proposed by the SDGs, the UN Statistical division defines convenient access as a 500-meter distance to public transport stations. However, due to the local climate/weather conditions in different geographical areas, convenient access can be adjusted for closer or further distances (e.g. the distance should be closer for tropical areas that have hot and humid weather). In Jakarta, walkability is as close as 450 m (Donny Koerniawan, 2014). Therefore, the distance has been considered for localising the indicator ([Table 8.1](#)). For creating the layer for areas with convenient access to public transport, three data layers are needed: roads, bus stops, and train stations. Initially, the layer for train stations and bus stops have been

created. Next, the layer for train stations points was created on My Map (<https://maps.google.com>) based on the retrieved data for the location of train stations. Finally, utilising network analysis method in ArcGIS, the road data layer can help to calculate the travel time to create areas where people can reach to bus stops and train stations with a 450 m walk (Figure 8.4). Later, the indicator has been measured for each sub-district by dividing the residential areas with convenient access to public transport by total residential area (Figure 8.3 & Figure 8.4).

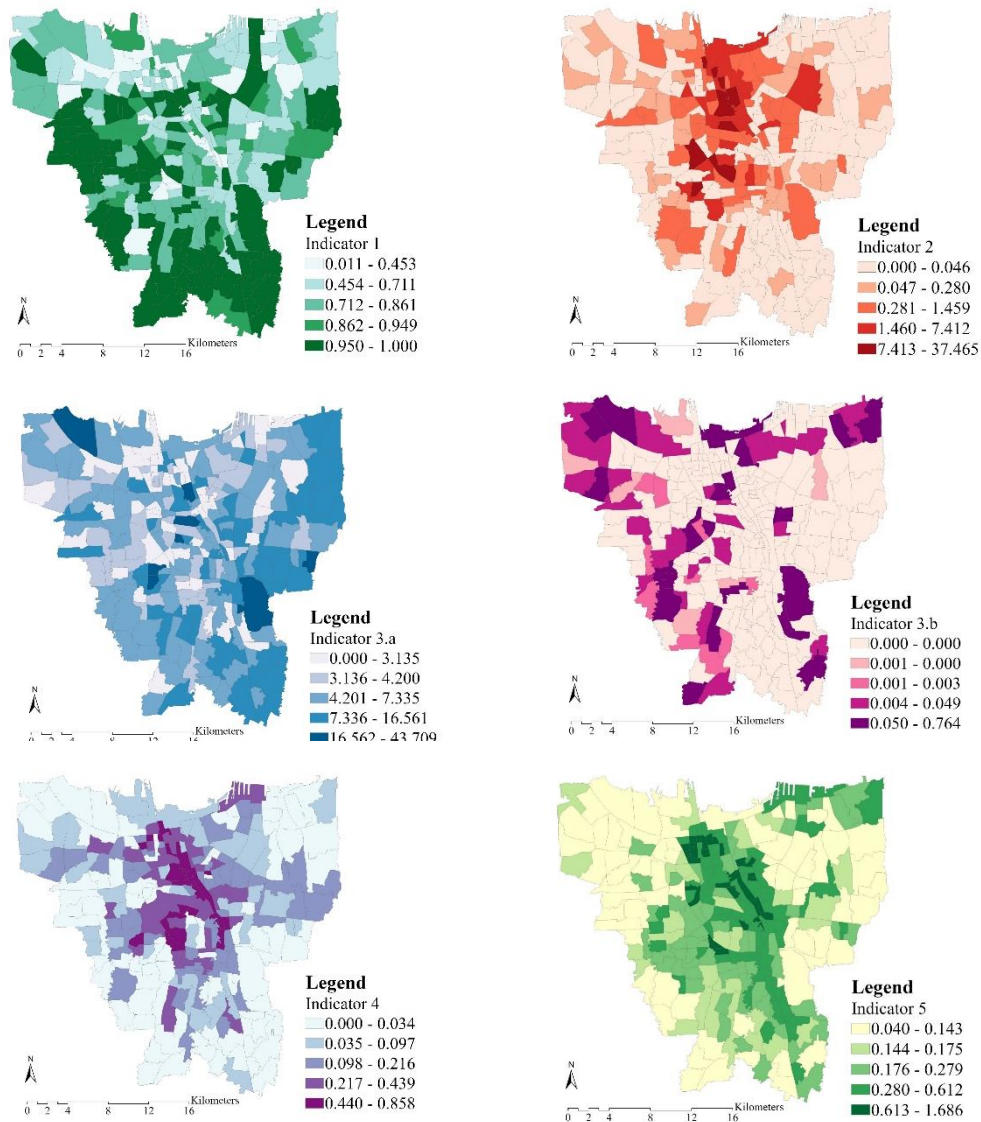


Fig. 8.3. Maps of indicators measured at the sub-district level (see Table 8.1 see for indicators' description).

Indicator 5 (SDGs indicator 9.1.1: Proportion of the rural population who live within 2 km of an all-season road) has been defined by the UN as access to available quality roads in rural areas. However, the indicator does not consider the road quality and accessibility to urban villages including informal

settlements. Accessibility inside the informal settlements is a general issue that prevents emergency vehicles to function properly in times of disaster. In Jakarta, roads in most of the informal settlements are very narrow (width < 2m) and cannot be accessed by emergency and personal vehicles (Assarkhaniki et al., 2021). To take this issue into account when measuring the SDG Index, the indicator has been aligned to the local context. Here the accessibility to quality roads in urban areas has been measured as “Area with access to quality roads to the residential area”. Later, since the highest street width measured in Jakarta was 9.8 meters, a 5 m buffer from the roads with the width equal to and wider than 2 meters has been created for selecting (using select by location function in ARCGIS Pro) the building blocks with access to quality roads. Next, the indicator has been calculated by dividing the residential areas with access to all season road by the total residential areas (Figure 8.3).

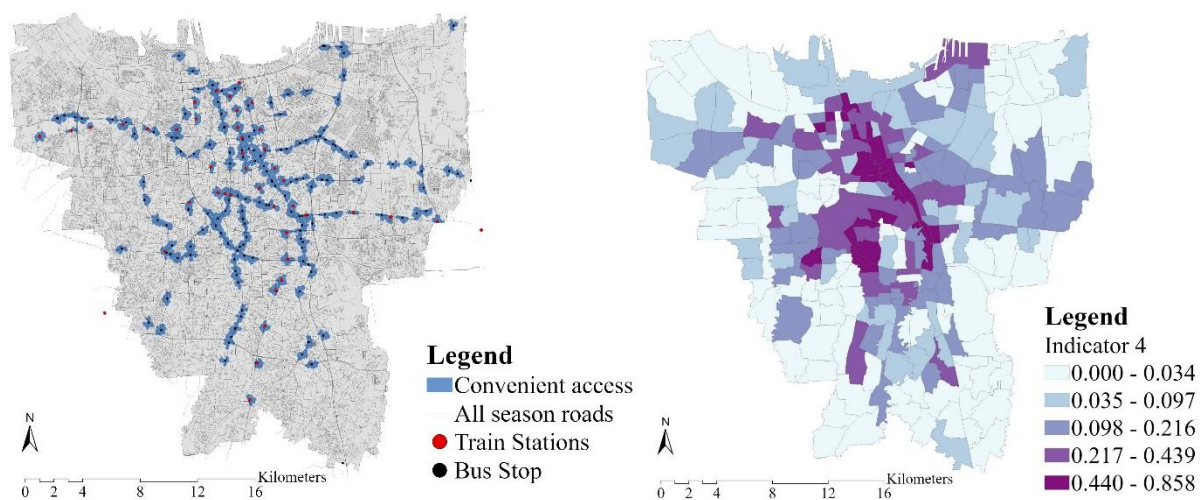


Fig. 8.4. Creating the travel time map using the points for public transport and road layer (featuring bus stops and train stations within a convenient walking distance in Jakarta).

Data Preparation: for indicator 2, the indicator does not need revisiting considering the local context. However, the data needs preparation. For this purpose, statistical data for hotels 2020 has been downloaded from Jakarta Open Data. The data includes the addresses for hotels. The addresses have been used to create spatial data for hotels as a data layer on My Maps (<https://maps.google.com>). Later the indicator has been calculated for each sub-district and the Choropleth map of each indicator has been created in ArcGIS Pro (Figure 8.3).

8.4.3 Analysing Indicators’ Significance in Measuring Resilience/ Sustainability at the Local Level

In the first step of indicator’s assessment for data availability and application at the local level, the spatial data layer for indicators (Figure 8.3) have been used to create the local SDG Index map (Figure 8.5). The

map shows the areas with high to low level of sustainability and resilience (shown with yellow to brown respectively in [Figure 8.5](#)).

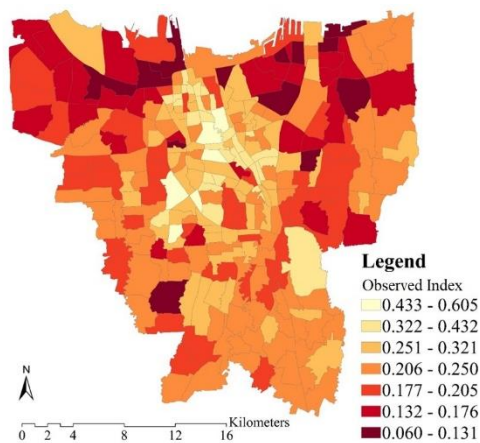


Fig. 8.5. Jakarta's pilot local SDG Index for physical infrastructure at sub-district level (higher to lower level of resilience and sustainability shown in yellow to brown respectively).

According to the regression analysis results ([Table 8.2](#)), all the variables (indicators) except for *AOpe* (indicator 2: Area of public open spaces to the residential area), significantly contribute to the local SDG Index. Based on the results, indicator 3.b (*AOpe*) has been withdrawn from the set of indicators. Also, all remaining variables except for *ATra* (indicator 4) have a 100% positive correlation with local SDGs Index, meaning there is a positive linear correlation between the indicators and the Index for all sub-districts. *ATra*'s simultaneous negative and positive correlation with the Index shows a negative correlation between the Index and indicator in some of the sub-districts, while it is positive for some others.

Table 8.2. Exploratory regression results for the variables' significance and collinearity.

Indicator No.	Variables	Source	% Statistically Significant	% Negative	% Positive	VIF
2	No. of hotels per 10,000 persons (NoHo)	BRF	100.00	0.00	100.00	1.35
3.a	No. of indoor shelters per 10,000 persons (NoSh)	BRF	100.00	0.00	100.00	1.35
1	Area of formal settlements to the residential area (AFor)	SDGs	74.19	0.00	100.00	1.21
4	Area with convenient access to public transport (450m) to the residential area (ATra)	SDGs	74.19	25.81	74.19	1.19
5	Area with access to quality roads to the residential area (ARoa)	SDGs	45.16	0.00	100.00	1.13
3.b	Area of public open spaces to the residential area (AOpe)	BRF	35.48	0.00	100.00	1.04

Where - large values (> 7.5, for example) of VIF (Max Variance Inflation Factor) indicates explanatory variable redundancy.
- % Positive/negative correlation demonstrates the percentage of the sub-district that have a positive/negative correlation with the index.
- % Statistical significance shows whether a factor is a good (high and moderate statistical significance (NoHo for high and AFor for moderate significance, for example) or not a good predictor (ARoa, for example) for the index (Feng & Tong, 2017).

Based on the regression analysis result, two of the BRF indicators (No. of hotels and No. of Shelters) significantly contribute to accurately estimating the index (static or stationary relationship between exploratory variables and the SDG Index variables across the study area). These indicators will be added to the SDGs indicator sets to enhance resilience assessment if the global and local models confirm the exploratory regression results.

8.5 Validation

After defining the best indicators to measure resilience in the SDGs, the effectiveness of additional indicators in calculated local SDG Index has been statistically validated through developing Ordinary Least Squares (OLS) and Geographical Weighted Regression (GWR) models for five different scenarios. A better performing model tends to have a higher R² that shows the strength of the model in estimating the dependent variable and a lower AICc that indicates relative information lost by the model (Fotheringham, Brunson and Charlton, 2003).

A standard residual map has been created for the GWR models of all scenarios ([Figures 8.6](#)). The accepted value for standard residual is -2 to 2 (Charlton & Fotheringham, 2011) when -2 shows under prediction and 2 indicates overprediction and the best value is around zero.

Table 8.3. Models' Summary of the results (for 262 observations).

	Global Model (OLS)				Local Model (GWR)		
	R ²	AdjR ²	<i>p value</i>	AICc	R ²	AdjR ²	AICc
Scenario 1	0.843903	0.841473	0.000000*	373.228987	0.8866	0.8743	321.7225
Scenario 2	0.667154	0.661974	0.000000*	571.615348	0.7141	0.6892	555.6673
Scenario 3	0.093810	0.083273	0.000003*	831.931656	0.0984	0.0785	832.4917
Scenario 4	0.999884	0.999882	0.000000*	-1512.648112	0.9999	0.9999	-1511.6398
Test Scenario	0.997577	0.997548	0.000000*	-720.168280	0.9982	0.9980	-769.8424

Coefficient of determination (R²): The square of the correlation coefficient that reflects the ability of a regression model to predict the measured values of the dependent variable. R² value varies from 0.0 to 1.0, with higher values being preferable.
Akaike Information Criterion (AICc): Indicates how much information has been lost during the estimation process.
Adjusted R² (AdjR²): R-squared adjusted for model complexity (number of variables).

The results from the OLS and GWR models show the highest accuracy of the index estimation when the additional resilience indicators are present, and this supports the hypothesis and accordingly validates the developed workflow for integrating resilience into the SDGs. Scenarios 1 and 2 are the models when only one of the additional indicators is kept. Scenario 4 has the highest accuracy when both additional indicators are contributing to the model's refinement. Scenario 3 is the model development only based on the SDGs indicators that shows the least accuracy. For the test scenario, instead of the resilience indicators, the SDGs indicators are excluded to find out if any exclusion would reduce the accuracy of the model. The results from the test model, however, show a high level of accuracy. In addition, the maps of the standard residual

([Figures 8.6](#)) confirm the results from [Table 8.3](#), showing the least over- and under-prediction (sub-districts with crossed lines) when BRF indicators exist.

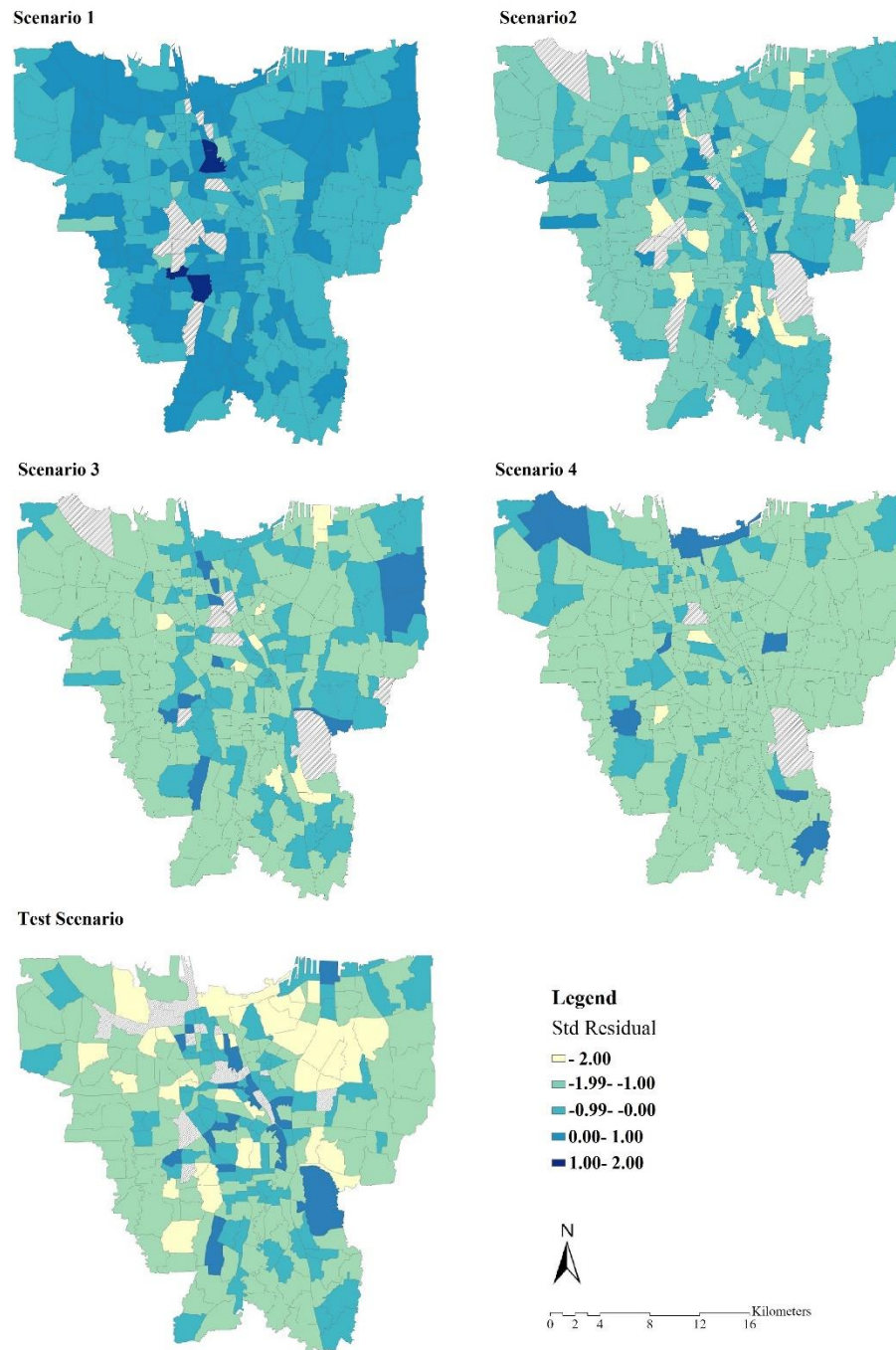


Fig. 8.6. Map of standard residual for GWR model developed based on each of the scenarios.

The results from exploratory regression in Jakarta ([Table 8.2](#)) showed low significance of one of the additional resilience indicators. Based on the results, the correlation between “Area of public open spaces to the residential area” the calculated local SDG Index is not statistically significant. That means the indicator is not a good indication of SDG Index in Jakarta. The reason is due to the local area’s spatial features: the lack of a heterogenous dispersion of public open spaces ([Figure 8.3](#)) that are mainly located in the marginal area. This reveals the importance of considering the local context and features and accordingly localisation when measuring SDGs, which has been suggested by other studies (EU-Report, 2018; Global Taskforce of Local and Regional Governments, 2018; P. Jones & Comfort, 2020).

The exploratory regression also generates more valuable information regarding the local features. Generally, the level of resilience is expected to be higher in areas with formal settlements and lower in the areas with informal ones (Dobson et al., 2015; Satterthwaite et al., 2020). [Figure 8.7](#), illustrates a similar result in most areas. However, in central areas, some sub-districts with a high level of resilience incorporate informal settlements. Exploratory regression is a good start for understanding the reason for a high level of resilience in these areas.

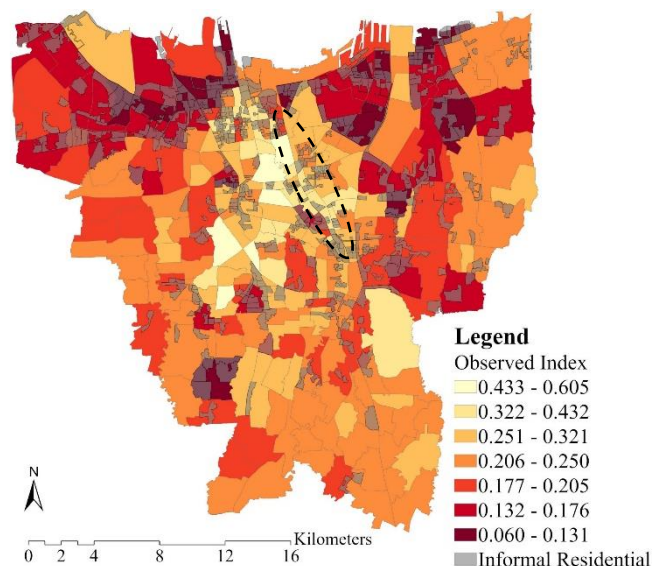


Fig. 8.7. Jakarta’s pilot local SDG index for physical infrastructure and the areas for informal settlements.

The results of the regression show both positive and negative regression between SDG Index and convenient access to public transport. Having relatively high statistically significant regression (74.19%), both negative (25.81%) and positive (74.19%) regression are considered valid. This means that in 25.81 percent of sub-districts with low local SDG Index (low resilience and sustainability), residents enjoy good access to public transport. According to the results, the negative correlation relates to the areas where

informal settlements are located around the railways. An overlay of the convenient access to public transport, informal settlements, and the index (Figure 8.8) explains the results from the exploratory regression since some informal settlements in Jakarta are located in the buffer zone of railways in the central areas with high access to all civic infrastructure.

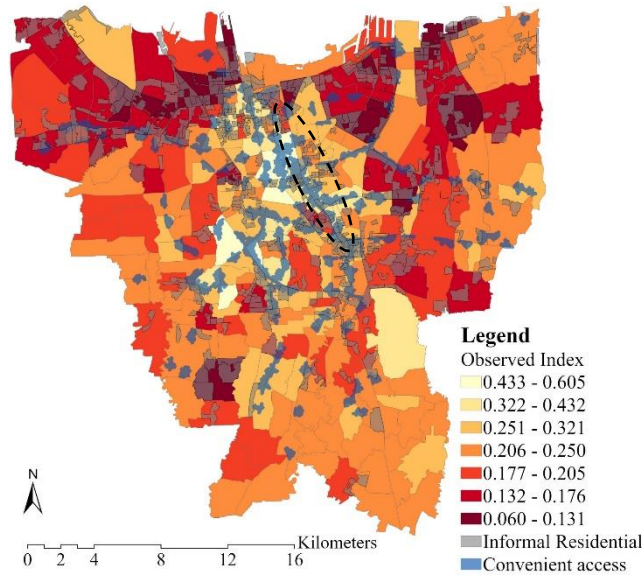


Fig. 8.8. Jakarta's pilot local SDG Index for physical infrastructure and the areas for informal settlements vs areas with convenient access to public transport (ATra). The dashed line shows the areas with informal settlement that have a high level of resilience.

Similarly, the results show a relatively low correlation between the index and access to quality roads. This outcome also describes another local feature in Jakarta in that the formal and informal settlements are interwoven. Both have poor quality roads in comparison to a small share of newly developed neighbourhoods. After selecting the effective resilience indicators according to the local features, the results have been validated by developing the OLS and GWR models based on the four scenarios, as well as a test scenario. The results from OLS and GWR confirm the highest accuracy of the pilot local SDG Index estimation when the additional BRF indicators exist; the lowest accuracy was obtained when the resilience indicators were removed. On the other hand, the test scenario in which the SDGs indicators have been removed confirm that the accuracy still remains very high. This proves that not every indicator's exclusion reduces the accuracy of the model estimation. Consequently, the results from the four scenarios are correct.

In this research, when the additional indicators with the highest local significance have been used in developing the GWR model to estimate the index, the resultant map has been very close to the observation (Figure 8.9). This supports the hypothesis of this research and proves that adding resilience indicators enhances the effectiveness of the SDGs in measuring resilience at the local level.

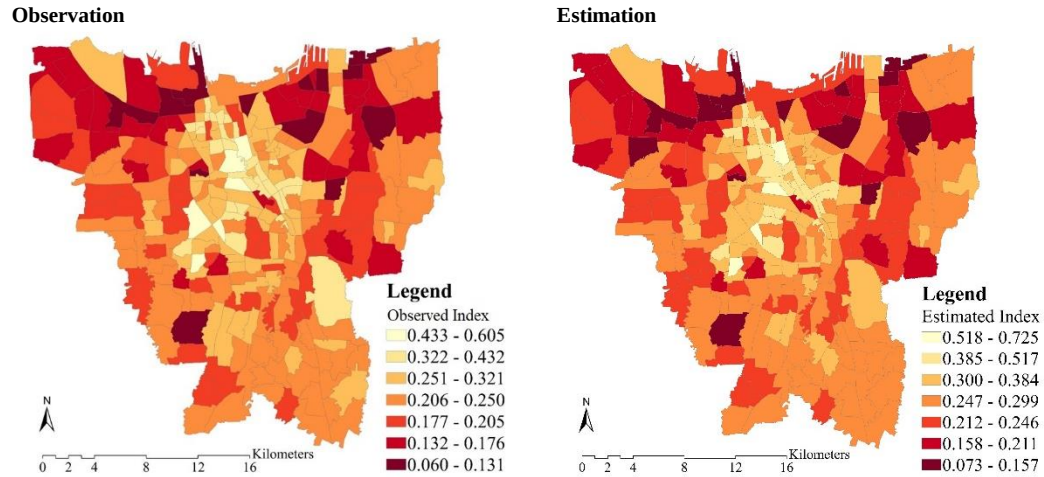


Fig. 8.9. Map of the observed local SDG Index vs the predicted index by GWR model based on the third scenario.

The fact that the Local SDG Index estimation is significantly weakened by omitting the BRF indicators, yet not significantly affected by omitting the SDGs illustrates the importance of resilience indicators in reflecting local characteristics. A possible explanation is that resilience indicators are established through decades of research to reflect local characteristics (e.g. resilience of communities or cities), whereas the Sustainable Development Goals are designed to measure sustainability at a national level. With this in mind, the results reveal that resilience indicators should be included when localising the SDGs, not from the perspective of resilience, but to ensure a more effective localisation process.

The proposed method for the SDGs' localisation, contrary to the current approaches which are mainly qualitative in character (Fox & Macleod, 2021; Krellenberg et al., 2019; Lucci, 2015), presents a quantitative robust workflow for selecting the most effective indicators to measure resilience that can be followed in different cities at diverse jurisdictional levels.

8.6 Chapter Summary

This chapter has tested and validated an innovative workflow that has been proposed for integrating resilience measurements into the SDGs at the local level. The workflow starts with indicator selection from the pool of baseline resilience indicators (BRF). After selecting the indicators based on the local data, the next step would be aligning the indicators to the local context. This is because, as explained in the method section, many resilience factors such as walkability, road quality, poverty, etc., could have different definitions according to local characteristics. After indicators are aligned, the final step of the proposed workflow is exploratory regression analysis to select the indicators that significantly contribute to accurate resilience assessment within the SDGs.

In addition to providing a novel workflow for SDGs' localisation, it also provides substantial information about the spatial features of the local context, such as dispersion of physical elements (e.g. green spaces, informal settlements) and how it relates to community resilience and sustainability. For instance, the exploratory regression analysis in Jakarta showed a positive correlation between informal settlements and resilience/sustainability, meaning high resilience/sustainability in informal settlements is evident. The reason for this was the central location of those sub-districts exhibiting positive correlations, where informal settlements are located close to public transport and other civic services. This analysis can support local stakeholders with data-driven budget allocation and policy-making.

Finally, the workflow has been evaluated by developing stationary OLS and GWR models based on four different scenarios and a test scenario. The results confirmed that adding baseline resilience indicators will enhance the effectiveness of the SDGs in measuring resilience at the local level, which proves the developed three-step workflow can be applied as an evidence-based strategy for integrating resilience measurement indicators. Furthermore, the workflow can be used as a novel method for localising the SDGs. Apart from the SDGs, the developed workflow can also serve as a guideline to incorporate additional indicators into other global frameworks.

CHAPTER 9

CONCLUSION

9 Conclusion

9.1 Introduction

This chapter presents an overview of the research, sums up the research aim and objectives and how they have been met, and subsequently contribute to the knowledge on this subject. Following, this suggestions for future research are proposed.

9.2 Research Aim, Objectives, and outcomes

The aim of this thesis was to strengthen resilience measurement in the SDGs, to be used as a framework for measuring and monitoring both sustainability and resilience, as well as developing a methodological workflow that functions well at the local level. To meet the aim of the research, the following objectives were investigated:

1. Identify and explain the overlooked aspects of resilience in the SDGs.
2. Develop a methodological workflow that integrates the proposed indicators into the SDGs at the local level.
3. Evaluate the effectiveness of the proposed workflow strategy.

9.2.1 First Objective and Outcome

To achieve the first objective, the resilience measurement context and method were reviewed. Key findings are stated below:

- Resilience has been measured in many studies using both quantitative and qualitative methods. The SDGs framework uses objective indicators to quantitatively measure resilience.
- In terms of resilience measurement, resilience is mainly estimated by defining resilience of what/ to what. However, a less common approach followed by the SDGs is measuring baseline resilience.
- Baseline resilience, which is also referred to as general resilience, provides a baseline index for measuring the overall state of a community's ability to withstand any stress and this could include disasters.

Later to address the first objective which is to define the overlooked aspects of resilience in the SDGs and to propose solutions, resilience dimensions and indicators were conceptualised and the study showed:

- A disagreement exists about the terminology referring to resilience, evidenced by the range of expressions, assumptions, meanings, etc., accorded to terms such as community capital, human capital, social capital, demographics.
- Among several dimensions addressed in the literature, the five key ones are infrastructural, social, economic, environmental, and institutional. The remaining dimensions are referred to as peripheral dimensions in this thesis.

Later, the indicators from the peripheral dimensions were categorised under the five key resilience dimensions to create the baseline resilience framework (BRF) and conceptualised as follows:

- The social dimension describes the features related to the population (population and demographics), people (education, health, and financial status), and communities (collective features, such as social engagement and protection).
- The economic dimension embodies the financial status of society at the levels of people (employment, income, etc.) and government (business activity and economic diversity and capacity).
- The institutional dimension demonstrates the government's ability to prepare for, respond to, and recover from any shocks and adverse changes.
- The infrastructural dimension evaluates the availability of different types of infrastructure in times of shock.
- Finally, the environmental dimension monitors environmental services for humans and the human's protection of environment.

In the final step to achieve the first objective, the similarity between the baseline resilience indicators from the BRF and the SDGs was measured. Doing this helped to answer the first two research questions: To what extent do the SDGs measure resilience?; and How to integrate a more comprehensive set of resilience indicators into the SDGs? The results showed:

- The SDGs indicators have high similarity with the BRF ([Table 6.1](#)).
- The least similarity between SDGs and BRF relates to institutional and infrastructural resilience.
- The highest similarity between SDGs and BRF relates to the social dimension.
- Some aspects of resilience (some variables) have been overlooked in the SDGs. Incorporating indicators into the SDGs to cover them might enhance the accuracy of how SDGs measure resilience.
- Based on the investigated similarity between the BRF and SDGs, the variables of each resilience sub-domain that is incorporated in the SDGs, as well as the ones that should be integrated, are defined.
- The BRF indicators that cover the overlooked resilience variables along with the relevant SDGs' goals and targets have been defined (see [Appendix 3](#)).
- The indicators to measure five dimensions of resilience are distributed among all seventeen goals with different levels of coverage. Therefore, the seventeen goals should not be considered in isolation.
- Ranking the relevance of goals with the resilience dimensions has been done ([Figure 6.6](#)).

Chapter 1 (Section 1.1) demonstrated the need for a more inclusive measurement of resilience through the example of SDG indicator 3.8.1 - coverage of essential health services. There was an argument that only considering the availability of health services is not sufficient to ensure compliance with this criterion of sustainable development. If the resilience level of the provided health services is not assessed, it is unclear whether they will be available at emergency instances. Results from this research proved that a more comprehensive integration of resilience indicators into the SDGs would effectively address this gap. For example, the BRF indicators, such as "% Building infrastructure not in high hazard zones" or "% Commercial establishments outside of high hazard zones to total commercial establishment", that are suggested as potential additions to the SDGs, could evaluate the availability of health services during emergencies.

At this stage, the first and the second research questions have been answered and resilience indicators to be incorporated into the SDGs has been suggested.

9.2.2 Second Objective and Outcome

After integrating resilience indicators into the SDGs, since the local features directly shape the level of communities' resilience and to address the second objective, a novel quantitative workflow for integrating resilience assessment into the SDGs was created utilising a localised approach. The developed workflow limits the essential resilience indicators from the BRF to be integrated into the SDGs based on the local features through the following three steps:

1. Assessing indicators from SDGs and BRF for data availability and application at the local scale (to determine whether localisation is required).
2. Aligning indicators with the local context.
3. Analysing indicators' significance in measuring resilience/sustainability at the local level applying exploratory regression ([Figure 8.1](#)).

The results also address question four which is: "How is it possible to localise the SDGs so that they are fit for purpose at the local scale?" The framework was tested in a Jakarta-based case study to answer the last research question: "What is the effectiveness of the localised SDGs in benchmarking resilience?".

Analysing the significance of the BRF indicators in measuring resilience in Jakarta revealed that some of them did not effectively reflect the local characteristics of the area of interest. It was found that not all indicators will enhance the effectiveness of measuring resilience in the SDGs. As opposed to the current approaches to localising the SDGs, which are primarily qualitative (Fox & Macleod, 2021; Krellenberg et

al., 2019; Lucci, 2015), the proposed method presents a quantitative robust workflow for selecting the most effective indicators to measure resilience that can be applied to different cities in various jurisdictions.

This method also provides valuable insights into the spatial characteristics of the local context, such as the impact of the distribution of physical elements on community resilience and sustainability. For instance, it was found in exploratory regression analysis in Jakarta that informal settlements are positively correlated with resilience and sustainability. The results suggest that informal settlements appear to be highly resilient and sustainable, which is unexpected. The reason behind this is the spatial distribution of informal settlements, which are located in close proximity to public transportation and other civic amenities. The findings of this analysis can assist local stakeholders with evidence-based budget allocations and policy-making.

The proposed method has thereby made a substantial contribution to improving the effectiveness of SDGs in measuring resilience and sustainability, supporting city practitioners in future developments, as well as proposing a novel workflow for SDGs' localisation.

9.2.3 Third Objective and Outcome

The last objective relates to testing the developed workflow for the SDGs' localisation. This research chose Jakarta as the case study to explain how a local-based workflow for incorporating resilience indicators into SDGs would actually work. The first step was to collect data and generate missing data. The following key findings emerged from this case study:

- Freely available medium-resolution satellite images can be classified through machine learning algorithms as a cost-effective strategy for detecting informal settlements.
- Open data such as OSM is deemed to be effective for enhancing the rigour of the ML training set, when the structures and patterns of the formal and informal settlements are markedly different.

Having the required data, the workflow has been tested and evaluated by developing stationary Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models based on four different scenarios. The results from implementing the developed workflow indicated that:

- The workflow can cope with data scarcity starting with selecting indicators from the BRF pool.
- The results reflect the highest accuracy of the local SDG Index estimation occurs when additional resilience indicators exist.
- The workflow provides a quantitative method for localising the SDGs and incorporating the most effective resilience indicators into this framework. This contributes to the present knowledge and methods for the SDGs' localisation when the qualitative approach is employed.

Based on the results, the hypothesis that additional indicators enhance the effectiveness of the resilience measurement in SDGs has been accepted. Nevertheless, it is crucial to consider that not every indicator can improve the effectiveness of resilience measurement, which proves the importance of the proposed method for selecting the most suitable indicators.

9.3 Contributions

This research significantly contributes to the present knowledge on resilience and its quantification by: firstly, conceptualising resilience dimensions, resolving the inconsistency of the terminology in the domain; and secondly, filling the gap in the knowledge by devising baseline resilience framework (BRF) that measures resilience. Ultimately, this aspect of the research assists practitioners in understanding and measuring resilience, as a basis for future urban planning, and ensuring what needs to be enhanced as a priority. Also, the indicators direct city officials to collect the relevant data. The availability of data when conducting sensitive assessments has always been a challenge for city planners and managers. The data may be unavailable, obsolete or useless. Providing common frameworks such as BRF helps to inform future data collection based on existing and relevant indicators.

In addition, this research contributes to improving the Sustainable Development Goals, as a globally adopted framework for measuring and monitoring sustainability, by addressing a major criticism, namely the limitation in quantifying resilience and devising a workflow strategy for localising the SDGs. To respond to the criticism, the aspects of resilience that have been overlooked in the SDGs have been identified and proposed indicators for incorporating them. As part of this research's outcome, SDGs have been ranked based on their relevance to their coverage of the resilience dimensions ([Figure 6.6](#)). Rankings provide guidelines for how the SDGs can be used as an assessment tool in different contexts such as social, economic, infrastructure, institutional, and environmental resilience.

As the second contribution to refining the SDGs, this research proposes a workflow that emphasises the importance of localisation. In contrast to current approaches that are primarily qualitative, this robust and quantitative workflow can be followed at varying jurisdictional levels in different cities. The proposed workflow has been developed in response to the United Nations Development Programme's (UNDP) urgent call for localisation of the SDGs (UNDP 2019). The United Nations adopted the Sustainable Development Goals (SDGs) as a continuation of the Millennium Development Goals (MDGs). While the MDGs were intended primarily for developing countries to end extreme poverty, the SDGs were adopted for all countries to achieve sustainable development by 2030, regardless of whether they were rich or poor. As with the MDGs, the agenda expires in 2030, but the initiative continues, and the research contributes to the advancement of the SDGs and post-2030 Agenda ([Figure 9.1](#)).



Fig. 9.1. Evolution of the United Nations Agendas from MDG to post-2030 Agenda.

Along with contributing to the Sustainable Development Goals, the localisation workflow can be used by city practitioners and policy makers to determine the most significant factors for assessing and monitoring resilience at the local level and prioritising future developments based on those factors.

This research also presents a sample solution for coping with data availability issues in urban analytics, particularly when it comes to the local level analysis, as well as a novel method for the detection of informal settlements based on freely available open data that can be found online. Since the proposed method is based on freely available data, it can be used to map informal settlements in countries with limited financial resources in the global south. The informal settlement detection method may be used by policy-makers for how to devise informal settlement upgrading programs and strategic planning of the entire city.

9.4 Recommendations

To integrate resilience into the Sustainable Development Goals at a local level, the developed novel workflow utilises a quantitative top-down approach. It is suggested that future work should combine the proposed workflow with a complementary qualitative analysis in order to incorporate the vision of local experts. Despite the fact that the quantitative approach proposed is replicable and can be scaled up across several cities in a time-efficient and economical manner, adding the qualitative approach makes possible more detailed analysis wherever the financial and human resources are available.

The second recommendation pertains to the development of resilience indicators. Based on the baseline resilience approach, this study proposed indicators which could be applied to different jurisdictional levels and diverse locations in order to integrate resilience into the Sustainable Development Goals. The indicators, however, can be categorised based on the answers to the questions of "resilience of what?" and "resilience to what?", as discussed in Chapter 4. The approach can serve to develop local frameworks for different cities to answer the former question based on the most common natural hazards (e.g. floods), and the latter question based on the scale of interest (e.g. city resilience).

The third recommendation relates to the generation of data using open data, such as OpenStreetMap and freely available medium resolution satellite images. The proposed method for land-use classification and

informal settlement detection contributes to the present knowledge by facilitating data generation for countries with limited financial resources, where high resolution satellite images are not accessible or simply do not exist. Nevertheless, future studies should be conducted to: firstly, validate OSM in order to enhance its reliability; and secondly, develop methods or tools that encourage the analysis of high-resolution Google Map images (e.g. developing tools for image classification on Google Map Engine).

References

- Abdi, A. M. (2020). Land cover and land use classification performance of machine learning algorithms in a boreal landscape using Sentinel-2 data. *GIScience and Remote Sensing*, 57(1), 1–20. <https://doi.org/10.1080/15481603.2019.1650447>
- Abdrabo, M. A., & Hassaan, M. A. (2015). An integrated framework for urban resilience to climate change - Case study: Sea level rise impacts on the Nile Delta coastal urban areas. *Urban Climate*, 14, 554–565. <https://doi.org/10.1016/j.uclim.2015.09.005>
- Adams, W. M. (2006). The Future of Sustainability: Re-thinking Environment and Development in the Twenty-first Century. In *IUCN*. http://cmsdata.iucn.org/downloads/iucn_future_of_sustainability.pdf
- ADB. (2013). *Investing in Resilience: Ensuring a Disaster-Resistant Future*. Asian Development Bank. www.adb.org
- Adger, W. N. (2003). *BUILDING RESILIENCE TO PROMOTE SUSTAINABILITY* (Issue February).
- Ahern, J. (2011). From fail-safe to safe-to-fail: Sustainability and resilience in the new urban world. *Landscape and Urban Planning*, 100(4), 341–343. <https://doi.org/10.1016/j.landurbplan.2011.02.021>
- Ainuddin, S., & Routray, J. K. (2012). Earthquake hazards and community resilience in Baluchistan. *Natural Hazards*, 63(2), 909–937. <https://doi.org/10.1007/s11069-012-0201-x>
- Alam, G. M. M., Alam, K., Mushtaq, S., & Filho, W. L. (2018). How do climate change and associated hazards impact on the resilience of riparian rural communities in Bangladesh? Policy implications for livelihood development. *Environmental Science and Policy*, 84(March), 7–18. <https://doi.org/10.1016/j.envsci.2018.02.012>
- Alessa, L., Kliskey, A., Lammers, R., Arp, C., White, D., Hinzman, L., & Busey, R. (2008). The arctic water resource vulnerability index: An integrated assessment tool for community resilience and vulnerability with respect to freshwater. *Environmental Management*, 42(3), 523–541. <https://doi.org/10.1007/s00267-008-9152-0>
- Allan, M., Rajabifard, A., Foliente, G., & Sabri, S. (2021). SDG 11 as a ‘Glocal’ Framework. *GIM International*. <https://www.gim-international.com/content/article/sdg-11-as-a-glocal-framework>
- Allen, T., Prosperi, P., Cogill, B., Padilla, M., & Peri, I. (2019). A Delphi Approach to Develop Sustainable Food System Metrics. In *Social Indicators Research* (Vol. 141, Issue 3). Springer Netherlands. <https://doi.org/10.1007/s11205-018-1865-8>
- Alqadah, F., & Bhatnagar, R. (2010). Similarity measures in formal concept analysis. *11th International Symposium on Artificial Intelligence and Mathematics, ISAIM 2010*, 1–7.
- Alzamil, W. S. (2018). Evaluating Urban Status of Informal Settlements in Indonesia: A Comparative Analysis of Three Case Studies in North Jakarta. *Journal of Sustainable Development*, 11(4), 148. <https://doi.org/10.5539/jsd.v11n4p148>
- Angeon, V., & Bates, S. (2015). Reviewing composite vulnerability and resilience indexes: A sustainable approach and application. *World Development*, 72, 140–162. <https://doi.org/10.1016/j.worlddev.2015.02.011>
- Araya-Muñoz, D., Metzger, M. J., Stuart, N., Wilson, A. M. W., & Alvarez, L. (2016). Assessing urban adaptive capacity to climate change. *Journal of Environmental Management*, 183, 314–324. <https://doi.org/10.1016/j.jenvman.2016.08.060>
- Asadzadeh, A., Kötter, T., & Zebardast, E. (2015). An augmented approach for measurement of disaster resilience using connective factor analysis and analytic network process (F’ANP) model. *International Journal of Disaster Risk Reduction*, 14, 504–518. <https://doi.org/10.1016/j.ijdr.2015.10.002>
- Asmamaw, M., Mereta, S. T., & Ambelu, A. (2019). Exploring households’ resilience to climate change-induced shocks using Climate Resilience Index in Dinki watershed, central highlands of Ethiopia. *PLoS ONE*, 14(7), 1–21. <https://doi.org/10.1371/journal.pone.0219393>
- Assarkhaniki, Z., Rajabifard, A., & Sabri, S. (2020). The conceptualisation of resilience dimensions and comprehensive quantification of the associated indicators: A systematic approach. In *International Journal of Disaster Risk Reduction* (Vol. 51, p. 101840). <https://doi.org/10.1016/j.ijdr.2020.101840>
- Assarkhaniki, Z., Sabri, S., & Rajabifard, A. (2021). Using open data to detect the structure and pattern of informal settlements: an outset to support inclusive SDGs’ achievement. *Big Earth Data*, 5(4), 497–526. <https://doi.org/10.1080/20964471.2021.1948178>
- Avila-Foucat, V. S., & Martínez, A. F. (2018a). Households’ Resilience to Hurricanes in Coastal Communities of Oaxaca,

- Mexico. *Society and Natural Resources*, 31(7), 807–821. <https://doi.org/10.1080/08941920.2018.1443236>
- Avila-Foucat, V. S., & Martínez, A. F. (2018b). Households' Resilience to Hurricanes in Coastal Communities of Oaxaca, Mexico. *Society and Natural Resources*, 31(7), 807–821. <https://doi.org/10.1080/08941920.2018.1443236>
- Bahadur, A., Lovell, E., Wilkinson, E., & Tanner, T. (2015). Resilience in the SDGs purpose. *ODI Briefing*, August, 1–7.
- Bahadur, A., & Pichon, F. (2016). Analysis of Resilience Measurement Frameworks and Approaches. The Resilience Measurement, Evidence and Learning Community of Practice (CoP). *Overseas Development Institute, London, UK*, October, 54. <https://www.preventionweb.net/publications/view/52589>
- Barrington-Leigh, C., & Millard-Ball, A. (2017). The world's user-generated road map is more than 80% complete. *PLoS ONE*, 12(8), 1–20. <https://doi.org/10.1371/journal.pone.0180698>
- Beauchamp, E., Abdella, J., Fisher, S., McPeak, J., Patnaik, H., Koulibaly, P., Cissé, D., Touré, M., Bocoum, A., Ndao, M., Deme, Y., & Gueye, B. (2019). Resilience from the ground up: how are local resilience perceptions and global frameworks aligned? *Disasters*, 43(S3), S295–S317. <https://doi.org/10.1111/disa.12342>
- Bhatia, N., & Vandana. (2010). *Survey of Nearest Neighbor Techniques*. 8(2), 302–305. <http://arxiv.org/abs/1007.0085>
- Bhattacharya, A., Meltzer, J. P., Oppenheim, J., Qureshi, Z., & Stern, L. N. (2016). *Delivering on Sustainable Infrastructure for Better Development and Better Climate*. 160. <http://www.lse.ac.uk/grantham/>
- Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65(1), 2–16. <https://doi.org/10.1016/j.isprsjprs.2009.06.004>
- Braun, M. T., & Oswald, F. L. (2011). Exploratory regression analysis: A tool for selecting models and determining predictor importance. *Behavior Research Methods*, 43(2), 331–339. <https://doi.org/10.3758/s13428-010-0046-8>
- Breiman, L. (1996). Bagging predictions. *Machine Learning*, 24, 123–140.
- Breiman, L. (2001). Random Forests. *Machine Learning*, 45, 5–32.
- Brenkert, A. L., & Malone, E. L. (2005). Modeling vulnerability and resilience to climate change: A case study of India and Indian states. *Climatic Change*, 72(1–2), 57–102. <https://doi.org/10.1007/s10584-005-5930-3>
- Brodley, C. E., & Friedl, M. A. (1997). Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*, 61(3), 399–409. [https://doi.org/10.1016/S0034-4257\(97\)00049-7](https://doi.org/10.1016/S0034-4257(97)00049-7)
- Buckle, P., Marsh, G., & Smale, S. (2001). *Assessing Resilience & Vulnerability : Principles , Strategies & Actions: Guidelines* (Issue May). Emergency Management Australia.
- Burton, C. G. (2015). A Validation of Metrics for Community Resilience to Natural Hazards and Disasters Using the Recovery from Hurricane Katrina as a Case Study. *Annals of the Association of American Geographers*, 105(1), 67–86. <https://doi.org/10.1080/00045608.2014.960039>
- Cahill, H., Beadle, S., Farrelly, A., Forster, R., & Smith, K. (2012). *Building resilience in children and young people* (Vol. 48, Issue 42). <https://www.education.vic.gov.au/documents/about/departments/resiliencelitereview.pdf>
- Cai, H., Lam, N. S. N., Qiang, Y., Zou, L., Correll, R. M., & Mihunov, V. (2018). A synthesis of disaster resilience measurement methods and indices. *International Journal of Disaster Risk Reduction*, 31(April), 844–855. <https://doi.org/10.1016/j.ijdr.2018.07.015>
- Campos-Taberner, M., García-Haro, F. J., Martínez, B., Izquierdo-Verdiguier, E., Atzberger, C., Camps-Valls, G., & Gilabert, M. A. (2020). Understanding deep learning in land use classification based on Sentinel-2 time series. *Scientific Reports*, 10(1), 1–12. <https://doi.org/10.1038/s41598-020-74215-5>
- Carleer, A. P., & Wolff, E. (2006). Urban land cover multi - level region - based classification of VHR data by selecting relevant features. *International Journal of Remote Sensing ISSN*, 1161. <https://doi.org/10.1080/01431160500297956>
- Casier, L. (2015). Why Infrastructure is Key to the Success of the SDGs. *International Institute for Sustainable Development*. <https://www.iisd.org/articles/insight/why-infrastructure-key-success-sdgs>
- Charlie Loyd. (2013). *Landsat 8 Bands*. NASA Landsat Science. <https://landsat.gsfc.nasa.gov/landsat-8/landsat-8-bands>
- Charlton, M., & Fotheringham, A. S. (2011). *Geographically Weighted Regression*. National Centre for Geocomputation, National University of Ireland Maynooth.

- Chu, A., Lin, Y.-C., & Chiueh, P.-T. (2017). Incorporating the effect of urbanization in measuring climate adaptive capacity. *Land Use Policy*, 68, 28–38. <https://doi.org/10.1016/j.landusepol.2017.07.019>
- Chung, U., Choi, J., & Yun, J. I. (2004). Urbanization effect on the observed change in mean monthly temperatures between 1951-1980 and 1971-2000 in Korea. *Climatic Change*, 66(1–2), 127–136. <https://doi.org/10.1023/B:CLIM.0000043136.58100.ce>
- Clarke, T., & Clegg, S. (200 C.E.). *Changing Paradigms*. Longman.
- Collier, Z. A., Wang, D., Vogel, J. T., Tatham, E. K., & Linkov, I. (2013). Sustainable roofing technology under multiple constraints: A decision-analytical approach. *Environment Systems and Decisions*, 33(2), 261–271. <https://doi.org/10.1007/s10669-013-9446-5>
- Costanza, R., & Patten, B. C. (1995). Defining and predicting sustainability. *Ecological Economics*, 15(3), 193–196. [https://doi.org/10.1016/0921-8009\(95\)00048-8](https://doi.org/10.1016/0921-8009(95)00048-8)
- Counihan, C. H. (2017). *An Incremental Intervention In Jakarta : An Empowering Infrastructural Approach For Upgrading Informal Settlements* (Issue July). University of Massachusetts Amherst.
- Creswell, J. W. (2014). *Research Design* (4th ed.). SAGE.
- Cumming, G. S., Barnes, G., Perz, S., Schmink, K. E., Sieving, J., Southworth, J., Binford, M., Holt, R. D., Stickler, C., & Holt, T. Van. (2005). An Exploratory Measurement Empirical Framework of Resilience. *Ecosystems*, 8(8), 975–987. <https://doi.org/10.1007/s10021-005-0129-z>
- Cumming, G. S., Barnes, G., Perz, S., Schmink, M., Sieving, K. E., Southworth, J., Binford, M., Holt, R. D., Stickler, C., & Van Holt, T. (2005). An exploratory framework for the empirical measurement of resilience. *Ecosystems*, 8(8), 975–987. <https://doi.org/10.1007/s10021-005-0129-z>
- Cutter, S. L. (2016). The landscape of disaster resilience indicators in the USA. *Natural Hazards*, 80(2), 741–758. <https://doi.org/10.1007/s11069-015-1993-2>
- Cutter, S. L., Ash, K. D., & Emrich, C. T. (2014). The geographies of community disaster resilience. *Global Environmental Change*, 29, 65–77. <https://doi.org/10.1016/j.gloenvcha.2014.08.005>
- Cutter, S. L., Ash, K. D., & Emrich, C. T. (2016). Urban–Rural Differences in Disaster Resilience. *Annals of the American Association of Geographers*, 106(6), 1236–1252. <https://doi.org/10.1080/24694452.2016.1194740>
- Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster Resilience Indicators for Benchmarking Baseline Conditions. *Journal of Homeland Security and Emergency Management*, 7(1). <https://doi.org/10.2202/1547-7355.1732>
- Cutter, S. L., & Derakhshan, S. (2018). Temporal and spatial change in disaster resilience in US counties, 2010–2015*. *Environmental Hazards*, 0(0), 1–20. <https://doi.org/10.1080/17477891.2018.1511405>
- Cutter, S. L., & Finch, C. (2008). Temporal and spatial changes in social vulnerability to natural hazards. *Proceedings of the National Academy of Sciences of the United States of America*, 105(7), 2301–2306. <https://doi.org/10.1073/pnas.0710375105>
- Das, S., Majumder, M., Roy, D., & Mazumdar, A. (2010). Determination of Urbanization Impact on Rain Water Quality with the Help of Water Quality Index and Urbanization Index. In *Impact of Climate Change on Natural Resource Management* (pp. 1–493). <https://doi.org/10.1007/978-90-481-3581-3>
- DasGupta, R., & Shaw, R. (2015). An indicator based approach to assess coastal communities’ resilience against climate related disasters in Indian Sundarbans. *Journal of Child and Family Studies*, 24(3), 85–101. <https://doi.org/10.1007/s11852-014-0369-1>
- David R, G. (2003). Urban Hazard Mitigation: Creating Resilient Cities. *Natural Hazards Review*, 4(3), 91–95. [https://doi.org/10.1061/\(ASCE\)1527-6988\(2003\)4:3\(136\)](https://doi.org/10.1061/(ASCE)1527-6988(2003)4:3(136))
- Davoudi, S., Shaw, K., Haider, L. J., Quinlan, A. E., Peterson, G. D., Wilkinson, C., Fünfgeld, H., McEvoy, D., & Porter, L. (2012). Resilience: A Bridging Concept or a Dead End? “Reframing” Resilience: Challenges for Planning Theory and Practice Interacting Traps: Resilience Assessment of a Pasture Management System in Northern Afghanistan Urban Resilience: What Does it Mean in Planni. *Planning Theory and Practice*, 13(2), 299–333. <https://doi.org/10.1080/14649357.2012.677124>
- De Sherbinin, A., Chai-Onn, T., Jaiteh, M., Mara, V., Pistolesi, L., Schnarr, E., & Trzaska, S. (2015). Data integration for climate

- vulnerability mapping in West Africa. *ISPRS International Journal of Geo-Information*, 4(4), 2561–2582. <https://doi.org/10.3390/ijgi4042561>
- Deininger, N., Lu, Y., Griess, J., & Santamaria, R. (2019). *Cities Taking the Lead on the Sustainable Development Goals: A Voluntary Local Review Handbook for Cities*. Carnegie Mellon University.
- Delgado-Ramos, G. C., & Guibrunet, L. (2017a). Assessing the ecological dimension of urban resilience and sustainability. *International Journal of Urban Sustainable Development*, 9(2), 151–169. <https://doi.org/10.1080/19463138.2017.1341890>
- Delgado-Ramos, G. C., & Guibrunet, L. (2017b). Assessing the ecological dimension of urban resilience and sustainability. *International Journal of Urban Sustainable Development*, 9(2), 151–169. <https://doi.org/10.1080/19463138.2017.1341890>
- Deppy Keranidou, M. van L., & Hans Sakkers, D. van de V. (2018). *Utrecht: A Global Goals City Utrecht's Approach to Localising the UN Sustainable Development Goals*.
- Diaz-Sarachaga, J. M., & Jato-Espino, D. (2019). Do sustainable community rating systems address resilience? *Cities*, 93(February), 62–71. <https://doi.org/10.1016/j.cities.2019.04.018>
- Dittakan, K., Coenen, F., Christley, R., & Wardeh, M. (2013). Population estimation mining using satellite imagery. In L. Bellatreche & M. K. Mohania (Eds.), *Data Warehousing and Knowledge Discovery: 15th International Conference DaWaK 2013: Vol. 8057 LNCS* (pp. 285–296). Springer. https://doi.org/10.1007/978-3-642-40131-2_25
- Dixon, B., & Candade, N. (2008). Multispectral landuse classification using neural networks and support vector machines : one or the other , or both? *International Journal of Remote Sensing ISSN:*, 29(4). <https://doi.org/10.1080/01431160701294661>
- Dobson, S., Nyamweru, H., & Dodman, D. (2015). Local and participatory approaches to building resilience in informal settlements in Uganda. *Environment and Urbanization*, 27(2), 605–620. <https://doi.org/10.1177/0956247815598520>
- Donny Koerniawan, M. (2014). *Thermal Comfort and Walkability In Open Spaces of Mega Kuningan Superblock in Jakarta Liveable and Walkable City View project Building Performance Simulation for Hot-Humid Climate View project. November*. <https://doi.org/10.13140/2.1.4388.5766>
- Dovey, K., & King, R. (2011). Forms of informality: Morphology and visibility of informal settlements. *Built Environment*, 37(1), 11–29. <https://doi.org/10.2148/benv.37.1.11>
- Du, S., Zhang, F., & Zhang, X. (2015). Semantic classification of urban buildings combining VHR image and GIS data: An improved random forest approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, 105, 107–119. <https://doi.org/10.1016/j.isprsjprs.2015.03.011>
- Dubovyk, O., Sliuzas, R., & Flacke, J. (2011). Spatio-temporal modelling of informal settlement development in Sancaktepe district, Istanbul, Turkey. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(2), 235–246. <https://doi.org/10.1016/j.isprsjprs.2010.10.002>
- Dudovskiy, J. (2016). *The Ultimate Guide to Writing a Dissertation in Business Studies: A Step-by-Step Assistance*. research-methodology.net. <http://research-methodology.net/about-us/ebook/>
- Duro, D. C., Franklin, S. E., & Dubé, M. G. (2012). A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery. *Remote Sensing of Environment*, 118, 259–272. <https://doi.org/10.1016/j.rse.2011.11.020>
- Elasha, B. O., Nagmeldin, G. E., Hanafi, A., & Sumaya, Z. (2005). Sustainable livelihood approach for assessing community resilience to climate change : case studies from Sudan. In *AIACC Working Paper* (Issue 17).
- Engle, N. L., & Bank, W. (2011). Adaptive Capacity and Its Assessment. *Global Environmental Change*. <https://doi.org/10.1016/j.gloenvcha.2011.01.019>
- Esri. (2021). *ArcGIS Pro 2.8 Handbook*. <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/exploratory-regression.htm>
- Estima, J., & Painho, M. (2015). Investigating the potential of OpenStreetMap for land use/land cover production: A case study for continental Portugal. In J. J. Arsanjani, A. Zipf, Peter, & M. Helbich (Eds.), *OpenStreetMap in GIScience: Experiences, Research, and Applications* (pp. 273–293). Springer. https://doi.org/10.1007/978-3-319-14280-7_14
- EU-Report. (2018). *Delivering the sustainable development goals at local and regional level*. 1–4.
- Fallatah, A., Jones, S., & Mitchell, D. (2020). Object-based random forest classification for informal settlements identification in the Middle East: Jeddah a case study. *International Journal of Remote Sensing*, 41(11), 4421–4445.

<https://doi.org/10.1080/01431161.2020.1718237>

- Feng, Y., & Tong, X. (2017). Using exploratory regression to identify optimal driving factors for cellular automaton modeling of land use change. *Environmental Monitoring and Assessment*, 189(10). <https://doi.org/10.1007/s10661-017-6224-8>
- Fenton, P., & Gustafsson, S. (2017). Moving from high-level words to local action — governance for urban sustainability in municipalities. *Current Opinion in Environmental Sustainability*, 26–27, 129–133. <https://doi.org/10.1016/j.cosust.2017.07.009>
- Folke, C., Carpenter, S. R., Walker, B., Scheffer, M., & Chapin, T. (2010). Resilience Thinking: Integrating Resilience, Adaptability and Transformability. *Ecology and Society*, 15(4), 20.
- Folke, C., Carpenter, S., Walker, B., Scheffer, M., Chapin, T., & Rockstrom, J. (2010). Resilience thinking: Integrating resilience, adaptability and transformability. *Ecology and Society*, 15(4).
- Foody, G. M., & Arora, M. K. (1997). An evaluation of some factors affecting the accuracy of classification by an artificial neural network. *International Journal of Remote Sensing*, 18(4), 799–810. <https://doi.org/10.1080/014311697218764>
- Forget, Y., Linard, C., & Gilbert, M. (2018). Supervised classification of built-up areas in Sub-Saharan African cities using Landsat imagery and openstreetmap. *Remote Sensing*, 10(7), 1–16. <https://doi.org/10.3390/rs10071145>
- Fotheringham, A., Brunson, C., & Charlton, M. (2003). *Geographically weighted regression: the analysis of spatially varying relationships*. Wiley.
- Fox, S., & Macleod, A. (2021). Localizing the SDGs in cities : reflections from an action research project in Bristol , UK. *Urban Geography*, 00(00), 1–21. <https://doi.org/10.1080/02723638.2021.1953286>
- Frazier, T. G., Thompson, C. M., & Dezzani, R. J. (2014). A framework for the development of the SERV model: A Spatially Explicit Resilience-Vulnerability model. *Applied Geography*, 51, 158–172. <https://doi.org/10.1016/j.apgeog.2014.04.004>
- French, D., Kotzé, L., Scholtz, W., & Barnard, M. (2018). The environment and the Sustainable Development Goals: ‘We are on a road to nowhere.’ *Sustainable Development Goals*, 222–249. <https://doi.org/10.4337/9781786438768.00017>
- Fu, X., & Wang, X. (2018). Developing an integrative urban resilience capacity index for plan making. *Environment Systems and Decisions*, 38(3), 367–378. <https://doi.org/10.1007/s10669-018-9693-6>
- Füssel, H. M. (2007). Vulnerability: A generally applicable conceptual framework for climate change research. *Global Environmental Change*, 17(2), 155–167. <https://doi.org/10.1016/j.gloenvcha.2006.05.002>
- Gamba, P., Member, S., Acqua, F. D., Lisini, G., Trianni, G., & Member, S. (2007). Improved VHR Urban Area Mapping Exploiting Object Boundaries. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 45(8), 2676–2682.
- Garr, D. (1986). Kampung Improvement Program: Policy Issues and Local Impacts for Secondary Cities. *JPER*, 9(1), 79–83.
- Geerts, G. L. (2011). A design science research methodology and its application to accounting information systems research. *International Journal of Accounting Information Systems*, 12(2), 142–151. <https://doi.org/10.1016/j.accinf.2011.02.004>
- Gibbs, G. R. (2007). *Thematic Coding and Categorizing*. SAGE Publications Ltd. <https://doi.org/https://dx.doi.org/10.4135/9781849208574.n4>
- Global Taskforce of Local and Regional Governments. (2018). *Statement of the Local and Regional Governments Constituency Gathered in the Global Taskforce*. www.global-taskforce.org/sites/default/
- González, D. P., Monsalve, M., Moris, R., & Herrera, C. (2018). Risk and Resilience Monitor: Development of multiscale and multilevel indicators for disaster risk management for the communes and urban areas of Chile. *Applied Geography*, 94(April), 262–271. <https://doi.org/10.1016/j.apgeog.2018.03.004>
- Goodchild, M. F. (2007). Citizens as sensors: The world of volunteered geography. *GeoJournal*, 69(4), 211–221. <https://doi.org/10.1007/s10708-007-9111-y>
- Gram-Hansen, B. J., Azam, F., Helber, P., Coca-Castro, A., Bilinski, P., Varatharajan, I., & Kopackova, V. (2019). Mapping informal settlements in developing countries using machine learning and low resolution multi-spectral data. *AI/ACM Conference on AI, Ethics, and Society*, 361–368. <https://doi.org/10.1145/3306618.3314253>
- Green, J. J., Worstell, J., & Canarios, C. (2017). The Local Agrifood System Sustainability/Resilience Index (SRI): Constructing a data tool applied to counties in the southern United States. *Community Development*, 48(5), 697–710. <https://doi.org/10.1080/15575330.2017.1370001>

- Guest, G., MacQueen, K. M., & Namey, E. E. (2012). *Applied thematic analysis*. SAGE Publications.
<https://doi.org/10.4135/9781483384436>
- Guillaume Lafortune, Grayson Fuller, Jorge Moreno, Guido Schmidt-Traub, C. K. (2018). SDG Index and Dashboards Detailed Methodological paper. In *Sustainable Development Solutions Network* (Issue September).
- Haines, A., Kovats, R. S., Campbell-Lendrum, D., & Corvalan, C. (2006). Climate change and human health: Impacts, vulnerability and public health. *Public Health*, 120(7), 585–596. <https://doi.org/10.1016/j.puhe.2006.01.002>
- Haklay, M. (2010). How good is volunteered geographical information? A comparative study of OpenStreetMap and ordnance survey datasets. *Environment and Planning B: Planning and Design*, 37(4), 682–703. <https://doi.org/10.1068/b35097>
- Hardy, M. A. (1993). *Regression with Dummy Variables*. SAGE.
- Harte, E. W., Childs, I. R. W., & Hastings, P. A. (2009). Imizamo Yethu: A case study of community resilience to fire hazard in an informal settlement Cape Town, South Africa. *Geographical Research*, 47(2), 142–154. <https://doi.org/10.1111/j.1745-5871.2008.00561.x>
- Hermosilla, T., Wulder, M. A., White, J. C., Coops, N. C., & Hobart, G. W. (2018). Disturbance-Informed Annual Land Cover Classification Maps of Canada's Forested Ecosystems for a 29-Year Landsat Time Series. *Canadian Journal of Remote Sensing*, 44(1), 67–87. <https://doi.org/10.1080/07038992.2018.1437719>
- Hernandez, I. E. R., & Shi, W. (2018). A Random Forests classification method for urban land-use mapping integrating spatial metrics and texture analysis. *International Journal of Remote Sensing*, 39(4).
<https://doi.org/https://doi.org/10.1080/01431161.2017.1395968>
- Herrfahrdt-Pähle, E., & Pahl-Wostl, C. (2012). Continuity and change in social-ecological systems: The role of institutional resilience. *Ecology and Society*, 17(2). <https://doi.org/10.5751/ES-04565-170208>
- Hidayati, I., Yamu, C., & Tan, W. (2020). Realised pedestrian accessibility of an informal settlement in Jakarta, Indonesia. *Journal of Urbanism*, 00(00), 1–23. <https://doi.org/10.1080/17549175.2020.1814391>
- Hiete, M., Merz, M., Comes, T., & Schultmann, F. (2012). Trapezoidal fuzzy DEMATEL method to analyze and correct for relations between variables in a composite indicator for disaster resilience. *OR Spectrum*, 34(4), 971–995.
<https://doi.org/10.1007/s00291-011-0269-9>
- Hillson, R., Coates, A., Alejandre, J. D., Jacobsen, K. H., Ansumana, R., Bockarie, A. S., Bangura, U., Lamin, J. M., & Stenger, D. A. (2019). Estimating the size of urban populations using Landsat images: a case study of Bo, Sierra Leone, West Africa. *International Journal of Health Geographics*, 1–24. <https://doi.org/10.1186/s12942-019-0180-1>
- Hofmann, P., Strobl, J., Blaschke, T., & Kux, H. (2008). Detecting informal settlements from QuickBird data in Rio de Janeiro using an object-based approach. In T. Blaschke, S. Lang, & E. Hay, G. J. (Eds.), *Object-Based Image Analysis*. (Vol. 0, Issue 9783540770572, pp. 531–553). https://doi.org/10.1007/978-3-540-77058-9_29
- Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 4, 1–23.
- Holling, C. S. (1986). The resilience of terrestrial ecosystems: Local surprise and global change. In W. C. Clark & R. . Munn (Eds.), *Sustainable Development of the Biosphere*. Cambridge University Press.
- Hu, M., Zhang, J., & Huang, J. (2018). Assessing social-ecological system resilience in Mainland China. *Polish Journal of Environmental Studies*, 27(3), 1085–1096. <https://doi.org/10.15244/pjoes/76242>
- Huang, A. (2008). Similarity measures for text document clustering. *New Zealand Computer Science Research Student Conference, NZCSRSC 2008 - Proceedings, April*, 49–56.
- Huber, G. J., Gomes, J. O., & De Carvalho, P. V. R. (2012). A program to support the construction and evaluation of resilience indicators. *Work*, 41(1), 2810–2816. <https://doi.org/10.3233/WOR-2012-0528-2810>
- Hung, H.-C., Yang, C.-Y., Chien, C.-Y., & Liu, Y.-C. (2016). Building resilience: Mainstreaming community participation into integrated assessment of resilience to climatic hazards in metropolitan land use management. *Land Use Policy*, 50, 48–58. <https://doi.org/10.1016/j.landusepol.2015.08.029>
- Huong, H. T. L., & Pathirana, A. (2013). Urbanization and climate change impacts on future urban flooding in Can Tho city, Vietnam. *Hydrology and Earth System Sciences*, 17(1), 379–394. <https://doi.org/10.5194/hess-17-379-2013>
- IFRC. (2012). *Understanding Community Resilience* (Issue June).

- Imran, M. (M. ., Sumra, K., Mahmood, S. A., & Sajjad, S. F. (2019). Mapping flood vulnerability from socioeconomic classes and GI data: Linking socially resilient policies to geographically sustainable neighborhoods using PLS-SEM. *International Journal of Disaster Risk Reduction*, 41(August), 101288. <https://doi.org/10.1016/j.ijdrr.2019.101288>
- Jacob, S., Weeks, P., Blount, B., & Jepson, M. (2013). Development and evaluation of social indicators of vulnerability and resiliency for fishing communities in the Gulf of Mexico. *Marine Policy*, 37(1), 86–95. <https://doi.org/10.1016/j.marpol.2012.04.014>
- Jacobi, J., Mukhovi, S., Llanque, A., Augstburger, H., Käser, F., Pozo, C., Ngutu Peter, M., Delgado, J. M. F., Kiteme, B. P., Rist, S., & Ifejika Speranza, C. (2018). Operationalizing food system resilience: An indicator-based assessment in agroindustrial, smallholder farming, and agroecological contexts in Bolivia and Kenya. *Land Use Policy*, 79(August), 433–446. <https://doi.org/10.1016/j.landusepol.2018.08.044>
- Jain, S. (2007). Use of IKONOS satellite data to identify informal settlements in Dehradun, India. *International Journal of Remote Sensing*, 28(15), 3227–3233. <https://doi.org/10.1080/01431160600705122>
- Jarzebski, M. P., Tumilba, V., & Yamamoto, H. (2016). Application of a tri-capital community resilience framework for assessing the social–ecological system sustainability of community-based forest management in the Philippines. *Sustainability Science*, 11(2), 307–320. <https://doi.org/10.1007/s11625-015-0323-7>
- Jokar Arsanjani, J., Helbich, M., & Bakillah, M. (2013). Exploiting Volunteered Geographic Information To Ease Land Use Mapping of an Urban Landscape. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XL-4/W1, 51–55. <https://doi.org/10.5194/isprsarchives-xl-4-w1-51-2013>
- Jones, L., & D'Errico, M. (2019). Whose resilience matters? Like-for-like comparison of objective and subjective evaluations of resilience. *World Development*, 124, 104632. <https://doi.org/10.1016/j.worlddev.2019.104632>
- Jones, P. (2017). Formalizing the Informal: Understanding the Position of Informal Settlements and Slums in Sustainable Urbanization Policies and Strategies in Bandung , Indonesia. *Sustainability*. <https://doi.org/10.3390/su9081436>
- Jones, P. (2019). The shaping of form and structure in informal settlements: A case study of order and rules in lebak siliwangi, Bandung, Indonesia. *Journal of Regional and City Planning*, 30(1), 43–61. <https://doi.org/10.5614/jpww.2019.30.1.4>
- Jones, P., & Comfort, D. (2020). A commentary on the localisation of the sustainable development goals. *Journal of Public Affairs*, 20(1), 1–6. <https://doi.org/10.1002/pa.1943>
- Jorgensen, S. E. (1994). *Fundamentals of Ecological Modelling* (2nd ed.). Elsevier.
- Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, S. A. (2019). Resilience Assessment of Urban Communities. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems*, 5(1).
- Kammouh, O., Noori, A. Z., Taurino, V., Mahin, S. A., & Cimellaro, G. P. (2018). Deterministic and fuzzy-based methods to evaluate community resilience. *Earthquake Engineering and Engineering Vibration*, 17(2), 261–275. <https://doi.org/10.1007/s11803-018-0440-2>
- Karlsson, A. (2003). *Classification of high resolution satellite images* (Issue August). Chalmers University of Technology.
- Kaye-Blake, W., Stirrat, K., Smith, M., & Fielke, S. (2019). Testing indicators of resilience for rural communities. *Rural Society*, 28(2), 161–179. <https://doi.org/10.1080/10371656.2019.1658285>
- Khalili, S., Harre, M., & Morley, P. (2018). A temporal social resilience framework of communities to disasters in Australia. *Geoenvironmental Disasters*, 5(1). <https://doi.org/10.1186/s40677-018-0114-4>
- Khatibi, S. A., Golkarian, A., Mosaedi, A., & Sojasi Qeidari, H. (2019). Assessment of Resilience to Drought of Rural Communities in Iran. *Journal of Social Service Research*, 45(2), 151–165. <https://doi.org/10.1080/01488376.2018.1479342>
- Khorram, S., Nelson, S., & Cakir, H. (2013). Digital Image Processing: Post-processing and Data Integration. In J. N. Pelton, S. Madry, & S. Camacho-Lara (Eds.), *Handbook of Satellite Applications* (pp. 839–864). Springer. <https://doi.org/10.1007/978-1-4419-7671-0>
- Kim, E., & Park, H. (2018). Two-stage approach to quantify the resilience of maritime hazardous and noxious substance spill accidents. *International Journal of Disaster Risk Reduction*, 28(January), 595–601. <https://doi.org/10.1016/j.ijdrr.2018.01.009>
- Kit, O., Lüdeke, M., & Reckien, D. (2012). Texture-based identification of urban slums in Hyderabad, India using remote sensing

- data. *Applied Geography*, 32(2), 660–667. <https://doi.org/10.1016/j.apgeog.2011.07.016>
- Klavans, R., & Boyack, K. W. (2017). Which Type of Citation Analysis Generates the Most Accurate Taxonomy of Scientific and Technical Knowledge? *Journal of the Association for Information Science and Technology*, 68(4), 984–998. <https://doi.org/10.1002/asi.23734>
- Klawonn, F., Lee, M., Li, B., Weise, T., & Yao, X. (Eds.). (2013). *Intelligent Data Engineering and Automated Learning – IDEAL 2013* (Vol. 8206, Issue October). Springer.
- Kliskey, A., Williams, P., Abatzoglou, J. T., Alessa, L., & Lammers, R. B. (2019). Enhancing a community-based water resource tool for assessing environmental change: the arctic water resources vulnerability index revisited. *Environment Systems and Decisions*, 39(2), 183–197. <https://doi.org/10.1007/s10669-018-9712-7>
- Knippenberg, E., Jensen, N., & Constan, M. (2019). Quantifying household resilience with high frequency data: Temporal dynamics and methodological options. *World Development*, 121, 1–15. <https://doi.org/10.1016/j.worlddev.2019.04.010>
- Koh, E. H., Lee, E., & Lee, K. K. (2020). Application of geographically weighted regression models to predict spatial characteristics of nitrate contamination: Implications for an effective groundwater management strategy. *Journal of Environmental Management*, 268, 110646. <https://doi.org/10.1016/j.jenvman.2020.110646>
- Kotzee, I., & Reyers, B. (2016). Piloting a social-ecological index for measuring flood resilience: A composite index approach. *Ecological Indicators*, 60, 45–53. <https://doi.org/10.1016/j.ecolind.2015.06.018>
- Krantz, V., & Gustafsson, S. (2021). Localizing the sustainable development goals through an integrated approach in municipalities: early experiences from a Swedish forerunner. *Journal of Environmental Planning and Management*, 64(14), 2641–2660. <https://doi.org/10.1080/09640568.2021.1877642>
- Krellenberg, K., Bergsträßer, H., Bykova, D., Kress, N., & Tyndall, K. (2019). Urban Sustainability Strategies Guided by the SDGs — A Tale of Four Cities. *Sustainability*, 1–20. <https://doi.org/10.3390/su11041116>
- Kusumo, A. N. L., Reckien, D., & Verplanke, J. (2017). Utilising volunteered geographic information to assess resident's flood evacuation shelters. Case study: Jakarta. *Applied Geography*, 88, 174–185. <https://doi.org/10.1016/j.apgeog.2017.07.002>
- Lam, N. S. N., Reams, M., Li, K., Li, C., & Mata, L. P. (2016). Measuring Community Resilience to Coastal Hazards along the Northern Gulf of Mexico. *Natural Hazards Review*, 17(1), 1–12. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000193](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000193)
- Land Tenure Studies: Land tenure and rural development. (2002). In FAO (Vol. 4, Issue 4). <https://doi.org/10.1080/03768358708439359>
- Lavigne, P. D., & Durand-Lasserve, A. (2009). Land Governance and Security of Tenure in Developing Countries. In *French Development Cooperation* (Issue June).
- Lew, A. A., Ng, P. T., Ni, C. cheng (Nickel), & Wu, T. chiung (Emily). (2016). Community sustainability and resilience: similarities, differences and indicators. *Tourism Geographies*, 18(1), 18–27. <https://doi.org/10.1080/14616688.2015.1122664>
- Li, X., Lam, N., Qiang, Y., Li, K., Yin, L., Liu, S., & Zheng, W. (2016). Measuring County Resilience After the 2008 Wenchuan Earthquake. *International Journal of Disaster Risk Science*, 7(4), 393–412. <https://doi.org/10.1007/s13753-016-0109-2>
- Li, X., Philp, J., Cremades, R., Roberts, A., He, L., Li, L., & Yu, Q. (2016). Agricultural vulnerability over the Chinese Loess Plateau in response to climate change: Exposure, sensitivity, and adaptive capacity. *Ambio*, 45(3), 350–360. <https://doi.org/10.1007/s13280-015-0727-8>
- Li, X., Wang, L., & Liu, S. (2016). Geographical Analysis of Community Resilience to Seismic Hazard in Southwest China. *International Journal of Disaster Risk Science*, 7(3), 257–276. <https://doi.org/10.1007/s13753-016-0091-8>
- Lim, Y. K., Cai, M., Kalnay, E., & Zhou, L. (2005). Observational evidence of sensitivity of surface climate changes to land types and urbanization. *Geophysical Research Letters*, 32(22), 1–4. <https://doi.org/10.1029/2005GL024267>
- Links, J. M., Schwartz, B. S., Lin, S., Kanarek, N., Mitrani-Reiser, J., Sell, T. K., Watson, C. R., Ward, D., Slemp, C., Burhans, R., Gill, K., Igusa, T., Zhao, X., Aguirre, B., Trainor, J., Nigg, J., Inglesby, T., Carbone, E., & Kendra, J. M. (2018). COPEWELL: A Conceptual Framework and System Dynamics Model for Predicting Community Functioning and Resilience after Disasters. *Disaster Medicine and Public Health Preparedness*, 12(1), 127–137. <https://doi.org/10.1017/dmp.2017.39>
- Liu, S. (2008). Global Sensitivity Analysis: The Primer by Andrea Saltelli, Marco Ratto, Terry Andres, Francesca Campolongo,

- Jessica Cariboni, Debora Gatelli, Michaela Saisana, Stefano Tarantola. In *International Statistical Review* (Vol. 76, Issue 3). https://doi.org/10.1111/j.1751-5823.2008.00062_17.x
- Livesley, R. K. (1964). Vectors and Matrices. In *Matrix Methods of Structural Analysis* (pp. 15–45). <https://doi.org/10.1016/b978-0-08-010355-6.50006-5>
- Lokonon, B. O. K. (2019). Farmers' vulnerability to climate shocks: insights from the Niger basin of Benin. *Climate and Development*, 11(7), 585–596. <https://doi.org/10.1080/17565529.2018.1511403>
- Lu, Z., Im, J., Quackenbush, L., & Halligan, K. (2010). Population estimation based on multi-sensor data fusion. *International Journal of Remote Sensing*, 1161. <https://doi.org/10.1080/01431161.2010.496801>
- Lu, Z., Szafron, D., Greiner, R., Lu, P., Wishart, D. S., Poulin, B., Anvik, J., Macdonell, C., & Eisner, R. (2004). *Predicting subcellular localization of proteins using machine-learned classifiers*. 20(4), 547–556. <https://doi.org/10.1093/bioinformatics/btg447>
- Lucci, P. (2015). 'Localising' the Post-2015 agenda: What does it mean in practice? (Issue January). <http://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/9395.pdf>
- Luh, J., Christenson, E. C., Toregozhina, A., Holcomb, D. A., Witsil, T., Hamrick, L. R., Ojomo, E., & Bartram, J. (2015). Vulnerability assessment for loss of access to drinking water due to extreme weather events. *Climatic Change*, 133(4), 665–679. <https://doi.org/10.1007/s10584-015-1493-0>
- Lv, Z., Liu, T., & Benediktsson, J. A. (2020). Object-Oriented Key Point Vector Distance for Binary Land Cover Change Detection Using VHR Remote Sensing Images. *IEEE Transactions on Geoscience and Remote Sensing*, 58(9), 6524–6533.
- M.MacQueen, Kathleen McLellan, E., Metzger, D. S., Kegeles, S., Strauss, R. P., Scotti, R., Blanchard, L., & II, R. T. T. (2001). What Is Community? An Evidence-Based Definition for Participatory Public Health Increased. *American Journal of Public Health*, 91(12), 1929–1938.
- Magis, K. (2010). Community resilience: An indicator of social sustainability. *Society and Natural Resources*, 23(5), 401–416. <https://doi.org/10.1080/08941920903305674>
- Makinde, E. O., Salami, A. T., Olaleye, J. B., & Okewusi, O. C. (2016). Object Based and Pixel Based Classification Using Rapideye Satellite Imager of ETI-OSA, Lagos, Nigeria. *Geoinformatics FCE CTU*, 15(2), 59–70. <https://doi.org/10.14311/gi.15.2.5>
- Manyena, B., Machingura, F., & O'Keefe, P. (2019). Disaster Resilience Integrated Framework for Transformation (DRIFT): A new approach to theorising and operationalising resilience. *World Development*, 123, 104587. <https://doi.org/10.1016/j.worlddev.2019.06.011>
- Marchese, D., Reynolds, E., Bates, M. E., Morgan, H., Clark, S. S., & Linkov, I. (2018). Resilience and sustainability: Similarities and differences in environmental management applications. *Science of the Total Environment*, 613–614, 1275–1283. <https://doi.org/10.1016/j.scitotenv.2017.09.086>
- Mark Bilandzic, J. V. (2011). Towards Participatory Action Design Research: Adapting Action Research and Design Science Research Methods for Urban Informatics Title. *Journal of Community Informatic*, 7(3).
- Marshall, N. A., & Marshall, P. A. (2007). Conceptualizing and operationalizing social resilience within commercial fisheries in northern Australia. *Ecology and Society*, 12(1). <https://doi.org/10.5751/ES-01940-120101>
- Matin, N., Forrester, J., & Ensor, J. (2018). What is equitable resilience? *World Development*, 109, 197–205. <https://doi.org/10.1016/j.worlddev.2018.04.020>
- Mavhura, E., & Manyena, B. (2018). Spatial quantification of community resilience in contexts where quantitative data are scarce: The case of Muzarabani district in Zimbabwe. *Geo: Geography and Environment*, 5(2), e00065. <https://doi.org/10.1002/geo2.65>
- Mayunga, S. D., Coleman, D. J., & Zhang, Y. (2007). A semi-automated approach for extracting buildings from QuickBird imagery applied to informal settlement mapping. *International Journal of Remote Sensing*, 28(10), 2343–2357. <https://doi.org/10.1080/01431160600868474>
- McLaren, R., Coleman, D., & Mayunga, S. (2005). Sustainable Management of Mega Growth in Megacities. *International Federation of Surveyors*, 1–15.
- Menoni, S., Molinari, D., Parker, D., Ballio, F., & Tapsell, S. (2012). Assessing multifaceted vulnerability and resilience in order

- to design risk-mitigation strategies. *Natural Hazards*, 64(3), 2057–2082. <https://doi.org/10.1007/s11069-012-0134-4>
- Mihalcea, R., Corley, C., & Strapparava, C. (2006). Corpus-based and knowledge-based measures of text semantic similarity. *Proceedings of the National Conference on Artificial Intelligence*, 1, 775–780.
- Mihunov, V. V., Lam, N. S. N., Rohli, R. V., & Zou, L. (2019). Emerging disparities in community resilience to drought hazard in south-central United States. *International Journal of Disaster Risk Reduction*, 41(August), 101302. <https://doi.org/10.1016/j.ijdr.2019.101302>
- Mihunov, V. V., Lam, N. S. N., Zou, L., Rohli, R. V., Bushra, N., Reams, M. A., & Argote, J. E. (2018). Community Resilience to Drought Hazard in the South-Central United States. *Annals of the American Association of Geographers*, 108(3), 739–755. <https://doi.org/10.1080/24694452.2017.1372177>
- Milman, A., & Short, A. (2008). Incorporating resilience into sustainability indicators: An example for the urban water sector. *Global Environmental Change*, 18(4), 758–767. <https://doi.org/10.1016/j.gloenvcha.2008.08.002>
- Ming, D., Zhou, T., Wang, M., & Tan, T. (2016). Land cover classification using random forest with genetic algorithm-based parameter optimization. *Journal of Applied Remote Sensing*, 10(3), 035021. <https://doi.org/10.1117/1.jrs.10.035021>
- Moghadas, M., Asadzadeh, A., Vafeidis, A., Fekete, A., & Kötter, T. (2019). A multi-criteria approach for assessing urban flood resilience in Tehran, Iran. *International Journal of Disaster Risk Reduction*, 35(January), 101069. <https://doi.org/10.1016/j.ijdr.2019.101069>
- Mohammed, A., Li, J., Elaru, J., Elbasher, M. M. A., Keesstra, S., Artemi, C., Martin, K., Reuben, M., & Teffera, Z. (2018a). Assessing drought vulnerability and adaptation among farmers in Gadaref region, Eastern Sudan. *Land Use Policy*, 70, 402–413. <https://doi.org/10.1016/j.landusepol.2017.11.027>
- Mohammed, A., Li, J., Elaru, J., Elbasher, M. M. A., Keesstra, S., Artemi, C., Martin, K., Reuben, M., & Teffera, Z. (2018b). Assessing drought vulnerability and adaptation among farmers in Gadaref region, Eastern Sudan. *Land Use Policy*, 70(May 2017), 402–413. <https://doi.org/10.1016/j.landusepol.2017.11.027>
- Movia, A., Beinath, A., & Crosilla, F. (2016). Shadow detection and removal in RGB VHR images for land use unsupervised classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 119, 485–495. <https://doi.org/10.1016/j.isprsjprs.2016.05.004>
- Muflikhah, L., & Baharudin, B. (2009). Document clustering using concept space and cosine similarity measurement. *ICCTD 2009 - 2009 International Conference on Computer Technology and Development*, 1, 58–62. <https://doi.org/10.1109/ICCTD.2009.206>
- Nelson, K. C., & Palmer, M. A. (2007). Stream temperature surges under urbanization and climate change: Data, models, and responses. *Journal of the American Water Resources Association*, 43(2), 440–452. <https://doi.org/10.1111/j.1752-1688.2007.00034.x>
- Neuendorf, K. A. (2019). Content analysis and thematic analysis. *Advanced Research Methods for Applied Psychology*, 211–223. <https://doi.org/10.4324/9781315517971-21>
- Nilsson, N. J. (1965). *Learning Machines*. McGrawHill.
- Noi, P. T., & Kappas, M. (2017). Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery. *Sensors*, 18(18). <https://doi.org/10.3390/s18010018>
- Norris, F. H., Stevens, S. P., Pfefferbaum, B., Wyche, K. F., & Pfefferbaum, R. L. (2008). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal of Community Psychology*, 41(1–2), 127–150. <https://doi.org/10.1007/s10464-007-9156-6>
- Novack, T., Kux, H. J. H., Feitosa, R. Q., Costa, G. A., Sensing, R., José, S., Engineering, E., Janeiro, R. De, Vi, C., & Iv, W. G. (2003). Per block urban land use interpretation using optical VHR data and the knowledge-based system interimage. *The International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences*, 38(4/C7).
- Núñez, J., Vergara, A., Leyton, C., Metzkes, C., Mancilla, G., & Bettancourt, D. (2017). Reconciling drought vulnerability assessment using a convergent approach: Application to Water Security in the Elqui River basin, North-Central Chile. *Water*, 9(8). <https://doi.org/10.3390/w9080589>
- NYC Mayor's Ofce for International Affairs. (2018). *Voluntary Local Review: New York City's Implementation of the 2030 Agenda for Sustainable Development* (Issue July). https://www1.nyc.gov/assets/international/downloads/pdf/NYC_VLR_2018_FINAL.pdf

- O'Brien, K., Pelling, M., Patwardhan, A., Hallegatte, S., Maskrey, A., Oki, T., Oswald-Spring, U., Wilbanks, T., & Yanda, P. Z. (2012). Toward a sustainable and resilient future. In M. T. and P. M. M. C.B. Field; V. Barros, T.F.Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K.Plattner, S.K. Allen, M. Tignor and P.M. Midgley B. Field; V. Barros, T.F.Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K.Plattn (Ed.), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change* (Vol. 9781107025, pp. 339–392). A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC), Cambridge University Press.
<https://doi.org/10.1017/CBO9781139177245.009>
- Ogrosky, C. E. (1975). Population Estimates from Satellite Imagery. *Photogrammetric Engineering & Remote Sensing*, 41, 707–712.
- Oladokun, V. O., Proverbs, D. G., & Lamond, J. (2017). Measuring flood resilience: a fuzzy logic approach. *International Journal of Building Pathology and Adaptation*, 35(5), 470–487. <https://doi.org/10.1108/IJBPA-12-2016-0029>
- OpenStreetMap. (2021). <https://www.openstreetmap.org/about>
- Ouyang, Z., Zhang, M., Xie, X., Shen, Q., Guo, H., & Zhao, B. (2011). A comparison of pixel-based and object-oriented approaches to VHR imagery for mapping saltmarsh plants. *Ecological Informatics*, 6(2), 136–146.
<https://doi.org/10.1016/j.ecoinf.2011.01.002>
- Owen, K. K., & Wong, D. W. (2013). An approach to differentiate informal settlements using spectral, texture, geomorphology and road accessibility metrics. *Applied Geography*, 38(1), 107–118. <https://doi.org/10.1016/j.apgeog.2012.11.016>
- Pal, M. (2005). Random forest classifier for remote sensing classification. *International Journal of Remote Sensing ISSN:*, 26(1).
<https://doi.org/10.1080/01431160412331269698>
- Pal, M., & Mather, P. M. (2003). An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment*, 86(4), 554–565. [https://doi.org/10.1016/S0034-4257\(03\)00132-9](https://doi.org/10.1016/S0034-4257(03)00132-9)
- Palei, T. (2015). Assessing the Impact of Infrastructure on Economic Growth and Global Competitiveness. *Procedia Economics and Finance*, 23(October 2014), 168–175. [https://doi.org/10.1016/s2212-5671\(15\)00322-6](https://doi.org/10.1016/s2212-5671(15)00322-6)
- Pang-Ning, T., Steinbach, M., & Kumar, V. (2005). *Introduction To Data Mining*. Pearson Education.
- Pangeran, A., & Akbar, R. J. (2020). *Cities for Marginal Community: Lesson Learned from Indonesia's Slum Alleviation Program*.
- Paul, C. L. (2014). Analyzing Card-Sorting Data Using Graph Visualization FLOSS Usability View project IEEE VAST Challenge View project. *Jurnal of Usability Studies*, 9(3), 87–104. <http://www.upassoc.org>.
- Pontarollo, N., & Mendieta Muñoz, R. (2020). Land consumption and income in Ecuador: A case of an inverted environmental Kuznets curve. *Ecological Indicators*, 108. <https://doi.org/10.1016/j.ecolind.2019.105699>
- Prabhu, R., Parvathavarthini, B., & Raja, R. A. A. (2021). Slum Extraction from High Resolution Satellite Data using Mathematical Morphology based approach. *International Journal of Remote Sensing*, 42(1), 172–190.
<https://doi.org/10.1080/01431161.2020.1834167>
- Price, O., & Bradstock, R. (2014). Countervailing effects of urbanization and vegetation extent on fire frequency on the Wildland urban interface: Disentangling fuel and ignition effects. *Landscape and Urban Planning*, 130(1), 81–88.
<https://doi.org/10.1016/j.landurbplan.2014.06.013>
- Principles of Ecosystem Stewardship: Resilience-Based Natural Resource Management in a Changing World. (2009). In F. S. Chapin, G. P. Kofina, & C. Folke (Eds.), *Principles of Ecosystem Stewardship: Resilience-Based Natural Resource Management in a Changing World*. Springer. https://doi.org/10.1007/978-0-387-73033-2_13
- Quandt, A. (2018). Measuring livelihood resilience: The Household Livelihood Resilience Approach (HLRA). *World Development*, 107, 253–263. <https://doi.org/10.1016/j.worlddev.2018.02.024>
- Rangelova, E., Weel, B., Roy, D., Kuffer, M., Pfeffer, K., & Lees, M. (2019). Image based classification of slums, built-up and non-built-up areas in Kalyan and Bangalore, India. *European Journal of Remote Sensing*, 52(sup1), 40–61.
<https://doi.org/10.1080/22797254.2018.1535838>
- Redman, C. L. (2014). Should sustainability and resilience be combined or remain distinct pursuits? *Ecology and Society*, 19(2).
<https://doi.org/10.5751/ES-06390-190237>

- Rizzo, A. (2020). Megaprojects and the limits of 'green resilience' in the global South: Two cases from Malaysia and Qatar. *Urban Studies*, 57(7), 1520–1535. <https://doi.org/10.1177/0042098018812009>
- Rodriguez-Galiano, V. F., & Chica-Rivas, M. (2014). Evaluation of different machine learning methods for land cover mapping of a Mediterranean area using multi-seasonal Landsat images and Digital Terrain Models. *International Journal of Digital Earth*, 7(6), 492–509. <https://doi.org/10.1080/17538947.2012.748848>
- Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 67(1), 93–104. <https://doi.org/10.1016/j.isprsjprs.2011.11.002>
- Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M., & Chica-Rivas, M. (2015). Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. *Ore Geology Reviews*, 71, 804–818. <https://doi.org/10.1016/j.oregeorev.2015.01.001>
- Roostaie, S., Nawari, N., & Kibert, C. J. (2019). Sustainability and resilience: A review of definitions, relationships, and their integration into a combined building assessment framework. *Building and Environment*, 154(March), 132–144. <https://doi.org/10.1016/j.buildenv.2019.02.042>
- Roy, R., Gain, A. K., Samat, N., Hurlbert, M., Tan, M. L., & Chan, N. W. (2019). Resilience of coastal agricultural systems in Bangladesh: Assessment for agroecosystem stewardship strategies. *Ecological Indicators*, 106(March), 105525. <https://doi.org/10.1016/j.ecolind.2019.105525>
- Rubinowicz, P. (2000). Chaos and geometric order in architecture and design. *Journal for Geometry and Graphics*, 4(2), 197–207.
- Rukmana, D. (2008). The Growth of Jakarta Metropolitan Area and the Sustainability of Urban Development in Indonesia. *The International Journal of Environmental, Cultural, Economic, and Social Sustainability: Annual Review*, 4(1), 99–106. <https://doi.org/10.18848/1832-2077/cgp/v04i01/54398>
- Rumbach, A., & Shirgaokar, M. (2017). Predictors of household exposure to monsoon rain hazards in informal settlements. *Natural Hazards*, 85(2), 709–728. <https://doi.org/10.1007/s11069-016-2599-z>
- Rumelhart, D. E., Hintont, G. E., & Williams, H. & R. J. (1986). Learning representations by back-propagating errors. *Nature*, 323(9), 533–536.
- Rus, K., Kilar, V., & Koren, D. (2018). Resilience assessment of complex urban systems to natural disasters: A new literature review. *International Journal of Disaster Risk Reduction*, 31(January), 311–330. <https://doi.org/10.1016/j.ijdrr.2018.05.015>
- Santos, A. S., & Ribeiro, S. K. (2015). The role of transport indicators to the improvement of local governance in Rio de Janeiro City: A contribution for the debate on sustainable future. *Case Studies on Transport Policy*, 3(4), 415–420. <https://doi.org/10.1016/j.cstp.2015.08.006>
- Satterthwaite, D., Archer, D., Colenbrander, S., Dodman, D., Hardoy, J., Mitlin, D., & Patel, S. (2020). Building Resilience to Climate Change in Informal Settlements. *One Earth*, 2(2), 143–156. <https://doi.org/10.1016/j.oneear.2020.02.002>
- Saunders, W. S. A., & Becker, J. S. (2015). A discussion of resilience and sustainability: Land use planning recovery from the Canterbury earthquake sequence, New Zealand. *International Journal of Disaster Risk Reduction*, 14, 73–81. <https://doi.org/10.1016/j.ijdrr.2015.01.013>
- Scherzer, S., Lujala, P., & Rød, J. K. (2019). A community resilience index for Norway: An adaptation of the Baseline Resilience Indicators for Communities (BRIC). *International Journal of Disaster Risk Reduction*, 36(March), 101107. <https://doi.org/10.1016/j.ijdrr.2019.101107>
- Schipper, E. L. F., & Langston. (2015). A comparative overview of resilience measurement frameworks: analysing indicators and approaches. In *Spain, China and Japan in Manila, 1571-1644* (422, Issue July). <https://doi.org/10.1515/9789048526819-003>
- Schleicher-Tappeser, R. (2014). Assessing Sustainable Development in the European Union. In *Greener Management International* (Vol. 2001, Issue 36). <https://doi.org/10.9774/gleaf.3062.2001.wi.00007>
- Seager, T. P. (2008). The Sustainability Spectrum and the Sciences of Sustainability. *Business Strategy and the Environment*, 17(5), 444–453. <https://doi.org/10.1002/bse.632>
- Sharifi, A. (2016). A critical review of selected tools for assessing community resilience. *Ecological Indicators*, 69, 629–647.

<https://doi.org/10.1016/j.ecolind.2016.05.023>

- Sharifi, A., Chelleri, L., Fox-Lent, C., Grafakos, S., Pathak, M., Olazabal, M., Moloney, S., Yumagulova, L., & Yamagata, Y. (2017). Conceptualizing dimensions and characteristics of urban resilience: Insights from a co-design process. *Sustainability*, 9(6), 1–21. <https://doi.org/10.3390/su9061032>
- Shukla, R., Sachdeva, K., & Joshi, P. K. (2016). An indicator-based approach to assess village-level social and biophysical vulnerability of agriculture communities in Uttarakhand, India. *Journal of Mountain Science*, 13(12), 2260–2271. <https://doi.org/10.1007/s11629-016-4058-4>
- Siebeneck, L., Arlikatti, S., & Andrew, S. A. (2015). Using provincial baseline indicators to model geographic variations of disaster resilience in Thailand. *Natural Hazards*, 79(2), 955–975. <https://doi.org/10.1007/s11069-015-1886-4>
- Siebeneck, L. K., & Cova, T. J. (2012). Spatial and Temporal Variation in Evacuee Risk Perception Throughout the Evacuation and Return-Entry Process. *Risk Analysis*, 32(9), 1468–1480. <https://doi.org/10.1111/j.1539-6924.2011.01781.x>
- Singh-Peterson, L., Salmon, P., Goode, N., & Gallina, J. (2014). Translation and evaluation of the Baseline Resilience Indicators for Communities on the Sunshine Coast, Queensland Australia. *International Journal of Disaster Risk Reduction*, 10(PA), 116–126. <https://doi.org/10.1016/j.ijdrr.2014.07.004>
- Soman, S., Beukes, A., Nederhooft, C., Marchio, N., & Bettencourt, L. (2020). Worldwide Detection of Informal Settlements via Topological Analysis of Crowdsourced Digital Maps. *ISPRS International Journal of Geo-Information*, 9(11), 685. <https://doi.org/10.3390/ijgi9110685>
- Song, G., Li, Z., Yang, Y., Semakula, H. M., & Zhang, S. (2015). Assessment of ecological vulnerability and decision-making application for prioritizing roadside ecological restoration: A method combining geographic information system, Delphi survey and Monte Carlo simulation. *Ecological Indicators*, 52, 57–65. <https://doi.org/10.1016/j.ecolind.2014.11.032>
- Song, J., Huang, B., & Li, R. (2017). Measuring recovery to build up metrics of flood resilience based on pollutant discharge data: A case study in East China. *Water*, 9(8). <https://doi.org/10.3390/w9080619>
- Song, J., Huang, B., & Li, R. (2018). Assessing local resilience to typhoon disasters: A case study in Nansha, Guangzhou. *PLoS ONE*, 13(3), 1–22. <https://doi.org/10.1371/journal.pone.0190701>
- Stafford-smith, M., Griggs, D., Gaffney, O., Ullah, F., Reyers, B., Kanie, N., Stigson, B., Shrivastava, P., Leach, M., & O’Connell, D. (2017). Integration : the key to implementing the Sustainable Development Goals. *Sustainability Science*, 12(6), 911–919. <https://doi.org/10.1007/s11625-016-0383-3>
- Statistics Indonesia- Badan Pusat Statistik (BPS). (2020). *Population*. <https://www.bps.go.id/>
- Stratford, D. S., Grigg, G. C., McCallum, H. I., & Hines, H. B. (2010). Breeding ecology and phenology of two stream breeding myobatrachid frogs (*Mixophyes fleayi* and *M. fasciolatus*) in south-east Queensland. *Australian Zoologist*, 35(2), 189–197. <https://doi.org/10.7882/AZ.2010.007>
- Suhartini, N., & Jones, P. (2020). Better understanding self-organizing cities: A typology of order and rules in informal settlements. *Journal of Regional and City Planning*, 31(3), 237–263. <https://doi.org/10.5614/jpwk.2020.31.3.2>
- Sweeting, D. (2017). *The informal city and rights in South East Asian Cities: the cases of Kampung Improvement Programme and Baan Mankong*. 192. https://www.ucl.ac.uk/bartlett/development/sites/bartlett/files/wp192_david_sweeting.pdf
- Tambo, J. A. (2016a). Adaptation and resilience to climate change and variability in north-east Ghana. *International Journal of Disaster Risk Reduction*, 17, 85–94. <https://doi.org/10.1016/j.ijdrr.2016.04.005>
- Tambo, J. A. (2016b). Adaptation and resilience to climate change and variability in north-east Ghana. *International Journal of Disaster Risk Reduction*, 17, 85–94. <https://doi.org/10.1016/j.ijdrr.2016.04.005>
- Tan, J., Zhang, P., Lo, K., Li, J., & Liu, S. (2017). Conceptualizing and measuring economic resilience of resource-based cities: Case study of Northeast China. *Chinese Geographical Science*, 27(3), 471–481. <https://doi.org/10.1007/s11769-017-0878-6>
- Teluguntla, P., Thenkabail, P., Oliphant, A., Xiong, J., Gumma, M. K., Congalton, R. G., Yadav, K., & Huete, A. (2018). A 30-m landsat-derived cropland extent product of Australia and China using random forest machine learning algorithm on Google Earth Engine cloud computing platform. *ISPRS Journal of Photogrammetry and Remote Sensing*, 144(August), 325–340. <https://doi.org/10.1016/j.isprsjprs.2018.07.017>
- Thacker, S., Adshead, D., Fay, M., Hallegatte, S., Harvey, M., Meller, H., O’Regan, N., Rozenberg, J., Watkins, G., & Hall, J.

- W. (2019). Infrastructure for sustainable development. *Nature Sustainability*, 2(4), 324–331. <https://doi.org/10.1038/s41893-019-0256-8>
- The Economist Intelligence Unit. (2019). *The critical role of infrastructure for the Sustainable Development Goals*. <https://unops.economist.com/wp-content/uploads/2019/01/ThecriticalroleofinfrastructurefortheSustainableDevelopmentGoals.pdf>
- The global commission on the Economy and Climate. (2016). *The Sustainable Infrastructure Imperative: Financing for Better Growth and Development*. <https://doi.org/978-0-9906845-9-6>
- The World Bank-DataBank. (2020). <https://databank.worldbank.org/>
- The World Bank. (2011). *Jakarta Urban Challenges in a Changing Climate*. <http://documents.worldbank.org/curated/en/132781468039870805/pdf/650180WP0Box360ange0Jakarta0English.pdf>
- The World Bank. (2015). *DKI Jakarta: Informal Settlement Mapping*. <http://pubdocs.worldbank.org/en/408201444418421010/Output-DKI-JAKARTA-INFORMAL-SETTLEMENT-MAPPING>
- The World Bank. (2016). *Indonesia: Improving Infrastructure for Millions of Urban Poor*. <https://www.worldbank.org/en/news/press-release/2016/07/12/indonesia-improving-infrastructure-for-millions-of-urban-poor>
- The World Commission on Environment and Development. (1987). Our Common Future. In *Oxford University Press*. <https://doi.org/10.1080/07488008808408783>
- Thulstrup, A. W. (2015). Livelihood Resilience and Adaptive Capacity: Tracing Changes in Household Access to Capital in Central Vietnam. *World Development*, 74, 352–362. <https://doi.org/10.1016/j.worlddev.2015.05.019>
- Toll, L. (1984). An Evaluation of Simulated Thematic Mapper Data and Landsat MSS Data for- iscriminating Suburban and Regional Land Use and Land Cover. *Photogrammetric Engineering and Remote Sensing*, 50(12).
- Toubes, D., Gössling, S., Hall, C., & Scott, D. (2017). Vulnerability of Coastal Beach Tourism to Flooding: A Case Study of Galicia, Spain. *Environments*, 4(4), 83. <https://doi.org/10.3390/environments4040083>
- Transforming our world: the 2030 Agenda for Sustainable Development*. (2015). <https://www.refworld.org/docid/57b6e3e44.html>
- Tumini, I., Villagra-Islas, P., & Herrmann-Lunecke, G. (2017). Evaluating reconstruction effects on urban resilience: a comparison between two Chilean tsunami-prone cities. *Natural Hazards*, 85(3), 1363–1392. <https://doi.org/10.1007/s11069-016-2630-4>
- Turner, B. L., Kasperson, R. E., Matsone, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., & Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences of the United States of America*, 100(14), 8074–8079. <https://doi.org/10.1073/pnas.1231335100>
- U.S. Geological Survey. (2016). Landsat 8 Data Users Handbook. In NASA (Vol. 8, Issue June). <https://landsat.usgs.gov/documents/Landsat8DataUsersHandbook.pdf>
- UN-Habitat. (2007). *UN-HABITAT and the Kenya Slum Upgrading Programme* (Issue April).
- UN-Habitat. (2013a). *State of the World's Cities 2012-2013: Prosperity of Cities*. <https://books.google.co.uk/books?id=%0A6cGzNAEACAAJ%0A>
- UN-Habitat. (2013b). *Streets as Public Spaces and Drivers of Urban Prosperity*.
- UN-Habitat. (2014). *Promoting Resilient Housing and Secure Tenure in a Changing Climate* (Issue 3).
- UN-Habitat. (2015). *The State of Asian and Pacific Cities 2015: Urban transformations Shifting from quantity to quality*. <https://unhabitat.org/books/the-state-of-asian-and-pacific-cities-2015/>
- UN-Habitat. (2020). *World Cities Report 2020: The Value of Sustainable Urbanization*.
- UNDP. (2016). Report of the Inter-Agency and Expert Group on Sustainable Development Goal Indicators. In *Report of the Inter-Agency and Expert Group on Sustainable Development Goal Indicators*.

- UNDP. (2019). *SDG Localization In ASEAN: Experiences In Shaping Policy*.
- United Nations. (2017). *New Urban Agenda*. United Nations (Habitat III). www.habitat3.org
- United Nations. (2018). World Urbanization Prospects: The 2018 revision. In *Department of Economic & Social Affairs*. <https://doi.org/10.4054/demres.2005.12.9>
- UNSD. (2020). Global Indicator Framework for the Sustainable Development Goals and Targets of the 2030 Agenda for Sustainable Development. In *Work of the Statistical Commission pertaining to the 2030 Agenda for Sustainable Development*. [https://unstats.un.org/sdgs/indicators/Global Indicator Framework after 2019 refinement_Eng.pdf](https://unstats.un.org/sdgs/indicators/Global%20Indicator%20Framework%20after%202019%20refinement_Eng.pdf) [https://unstats.un.org/sdgs/indicators/Global Indicator Framework_A.RES.71.313 Annex.pdf](https://unstats.un.org/sdgs/indicators/Global%20Indicator%20Framework_A.RES.71.313%20Annex.pdf)
- UNSD. (2023). *SDG indicator metadata*.
- Urruty, N., Tailliez-Lefebvre, D., & Huyghe, C. (2016). Stability, robustness, vulnerability and resilience of agricultural systems. A review. *Agronomy for Sustainable Development*, 36(1), 1–15. <https://doi.org/10.1007/s13593-015-0347-5>
- van Eck, N. J., & Waltman, L. (2017). Citation-based clustering of publications using CitNetExplorer and VOSviewer. *Scientometrics*, 111(2), 1053–1070. <https://doi.org/10.1007/s11192-017-2300-7>
- Van Eck, N. J., & Waltman, L. (2010). *Software survey: VOSviewer, a computer program for bibliometric mapping*. *Scientometrics*, 84(2), 523–538.
- Van Eck, N. J., & Waltman, L. (2014). Visualizing bibliometric networks. In Y. Ding, R. Rousseau, & D. W. (Eds.) (Eds.), *Measuring scholarly impact: Methods and practice*. Springer.
- Vijaymeena, M. K., & Kavitha, K. (2016). A survey on similarity measures in text mining. *Machine Learning and Applications: An International Journal (MLAIJ)*, 3(1).
- Voghera, A., & Giudice, B. (2019). Evaluating and planning green infrastructure: A strategic perspective for sustainability and resilience. *Sustainability*, 11(10). <https://doi.org/10.3390/su11102726>
- Volpi, M., Tuia, D., Bovolo, F., Kanevski, M., & Bruzzone, L. (2013). Supervised change detection in VHR images using contextual information and support vector machines. *International Journal of Applied Earth Observations and Geoinformation*, 20, 77–85. <https://doi.org/10.1016/j.jag.2011.10.013>
- Voorde, T. Van De, Genst, W. De, & Canters, F. (2007). Improving Pixel-based VHR Land-cover Classifications of Urban Areas with Post-classification Techniques. *Photogramm. Eng. Remote Sensing*, 1017–1027.
- Wang, D., Zheng, J., Song, X., Ma, G., & Liu, Y. (2017a). Assessing industrial ecosystem vulnerability in the coal mining area under economic fluctuations. *Journal of Cleaner Production*, 142, 4019–4031. <https://doi.org/10.1016/j.jclepro.2016.10.049>
- Wang, D., Zheng, J., Song, X., Ma, G., & Liu, Y. (2017b). Assessing industrial ecosystem vulnerability in the coal mining area under economic fluctuations. *Journal of Cleaner Production*, 142, 4019–4031. <https://doi.org/10.1016/j.jclepro.2016.10.049>
- Wang, L., Fan, H., & Wang, Y. (2020). Improving population mapping using LuoJia 1-01 nighttime light image and location-based social media data. *Science of the Total Environment*, 730, 139148. <https://doi.org/10.1016/j.scitotenv.2020.139148>
- Wang, M.-X., Huang, D., Wang, G., & Li, D.-Q. (2020). SS-XGBoost: A Machine Learning Framework for Predicting Newmark Sliding Displacements of Slopes. *Journal of Geotechnical and Geoenvironmental Engineering*, 146(9), 04020074. [https://doi.org/10.1061/\(asce\)gt.1943-5606.0002297](https://doi.org/10.1061/(asce)gt.1943-5606.0002297)
- Wei, Y., Wang, S., Fang, Y., & Nawaz, Z. (2017). Integrated assessment on the vulnerability of animal husbandry to snow disasters under climate change in the Qinghai-Tibetan Plateau. *Global and Planetary Change*, 157(September), 139–152. <https://doi.org/10.1016/j.gloplacha.2017.08.017>
- Weir, D., McQuillan, D., & Francis, R. A. (2019). Civilian science: the potential of participatory environmental monitoring in areas affected by armed conflicts. *Environmental Monitoring and Assessment*, 191(10). <https://doi.org/10.1007/s10661-019-7773-9>
- Williges, K., Mechler, R., Bowyer, P., & Balkovic, J. (2017). Towards an assessment of adaptive capacity of the European agricultural sector to droughts. *Climate Services*, 7, 47–63. <https://doi.org/10.1016/j.cliser.2016.10.003>
- Woolf, S., Twigg, J., Parikh, P., Karaoglou, A., & Cheab, T. (2016). Towards measurable resilience: A novel framework tool for the assessment of resilience levels in slums. *International Journal of Disaster Risk Reduction*, 19, 280–302.

<https://doi.org/10.1016/j.ijdr.2016.08.003>

- Worstell, J., & Green, J. (2017). Eight Qualities of Resilient Food Systems: Toward a Sustainability/Resilience Index. *Journal of Agriculture, Food Systems, and Community Development*, 7(3), 1–19. <https://doi.org/10.5304/jafscd.2017.073.001>
- Wu, C. C., Jhan, H. T., Ting, K. H., Tsai, H. C., Lee, M. T., Hsu, T. W., & Liu, W. H. (2016). Application of social vulnerability indicators to climate change for the southwest coastal areas of Taiwan. *Sustainability*, 8(12). <https://doi.org/10.3390/su8121270>
- Wurm, M., Taubenböck, H., Weigand, M., & Schmitt, A. (2017). Slum mapping in polarimetric SAR data using spatial features. *Remote Sensing of Environment*, 194, 190–204. <https://doi.org/10.1016/j.rse.2017.03.030>
- Xia, L. I. (2007). Technical Note. A method to improve classification with shape information. *International Journal of Remote Sensing* ISSN:, 17(8). <https://doi.org/10.1080/01431169608948718>
- Xu, L., Marinova, D., & Guo, X. (2015). Resilience thinking: a renewed system approach for sustainability science. *Sustainability Science*, 10(1), 123–138. <https://doi.org/10.1007/s11625-014-0274-4>
- Yenneti, K., Tripathi, S., Wei, Y. D., Chen, W., & Joshi, G. (2016). The truly disadvantaged? Assessing social vulnerability to climate change in urban India. *Habitat International*, 56, 124–135. <https://doi.org/10.1016/j.habitatint.2016.05.001>
- Yoon, D. K., Kang, J. E., & Brody, S. D. (2016). A measurement of community disaster resilience in Korea. *Journal of Environmental Planning and Management*, 59(3), 436–460. <https://doi.org/10.1080/09640568.2015.1016142>
- Yuan, J., Roy Chowdhury, P. K., McKee, J., Yang, H. L., Weaver, J., & Bhaduri, B. (2018). Exploiting deep learning and volunteered geographic information for mapping buildings in Kano, Nigeria. *Scientific Data*, 5, 1–8. <https://doi.org/10.1038/sdata.2018.217>
- Zahrotun, L. (2016). Comparison Jaccard similarity, Cosine Similarity and Combined Both of the Data Clustering With Shared Nearest Neighbor Method. *Computer Engineering and Applications Journal*, 5(1), 11–18. <https://doi.org/10.18495/comengapp.v5i1.160>
- Zamboni, L. M. (2017). Theory and Metrics of Community Resilience: A Systematic Literature Review Based on Public Health Guidelines. *Disaster Medicine and Public Health Preparedness*, 11(6), 756–763. <https://doi.org/10.1017/dmp.2017.22>
- Zhang, C., Li, Y., & Zhu, X. (2016). A social-ecological resilience assessment and governance guide for urbanization processes in east China. *Sustainability*, 8(11). <https://doi.org/10.3390/su8111101>
- Zhang, H. K., & Roy, D. P. (2017). Remote Sensing of Environment Using the 500 m MODIS land cover product to derive a consistent continental scale 30 m Landsat land cover classification. *Remote Sensing of Environment*, 197, 15–34. <https://doi.org/10.1016/j.rse.2017.05.024>
- Zhang, Y., Peng, D., & Huang, X. (2018). Object-Based Change Detection for VHR Images Based on Multiscale Uncertainty Analysis. *IEEE Geoscience and Remote Sensing Letters*, 15(1), 13–17.
- Zhou, B., Okin, G. S., & Zhang, J. (2020). Leveraging Google Earth Engine (GEE) and machine learning algorithms to incorporate in situ measurement from different times for rangelands monitoring. *Remote Sensing of Environment*, 236(December), 111521. <https://doi.org/10.1016/j.rse.2019.111521>
- Zhou, X., & Moinuddin, M. (2017). Sustainable Development Goals Interlinkages and Network Analysis: A practical tool for SDG integration and policy coherence. *The Institute for Global Environmental Strategies (IGES)*, June, 140. <https://doi.org/10.1128/MCB.05460-11>
- Zhu, Z., Gallant, A. L., Woodcock, C. E., Pengra, B., Olofsson, P., Loveland, T. R., Jin, S., Dahal, D., Yang, L., & Auch, R. F. (2016). Optimizing selection of training and auxiliary data for operational land cover classification for the LCMAP initiative. *ISPRS Journal of Photogrammetry and Remote Sensing*, 122, 206–221. <https://doi.org/10.1016/j.isprsjprs.2016.11.004>
- Zukowski, R. S. (2014). The impact of adaptive capacity on disaster response and recovery: Evidence supporting core community capabilities. *Prehospital and Disaster Medicine*, 29(4), 380–387. <https://doi.org/10.1017/S1049023X14000624>

Appendices

Appendix 1. Baseline resilience framework (BRF).

D	SD	Variable	Indicators	Impact	Justification
S	E&K	Education level & quality	Ratio of the population with college education to the population with less than high school education	+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Cutter, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population finished secondary level	+	(Kaye-Blake et al., 2019),(Kliskey et al., 2019),(Li, Lam, et al., 2016),(Hung et al., 2016),(Kotzee & Reyers, 2016),(Cutter, 2016),(Burton, 2015),(Ainuddin & Routray, 2012),(Yoon et al., 2016)
			% Population finished tertiary education	+	(Kaye-Blake et al., 2019)
			% Population who are illiterate	-	(Hu et al., 2018),(Wu et al., 2016),(Ainuddin & Routray, 2012),(DasGupta & Shaw, 2015),(Yoon et al., 2016)
			Pupil-to-teacher ratio at public schools	-	(Links et al., 2018)
			School dropout rate of children	-	(DasGupta & Shaw, 2015)
			Average years of education attainment of population 15 years and up	+	(L. Siebeneck et al., 2015)
			Adult education and training program per 1,000 persons	+	(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Traditional knowledge Expenditure Population structure	No. of people 50 + years old and indigenous per capita	+	(Kliskey et al., 2019)
			No. of people with 30 + years residence per capita	+	(Kliskey et al., 2019)
			Per capita expenditure on education	+	(Manyena et al., 2019),(Hu et al., 2018)
			% Population that is of working age (15-59)	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Kim & Park, 2018),(Kotzee & Reyers, 2016),(L. Siebeneck et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Li, Lam, et al., 2016),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(J. Song et al., 2017)
			Total number of population	-	(Hu et al., 2018)
			Ratio of men to women	+	(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Li, Lam, et al., 2016),(Asadzadeh et al., 2015),(Yoon et al., 2016),(J. Song et al., 2017)
			% Population of elders (above 65)	-	(Kim & Park, 2018),(Asadzadeh et al., 2015),(J. Song et al., 2018),(Mihunov et al., 2018),(Links et al., 2018),(Hung et al., 2016),(DasGupta & Shaw, 2015),(Yoon et al., 2016)
			*% Children in population	-	(J. Song et al., 2018),(Mihunov et al., 2018),(Links et al., 2018)
		Population change	% Annual population change	-	(Kaye-Blake et al., 2019),(Scherzer et al., 2019)
			% Population change over the last five years	-	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Population growth rate	-	(Abdrabo & Hassaan, 2015),(DasGupta & Shaw, 2015)
		Household features	% Households that are not single parents	+	(Scherzer et al., 2019)
			Average number of people per household	-	(Mihunov et al., 2018),(Links et al., 2018)
			% Single parent household	-	(Mihunov et al., 2018),(L. Siebeneck et al., 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Yoon et al., 2016)
		Urbanisation and density	Household density	-	(Abdrabo & Hassaan, 2015),(DasGupta & Shaw, 2015)
			% Population living in urban areas	+	(Hu et al., 2018),(C. Zhang et al., 2016),(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Li, Lam, et al., 2016)
			People per sq. km of land area	-	(J. Song et al., 2018),(Fu & Wang, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Tumini et al., 2017),(Li, Lam, et al., 2016),(Hung et al., 2016)
		Workforce	% Rural population	-	(DasGupta & Shaw, 2015)
			% Labour force employed	+	(Hu et al., 2018),(Li, Lam, et al., 2016),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Hung et al., 2016),(Abdrabo & Hassaan, 2015)
			Female workforce participation	+	(Mihunov et al., 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Equality	Gender Inequality Index (GII)	-	(Scherzer et al., 2019), (Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population whose income is below minimum wage	-	(L. Siebeneck et al., 2015),(Fu & Wang, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro,

D	SD	Variable	Indicators	Impact	Justification
					G.P., Mahin, 2019),(Links et al., 2018),(DasGupta & Shaw, 2015)
			Absolute difference between male and female median income	-	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Links et al., 2018)
			Ratio of nonminority population to minority population	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	He.	Health status	% Population without sensory, physical, or mental disability	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Links et al., 2018),(Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012),(Mihunov et al., 2018),(Kim & Park, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Mihunov et al., 2018),(Hung et al., 2016),(Yoon et al., 2016)
		Health services	Average life expectancy	+	(Links et al., 2018),(C. Zhang et al., 2016)
			3-year total low birthweight babies per 10,000 individuals	-	(Mihunov et al., 2018),(Mihunov et al., 2018)
			% Coverage of health service among 1 –year olds	+	(Manyena et al., 2019)
			*% Population with health insurance	+	(Cutter et al., 2014),(Cutter et al., 2010),(Asadzadeh et al., 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
			% Uninsured adults	-	(Links et al., 2018)
			Psychosocial support facilities per 10,000 persons	+	(Cutter et al., 2014),(Links et al., 2018)
			Child/elderly care program per 10,000 persons	+	(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Physicians/ nurses/ midwives per 10,000 persons	+	(Manyena et al., 2019),(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Links et al., 2018),(Cutter, 2016),(Burton, 2015),(Mihunov et al., 2018),(Mihunov et al., 2018),(DasGupta & Shaw, 2015)
			Hospital beds per 1,000 people	+	(Manyena et al., 2019),(Hu et al., 2018),(Links et al., 2018),(Li, Lam, et al., 2016),(J. Song et al., 2017)
			Distance to nearest health facility (e.g. health post, hospital, clinic)	-	(J. Song et al., 2018),(Tumini et al., 2017),(DasGupta & Shaw, 2015)
		Expenditure on health	Per capita expenditure on health/security	+	(Manyena et al., 2019),(Hu et al., 2018)
		Sanitation	% Population with access to improved sanitation facilities	+	(Manyena et al., 2019)
			Distance to nearest sanitation	-	(J. Song et al., 2018),(Tumini et al., 2017)
		Mortality	All-cause mortality per 100k population	-	(Links et al., 2018)
		Social welfare capacity	Number of social welfare home beds per 10,000 persons (including homeless shelters and nursing homes)	+	(Li, Lam, et al., 2016)
	CSt.	Land	% Area of urban green space	+	(Hu et al., 2018),(J. Song et al., 2018)
			% Land area set aside in protected area status	+	(Kliskey et al., 2019),(Tumini et al., 2017)
			Area of public open space	+	(Fu & Wang, 2018),(Tumini et al., 2017)
			Distance to open space	-	(Fu & Wang, 2018)
			The ratio of the sidewalk length over total area	+	(Fu & Wang, 2018)
		Social engagement	% Population involved in Red Cross volunteering activities	+	(Kaye-Blake et al., 2019),(Cutter et al., 2014),(Kim & Park, 2018),(Singh-Peterson et al., 2014)
			Budget of volunteer organisations	+	(Yoon et al., 2016)
			No. of registered volunteer/ volunteer organisations	+	(Yoon et al., 2016)
			% Voting age population participating in presidential election	+	(Kliskey et al., 2019),(Fu & Wang, 2018),(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Kotzee & Reyers, 2016),(Mihunov et al., 2018),(L. Siebeneck et al., 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Mihunov et al., 2018),(L. Siebeneck et al., 2015)
			Less than 3 parties are involved in the decision-making process	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			*Park/Sports facilities/Cinemas persons/ Museums/libraries/zoos/ botanical gardens/ youth centres/clubs/child care centre per 1,000 persons	+	(Tumini et al., 2017),(Scherzer et al., 2019),(Burton, 2015),(Moghadas et al., 2019),(L. Siebeneck et al., 2015)
			Ratio of entertainment and recreation land uses to areas of public open spaces	+	(Asadzadeh et al., 2015),(Fu & Wang, 2018),(Tumini et al., 2017)
			Persons affiliated with a religious organisation per 10,000 persons	+	(Cutter et al., 2014),(Cutter et al., 2010),(Links et al., 2018),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018),(Cutter, 2016),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Kaye-Blake et al., 2019)
			Places of worship per 1,000 persons	+	(Scherzer et al., 2019)
			No. of religious organisations	+	(Cutter, 2016),(Asadzadeh et al., 2015)
			% Population that is not minority	+	(Burton, 2015)
			No. of registered non-profit organisations	+	(Cutter, 2016)
		Communication	% Population with access to phone	+	(Kaye-Blake et al., 2019),(Cutter et al., 2014),(Moghadas et al., 2019),(Asadzadeh et al.,

D	SD	Variable	Indicators	Impact	Justification
					2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			% Population with access to internet/TV/radio	+	(Kaye-Blake et al., 2019),(Scherzer et al., 2019),(Links et al., 2018),(Burton, 2015)
			% Population proficient English speakers	+	(Cutter et al., 2014),(Cutter et al., 2010),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Mobility	% Households with at least one vehicle	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Links et al., 2018),(Kotzee & Reyers, 2016),(L. Siebeneck et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018), (L. Siebeneck et al., 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population that walk or cycle to work	+	(Links et al., 2018)
			Mobility mode Diversity (fixed-wing air, road, boat, ATV/trail)	+	(Kliskey et al., 2019)
			Regulation of transportation options	+	(Kliskey et al., 2019)
			Roads network density	+	(Hu et al., 2018),(J. Song et al., 2018),(Kotzee & Reyers, 2016)
			No. of traffic accidents	-	(Hu et al., 2018)
			Distance to nearest transport network	-	(J. Song et al., 2018)
			Walkways length per total street length	+	(Tumini et al., 2017)
		Place attachment	*% Population born in country of current residence	+	(J. Song et al., 2018),(Fu & Wang, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Moghadas et al., 2019),(Mihunov et al., 2018),(L. Siebeneck et al., 2015),(Hung et al., 2016),(Kaye-Blake et al., 2019)
			% Population who migrated to country within previous five/ten years	-	(Cutter et al., 2014),(Kotzee & Reyers, 2016),(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(L. Siebeneck et al., 2015),
			Net in and out migration	-	(Cutter et al., 2010),(Scherzer et al., 2019),(Kim & Park, 2018),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
	SP	Expenditure Organisations	Public spending on social assistance as % of GDP	+	(Manyena et al., 2019)
			Civic organisations per 10,000 persons	+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Kotzee & Reyers, 2016),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018),(Cutter, 2016)
			No. of social advocacy organisations per 10,000 population	+	(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018),(Links et al., 2018)
		Community disaster preparedness	Red Cross training workshop participants per 10,000 persons	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			No. of courses in disaster risk reduction (DRR) as part of the educational curriculum per schools and colleges	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			No. of education programs on DRR and disaster preparedness per each local community by local government per year	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Innovation	Percent population employed in creative class occupations (e.g. architects, engineers, and scientific researchers)	+	(Cutter et al., 2010),(Scherzer et al., 2019),(Tan et al., 2017),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Research & development firms per 1,000 persons	+	(Scherzer et al., 2019),(Burton, 2015)
			Business and professional organisations per 1,000 persons	+	(Burton, 2015)
		Cultural heritage	National Historic Registry sites area per population	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	Eco.C	Household economy	Median household income	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Hung et al., 2016),(Abdrabo & Hassaan, 2015)
			% Owner-occupied housing units	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Households saving value in bank	+	(Hung et al., 2016)
		Food capacity	Food security rate	+	(Cutter et al., 2014),(Tumini et al., 2017)
			% Employees not in farming, fishing, forestry, extractive industry, or tourism	+	(Hung et al., 2016),(DasGupta & Shaw, 2015)
			Area of commercial establishment per 10,000 persons	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
Eco.	HC	Household assets	% Owner-occupied housing units	+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Mihunov et al., 2018),(Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Ainuddin & Routray, 2012),(Hiete et al., 2012)

D	SD	Variable	Indicators	Impact	Justification
			% Households with at least one vehicle	+	(Cutter et al., 2014),(Cutter et al., 2010),(Mihunov et al., 2018)
			% Households with telephone service available	+	(Cutter et al., 2014),(Cutter et al., 2010),(Kotzee & Reyers, 2016)
			Households saving value in bank	+	(Fu & Wang, 2018),(Hu et al., 2018),(Tan et al., 2017),(C. Zhang et al., 2016)
	E	Workforce	% Labour force employed	+	(Kaye-Blake et al., 2019),(Cutter et al., 2014),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018),(Kim & Park, 2018),(J. Song et al., 2018),(Mihunov et al., 2018),(Links et al., 2018), (Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(L. Siebeneck et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
			% Employees not in farming, fishing, forestry, extractive industry, or tourism	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018),(Tan et al., 2017),(Asadzadeh et al., 2015),(Burton, 2015), (Singh-Peterson et al., 2014),(Hiete et al., 2012),(Mihunov et al., 2018)
			% Labour force employed by federal government	+	(Cutter et al., 2014)
		Equality	Physicians/ nurses/ midwives per 10,000 persons	+	(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			% Female labour force participation	+	(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kotzee & Reyers, 2016),(Burton, 2015),(Hiete et al., 2012)
	I	Income features	Average annual income per capita	+	(Kaye-Blake et al., 2019),(Fu & Wang, 2018),(Hu et al., 2018),(Mihunov et al., 2018),(Cutter, 2016),(Asadzadeh et al., 2015)
			Median household income	+	(Mihunov et al., 2018),(Links et al., 2018),(Chu et al., 2017),(Cutter, 2016),(Asadzadeh et al., 2015),(Burton, 2015)
			Minimum wage rate per day	+	(L. Siebeneck et al., 2015)
			% Population with multiple source of income	+	(Ainuddin & Routray, 2012)
			Disposable income per capita	+	(Hu et al., 2018),(Toubes et al., 2017),(C. Zhang et al., 2016)
		Equality	Income tax per capita	+	(Hu et al., 2018)
			% Population living below the poverty line	-	(Mihunov et al., 2018),(Asadzadeh et al., 2015),(Ainuddin & Routray, 2012)
			Gini coefficient	-	(Cutter et al., 2014),(Cutter et al., 2010),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Absolute difference between male and female median income	-	(Cutter et al., 2014)
	BA&P	Business features	Ratio of large to small businesses	+	(Cutter et al., 2014),(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Large retail stores per 10,000 persons	+	(Cutter et al., 2014),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Links et al., 2018),(Burton, 2015)
			No. of grocery stores per 100 square miles	+	(Links et al., 2018)
			No. of banks per 1,000 persons	+	(Scherzer et al., 2019),(Links et al., 2018)
			No. of enterprises per 1,000 persons	+	(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015)
		Commercial activities	Area of commercial establishment per 10,000 persons	+	(Moghadas et al., 2019)
			Density of commercial infrastructure in each district	-	(Moghadas et al., 2019),(J. Song et al., 2018),(Burton, 2015)
			Research & development firms per 1,000 persons	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Commercial establishments outside of high hazard zones to total commercial establishment	+	(Burton, 2015)
			Ratio of business (CBD centres) within build-up area	+	(J. Song et al., 2017)
			% Population living in urban areas	+	(J. Song et al., 2017)
		Income and expenditure	Total financial revenue from business	+	(Hu et al., 2018),(Tan et al., 2017),(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Ratio of public finance income and expenditure	+	(Tan et al., 2017)
			Total amount (\$) of imported and exported goods	+	(Hu et al., 2018),(Tan et al., 2017)
			% GDP from primary industry (farming, fishing, etc.)	-	(Li, Lam, et al., 2016)
			Amount of tax collected per capita	+	(Yoon et al., 2016)
			Net per capita spending for mitigation projects	+	(Yoon et al., 2016)
			Cost of road construction	-	(Fu & Wang, 2018)

D	SD	Variable	Indicators	Impact	Justification
Ins.	FS	Economy diversity	Price of land (RMB) per square meter	-	(J. Song et al., 2018)
			TRESS index	-	(Kotzee & Reyers, 2016)
			Energy use for residential, commercial and industrial land use	-	(Fu & Wang, 2018),(J. Song et al., 2018)
			Water use by households in the area	-	(Fu & Wang, 2018),(J. Song et al., 2018)
		Production type and features	Food security rate	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Gross regional domestic product per capita	+	(Kim & Park, 2018),(Hu et al., 2018),(Chu et al., 2017),(Tan et al., 2017),(C. Zhang et al., 2016),(Li, Lam, et al., 2016),(L. Siebeneck et al., 2015),(J. Song et al., 2017)
			Farm fixed assets investment density (amount of investment per area)	+	(Tan et al., 2017)
			Density of manufacturing within built up area	+	(J. Song et al., 2017)
			Farms marketing products through Community Supported Agriculture per 10,000 persons	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Proportion of cultivated land area	+	(Li, Lam, et al., 2016)
			Types of renewable sources	+	(Fu & Wang, 2018)
		Renewable energy	Crop insurance policies per square mile	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Housing units covered by disaster insurance	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	Pr.	Social	Local court convictions per capita	-	(Kaye-Blake et al., 2019)
			% Voting age population participating in presidential election	+	(Kaye-Blake et al., 2019),(Hung et al., 2016)
			Population change over previous five-year period	+	(Cutter et al., 2014),(Moghadas et al., 2019)
			% Population covered by a mitigation plan	+	(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018),(Burton, 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
			% Population living in hazardous area	-	(Asadzadeh et al., 2015)
			*% Population with access to local disaster training	+	(Cutter et al., 2014),(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
		Financial	Red Cross training workshop participants per 10,000 persons	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018)
			% Employed persons working in public administration, defense, social security or municipal activities	+	(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(C. Zhang et al., 2016),(Burton, 2015)
			Net per capita spending for mitigation projects	+	(Cutter et al., 2014),(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Cutter, 2016),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
		Infrastructure	% Governmental financial resources to carry out risk reduction activities	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Building infrastructure not in high hazard zones	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Essential infrastructures that are under regular assessment programs	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Local schools, hospitals and health facilities that remained operational during emergencies in past events	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population access to electricity/gas/safe water/radio/internet	+	(L. Siebeneck et al., 2015)
			Hospital/hotel beds per 10,000 persons	+	(L. Siebeneck et al., 2015)
			% Housing units that are not mobile homes	+	(L. Siebeneck et al., 2015)
			Principle arterial miles per square mile	+	(Fu & Wang, 2018),(L. Siebeneck et al., 2015)
			The ratio of the number of crossings over the length of roads (network connectivity)	+	(Fu & Wang, 2018)
			Daily average amount of marine cargo transported	+	(Kim & Park, 2018)
			Average size of registered fishery vehicles	+	(Kim & Park, 2018)
			No. of seamounts	+	(Kim & Park, 2018)
			% State owned and collective owned households	-	(Kaye-Blake et al., 2019),(Tan et al., 2017)
			No. of schools per 1000 students	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			No. of fire/ police/ambulance stations and shelters per 1,000 people	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			*Existence of structural measures that physically prevent extreme events	+	(Toubes et al., 2017)
			Average number of early warning centres per each independent zone	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018)

D	SD	Variable	Indicators	Impact	Justification
Inf.	RR	Environmental	No. of fire/ police/ambulance stations and shelters per 1,000 people	+	(Fu & Wang, 2018),(Kim & Park, 2018),(DasGupta & Shaw, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			No. of buildings units constructed over the last ten years	-	(Moghadas et al., 2019)
			% Land area that consists of windbreaks and environmental plantings	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Vulnerable shoreline protected by dykes/embankments	+	(DasGupta & Shaw, 2015)
			Ratio of % designed structural damage to % actual structural damage	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Area of residential, commercial, industrial and educational land uses (km2)	+	(Hung et al., 2016)
			% Population within 10 miles of nuclear power plant	-	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Mean distance in meters from denser settlement areas to nearest county capital	-	(Scherzer et al., 2019)
			Total financial revenue from business	+	(Mihunov et al., 2018)
			% Municipal wastewater treatment	+	(C. Zhang et al., 2016)
			*Amount of solid waste by source	-	(C. Zhang et al., 2016)
			The GDP growth rate of environment administration (%)	+	(C. Zhang et al., 2016)
			Fixed assets investment density (amount of investment per area)	+	(C. Zhang et al., 2016)
		Government performance regime	Proximity of county seat to state capital	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Proximity of county seat to nearest county seat within a Metropolitan Statistical Area	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Governments and special districts per 10,000 persons	+	(Cutter et al., 2014),(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Singh-Peterson et al., 2014)
			Existence of government plans (i.e. disaster, climate adaptation)	+	(Chu et al., 2017),(Burton, 2015)
			Net operating surplus as a percentage of gross operating revenues	+	(Scherzer et al., 2019)
			% Officials and leaders who are under regular training programs	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Net per capita general expenditures	+	(Mihunov et al., 2018),(Links et al., 2018)
			Per capita expenditure on education	+	(C. Zhang et al., 2016),(Mihunov et al., 2018),(Tan et al., 2017)
	RR	Financial support	Microfinancing, cash aid, soft loans, loan guarantees available to affected households after disasters to restart livelihoods	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Crop insurance policies per square mile	+	(Cutter et al., 2014),(Cutter, 2016)
			% Population under age 65 with health insurance	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			*% Housing units covered by disaster insurance	+	(Cutter et al., 2014),(Cutter et al., 2010),(Burton, 2015)
		Ecosystem support	Presidential disaster declarations divided by number of loss-causing hazard events	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Cutter, 2016)
			No. of paid disaster declarations	+	(Cutter et al., 2010),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Local government plan to support the restoration, protection and sustainable management of ecosystems services	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Coastal setback, shoreline restoration	+	(Cutter, 2016)
		Psychosocial support	Local government access to resources and expertise to assist victims of psychosocial impacts of disasters	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Electricity	+	(Manyena et al., 2019)
	EW&S	Plumbing and sewage	% Population with access to electricity	+	(Mihunov et al., 2018),(Links et al., 2018), (Kotzee & Reyers, 2016)
			% Households with access to plumbing/piped water/flush toilet	+	(Scherzer et al., 2019),(Mihunov et al., 2018),(Hung et al., 2016)
		Workforce	% Employed persons working in public utilities (electricity, water, waste, transportation, communication)	+	(Hung et al., 2016)
			% Infrastructure area per area (transportation, park, power, water services (ha.))	+	(Hung et al., 2016)
		Public establishment	Megawatt hours per energy consumer	-	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Ratio of water production to demand	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Energy/water usage	Ratio of gas production to demand	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
				+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	Ho.	Housing features	% Housing units that are not mobile homes	+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Mihunov et al., 2018),(Links et al., 2018),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Median number of room	+	(Moghadas et al., 2019)

D	SD	Variable	Indicators	Impact	Justification
Env.	A	Temporary housing availability	% Average housing age	-	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Links et al., 2018),(Burton, 2015),(Hiete et al., 2012)
			Area of informal settlements (ha.)	-	(Hung et al., 2016),(Kotzee & Reyers, 2016)
			% Population living in urban areas	+	(Scherzer et al., 2019)
			% Vacant units that are for rent	+	(Cutter et al., 2014),(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Hotels/motels per 10,000 persons	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(J. Song et al., 2018),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Hung et al., 2016)
			Distance to nearest public shelter	-	(J. Song et al., 2018)
			Hospital beds per 10,000 persons	+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Hung et al., 2016)
		HI	Health services		
		CSe.	Social engagement	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(J. Song et al., 2017)
		EI	Commercial establishment	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Commercial establishments outside of high hazard zones ÷ total commercial establishment	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Ed.	School restoration potential	+	(Hung et al., 2016)
			% Agricultural land to total land area	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			No. of public schools per 10,000 persons/or per square mile	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
		ER	Fire, police, ambulance stations and shelters	+	(Scherzer et al., 2019),(Moghadas et al., 2019),(Cutter, 2016),(Burton, 2015)
			Mean distance in meters from denser settlement areas to the nearest /hospital/fire/police station	-	(Scherzer et al., 2019),(J. Song et al., 2018),(Asadzadeh et al., 2015),(J. Song et al., 2017)
			Firefighting/police/medical capacity	+	(Kim & Park, 2018)
			No. of firefighters/ police officers/ medical staff per 1000 population	+	(Kim & Park, 2018)
			Transportation Access	+	(Kim & Park, 2018)
			Annual increasing rate of privately possessed cars (%)	-	(C. Zhang et al., 2016)
			% Building infrastructure not in high hazard zones	+	(Burton, 2015)
		T	Industrial re-supply potential	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Kim & Park, 2018),(Burton, 2015)
			Rail miles per square mile area	+	(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Access/evacuation potential	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Tumini et al., 2017),(J. Song et al., 2017)
			Principle arterial miles per square mile	+	(Manyena et al., 2019),(Scherzer et al., 2019),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
			Major road egress points per 10,000 persons	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Tumini et al., 2017),(J. Song et al., 2017)
			Roads network density	+	(Manyena et al., 2019),(Scherzer et al., 2019),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
		Road safety	Traffic accidents per 1,000 persons	-	(Scherzer et al., 2019),(Delgado-Ramos & Guibrunet, 2017a)
		Accessibility	Mean distance in meters from denser settlement areas to the nearest airport (only airports operated by Avinor or the military were included)	-	(Scherzer et al., 2019)
			No. of vehicle per 1,000 persons	+	(Delgado-Ramos & Guibrunet, 2017a)
			Extra travel time invested yearly or daily	-	(Delgado-Ramos & Guibrunet, 2017a)
			Total cost of carbon for private and public transport	-	(Delgado-Ramos & Guibrunet, 2017a)
			Economic benefit of street provides cycling/walking (\$/year)	+	(Delgado-Ramos & Guibrunet, 2017a)
		Co.	High speed internet	+	(Cutter et al., 2014),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Chu et al., 2017)
			% Population with access to broadband internet service	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Mihunov et al., 2018)
		Telecommunication	Average number of internet, television, radio, telephone, and telecommunications broadcasters per household	+	(Cutter et al., 2014),(Green et al., 2017),(Mihunov et al., 2018)
		Local food suppliers	Farms marketing products through Community Supported Agriculture per 10,000 persons	+	(Cutter et al., 2014),(Green et al., 2017),(Mihunov et al., 2018)
			No. of farms per square mile	+	(Mihunov et al., 2019)
			% Agricultural land to total land area	+	(Hu et al., 2018)

D	SD	Variable	Indicators	Impact	Justification
EF		Connectivity	% Agricultural lands not treated with herbicide/pesticide	+	(Green et al., 2017)
			% Farm operations with internet access	+	(Green et al., 2017)
			% Family and individual farm ownership	+	(Mihunov et al., 2019)
		Assets	Agricultural holdings per 1,000 persons	+	(Scherzer et al., 2019)
			% Farms paying interest (real estate/ non-real estate)	-	(Mihunov et al., 2019)
			% Farms with expenses (animal/ chemical/ labour/ feed/rent/tax/fuel/energy)	-	(Mihunov et al., 2019)
		Income	Per capita revenue/ farm products per square meter	+	(Mihunov et al., 2018)
			% Principal operators living on farm	+	(Green et al., 2017)
			% Operations with on-farm packing/ direct marketing to retail	+	(Green et al., 2017)
		Self-organisation	Average % of operations producing across seven different row crop options	+	(Green et al., 2017)
			Air quality index (AQI)	-	(Kaye-Blake et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Abdrabo & Hassaan, 2015)
		Air	No. of days per year with pollution concentration above the local norm or standard	-	(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
			Health cost of air pollution (\$/year)	-	(Delgado-Ramos & Guibrunet, 2017a)
			% Acid rain per total precipitation	-	(C. Zhang et al., 2016)
			Soil erosion ton/year/person	-	(Kaye-Blake et al., 2019)
			% Land that is not impervious	+	(Cutter et al., 2014),(Kaye-Blake et al., 2019),(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Chu et al., 2017),(Kotzee & Reyers, 2016)
		Soil	% Availability of quality agricultural land	+	(Manyena et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% People accessing quality agricultural land and forests	+	(Manyena et al., 2019),(Abdrabo & Hassaan, 2015)
			Normalized difference vegetation index (NDVI)	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Land	Ratio of land that turned to urban areas to total land area	-	(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016),(Moghadas et al., 2019)
			% Forest to total land area	+	(Manyena et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Chu et al., 2017),(Burton, 2015),(Hu et al., 2018)
			% Land area that is developed open space	+	(Scherzer et al., 2019),(Moghadas et al., 2019),(Burton, 2015)
			% Land area that is arable (cultivated) land	+	(Scherzer et al., 2019),(Burton, 2015)
			Ratio of built and unbuild spaces	-	(Moghadas et al., 2019)
			% Land area with no land-use change	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015)
			% Land area under protected status	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016),(Yoon et al., 2016)
			% Area of urban green space	+	(Kim & Park, 2018),(Delgado-Ramos & Guibrunet, 2017a),(J. Song et al., 2017)
			% Population with access to a green urban area less than 300 m away.	+	(Delgado-Ramos & Guibrunet, 2017a)
			% Area of beach	+	(Kim & Park, 2018),(Toubes et al., 2017)
			Average elevations in the area	-	(Mihunov et al., 2018),(Yoon et al., 2016),(Hung et al., 2016),(J. Song et al., 2018)
			Height in digital elevation model (DEM)	-	(J. Song et al., 2017)
			% Land in wetlands in not slide area	+	(Scherzer et al., 2019)
			% Land area with no wetland decline	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015)
		Wildlife	% Land area that consists of windbreaks and environmental plantings	+	(Burton, 2015)
			Degree of slope	-	(Yoon et al., 2016),(J. Song et al., 2018),(J. Song et al., 2017)
			Areas of potential debris flow torrents and landslides	-	(Hung et al., 2016)
			Distance from rivers less than 100 m	-	(Hung et al., 2016)
			% Land area that does not contain erodible soils	+	(Hu et al., 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015)
		Water	% Land in wetlands (natural flood buffer zone)	+	(Cutter et al., 2014),(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Chu et al., 2017),(Burton, 2015)
			% Natural vegetation	+	(Kotzee & Reyers, 2016)
			% Species susceptible to extinction	-	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Indigenous vegetation cover (protected biomass)	+	(Kaye-Blake et al., 2019),(Manyena et al., 2019)
			% Availability of quality water resources for agriculture	+	(Manyena et al., 2019),(Abdrabo & Hassaan, 2015)
	Wildlife	Water	No. of rainy days	+	(Yoon et al., 2016)
			No. of days with more than 80 mm precipitation	-	(Yoon et al., 2016)
			Averaged annual rainfall more than 1000 mm	-	(Hung et al., 2016)
			% People accessing quality water resources for agriculture	+	(Manyena et al., 2019),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)

D	SD	Variable	Indicators	Impact	Justification
			% Dam capacity	+	(Manyena et al., 2019)
			Number of river miles whose water is usable	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(J. Song et al., 2017)
		Natural disasters	Frequency of natural disasters	-	(Yoon et al., 2016)
	EP	Efficiency	Megawatt hours per energy consumer	-	(Cutter et al., 2014),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
			% Heating fuel	-	(Mihunov et al., 2019)
			Annual crude oil withdrawals, bbl per capita	-	(Mihunov et al., 2019)
			Annual natural gas withdr., 1000 ft3 per capita	-	(Mihunov et al., 2019)
			% Renewable energy to total energy production	+	(Manyena et al., 2019)
			Degree of resource depletion	-	(Tan et al., 2017),(Abdrabo & Hassaan, 2015)
			Water supply stress index	-	(Cutter et al., 2014)
			Total water consumption	-	(Hu et al., 2018),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
			% Total renewable water resources	+	(Mihunov et al., 2019),(Manyena et al., 2019)
			% Ground water withdrawals (agriculture, public supply, industry)	-	(Mihunov et al., 2019)
		Recycling	Recycling ratio of wastes	+	(Kim & Park, 2018)
		Emission	NO/SO2 emission	-	(Hu et al., 2018),(C. Zhang et al., 2016),(Yoon et al., 2016)
			GHG emission per capita per year	-	(Delgado-Ramos & Guibrunet, 2017a)
			Increase of global temperature	-	(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
		Sewage & waste	Amount of daily sewage treatment	+	(Hu et al., 2018),(Delgado-Ramos & Guibrunet, 2017a)
			*Amount of solid waste by source	-	(Hu et al., 2018),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
	SI	Crime	Environmental violations case	-	(C. Zhang et al., 2016)
		Gross production	Gross regional domestic product per capita	+	(Delgado-Ramos & Guibrunet, 2017a)
		population	Population density	-	(Yoon et al., 2016)

Appendix 2. the national-level data for the selected SDGs and BRF indicators.

NO	Country	SDG						RM					
		9.1.2	9.4.1	9.5.1	9.5.2	9.a.1	9.c.1	1	6	11	15	16	
1	Afghanistan	2209428	0.163691	N/A	N/A	543249440	55.15951	43.898	0.5	N/A	7	0.30545	
2	Albania	151632	0.184914	N/A	N/A	235381990	115.9979	39.584	N/A	N/A	60.1	8.139129	
3	Algeria	5021289	0.275526	N/A	N/A	10328030	111.2386	59.689	N/A	0.001595	29.5	7.961185	
4	American Samoa	76944	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	17.7448	
5	Andorra	N/A	N/A	N/A	N/A	N/A	83.6239	N/A	N/A	N/A	95.9	48.27112	
6	Angola	1409952	0.189387	N/A	N/A	573696990	52.15898	42.025	N/A	N/A	21.4	1.066804	
7	Antigua and Barbuda	1216152	0.281031	N/A	N/A	123150	129.6871	N/A	3.8	N/A	67.78	21.51531	
8	Argentina	12121913	0.252522	0.59278	1202.028	467708540	143.6158	75.294	5	0.006613	64.7	23.03714	
9	Armenia	0	0.238707	0.24151	N/A	188218400	118.7724	48.446	N/A	N/A	54.62281	19.66661	
10	Aruba	N/A	0.232496	N/A	N/A	N/A	134.6195	N/A	N/A	N/A	83.78	33.72714	
11	Australia	68123238	0.35254	N/A	N/A	N/A	106.2025	76.16	3.8	N/A	84	38.94658	
12	Austria	15210489	0.155262	3.08506	4937.555	N/A	150.3457	69.412	N/A	0.060056	80.99582	40.84518	
13	Azerbaijan	1770192	0.233278	0.20978	N/A	468258710	111.0135	48.945	N/A	0.024998	75.00002	18.88827	
14	Bahamas	991463.3	0.226022	N/A	N/A	N/A	84.9471	80.961	N/A	N/A	76.92	33.90362	
15	Bahrain	5171496	0.534943	0.10116	368.9024	N/A	174.3161	63.87	2	N/A	90.50313	21.30749	
16	Bangladesh	3051915	0.154435	N/A	N/A	964209150	82.10474	36.257	0.6	0.021441	13.9	0.630467	
17	Barbados	N/A	0.279972	N/A	N/A	N/A	107.243	77.826	5.8	N/A	75.16	47.66945	
18	Belarus	1317732	0.373715	0.50548	N/A	168403420	120.889	58.933	N/A	0.026949	59.02	47.86304	
19	Belgium	10535219	0.200934	2.38746	4529.75	N/A	113.4878	77.389	6.2	0.119914	85	40.39196	
20	Belize	877765	0.180984	N/A	N/A	8587790	48.75964	66.829	1.3	N/A	38.7	6.423934	
21	Benin	60264	0.306942	N/A	N/A	113464140	84.1894	39.035	N/A	N/A	6	1.902061	
22	Bermuda	N/A	N/A	0.21474	N/A	N/A	92.90678	N/A	N/A	N/A	96.8	45.65458	
23	Bhutan	302160	0.175027	N/A	N/A	64400590	86.85511	32.52	N/A	N/A	30.3	3.313098	
24	Bolivia	3563044	0.305529	N/A	N/A	226027930	97.60729	48.518	1.1	N/A	34.6	8.182969	
25	Bosnia and Herzegovina	36636	0.592107	0.25725	285.5018	391410190	100.2608	52.915	N/A	0.02006	49.91773	24.3443	
26	Botswana	205992	0.208186	N/A	N/A	16299620	163.2901	58.055	N/A	N/A	36.74475	8.102774	
27	Brazil	1E+08	0.168785	1.26991	881.3782	1.55E+09	138.4512	66.747	2.2	N/A	54.551	21.76335	
28	British Virgin Islands	N/A	N/A	N/A	N/A	N/A	188.913	N/A	N/A	N/A	N/A	40.87412	
29	Brunei	1061148	0.290773	N/A	N/A	N/A	110.3192	80.82	N/A	N/A	68.77	17.484	
30	Darussalam	1060147	0.359685	0.79492	1827.85	N/A	130.9328	62.877	N/A	0.037058	55.49	25.07677	
31	Bulgaria	117420	0.102392	0.22183	N/A	232023350	71.04725	38.065	N/A	0.001893	9.4	0.708488	
32	Burkina Faso	N/A	0.058168	N/A	N/A	94673030	32.43763	6.209	0.8	N/A	1.38	0.220117	
33	Burundi	590304	0.157451	N/A	N/A	N/A	118.3508	63.772	N/A	N/A	40.26	11.50383	
34	Cabo Verde	1071179	0.140114	N/A	N/A	195713160	133.8962	42.105	N/A	N/A	14	2.363782	
35	Cambodia	275760	0.098527	N/A	N/A	228603840	75.12199	38.309	N/A	N/A	16.21487	5.0976	
36	Cameroon	75528607	0.351311	1.71824	4549.452	N/A	80.7221	78.109	N/A	0.00517	87.12	45.99441	
37	Canada	N/A	0.141733	N/A	N/A	N/A	149.6499	N/A	N/A	N/A	74.1	54.07409	
38	Cayman Islands	N/A	0.100132	N/A	N/A	12861680	25.88653	17.495	N/A	N/A	3.6	0.01792	
39	Central African Republic	N/A											

NO	Country	SDG					RM					
		9.1.2	9.4.1	9.5.1	9.5.2	9.a.1	9.c.1	1	6	11	15	16
38	Chad	28332	0.025896	N/A	N/A	21588200	38.43477	15.903	N/A	N/A	2.9	0.172576
39	Channel Islands	N/A	N/A	N/A	N/A	N/A	N/A	70.253	N/A	N/A	N/A	N/A
40	Chile	14347893	0.211188	0.37497	430.6419	235656360	133.3452	67.111	N/A	N/A	61.11	19.30152
41	China	3.91E+08	0.592837	2.02114	1096.517	1.963E+09	91.89963	41.144	N/A	0.007135	47.9	17.82338
42	Colombia	28675159	0.138921	0.30799	57.29003	725117280	117.805	63.986	1.5	N/A	52.57	15.2891
43	Comoros	N/A	0.080299	N/A	N/A	9885460	50.43522	28.99	N/A	N/A	6.98	3.094589
44	Congo, Dem. Rep.	456228	0.080689	N/A	N/A	395180040	50.2972	20.396	N/A	0.001606	3	0
45	Congo, Rep.	553944	0.114728	N/A	N/A	N/A	104.0769	39.407	N/A	N/A	7.11	0.344101
46	Costa Rica	1427414	0.113478	0.57209	572.981	343576410	146.399	71.165	1.1	N/A	53	18.37631
47	Cote d'Ivoire	237120	0.160485	N/A	N/A	184966040	97.60192	43.637	N/A	0.002009	19.27423	1.071562
48	Croatia	1756070	0.195293	0.78324	1436.748	N/A	104.837	63.502	5.89	0.046533	68.57	36.86938
49	Cuba	1135200	N/A	0.41596	N/A	7148630	22.38236	64.207	5.2	N/A	29.07018	11.18624
50	Curacao	N/A	1.426719	N/A	N/A	N/A	121.5545	N/A	N/A	N/A	N/A	38.58681
51	Cyprus	688368	0.241509	0.50847	1064.925	N/A	130.1925	79.052	N/A	N/A	69.33	38.42874
52	Czech Republic	5009995	0.31477	1.97285	3400.445	N/A	131.3659	59.212	N/A	0.122476	74.23171	18.90171
53	Denmark	N/A	0.131738	2.91404	7311.022	N/A	126.4122	78.26	N/A	N/A	95.99	33.05684
54	Djibouti	N/A	N/A	N/A	N/A	27988970	31.94065	40.071	1.4	N/A	10.71	2.438202
55	Dominica	N/A	0.182447	N/A	N/A	9859260	103.9404	N/A	N/A	N/A	57.5	23.1399
56	Dominican Republic	16128	0.164361	N/A	N/A	55867400	81.68605	70.954	1.6	N/A	49.58	12.06185
57	Ecuador	5675088	0.253334	0.44266	400.714	99909480	104.0992	54.765	N/A	N/A	45.59039	15.30664
58	Egypt, Arab Rep.	10278013	0.22255	0.63649	665.0348	1.247E+09	105.4093	48.045	1.6	N/A	33.8946	6.984727
59	El Salvador	2816524	0.1458	0.09381	N/A	37941860	146.039	60.346	1.3	N/A	24.76171	15.15097
60	Equatorial Guinea	303024	0.150077	N/A	N/A	68850	46.02607	40.633	N/A	N/A	18.86	1.34637
61	Eritrea	N/A	N/A	N/A	N/A	1022740	12.60475	28.578	N/A	N/A	0.99	1.932689
62	Estonia	602880	0.551368	1.45063	3279.076	N/A	144.1605	65.994	N/A	0.023418	84.24153	30.9425
63	Eswatini	N/A	0.121338	N/A	N/A	24682900	83.72457	62.082	N/A	N/A	26.17501	4.054724
64	Ethiopia	6274582	0.083624	N/A	N/A	416279790	31.08235	20.894	N/A	N/A	7.7	0.835931
65	Faroe Islands	N/A	N/A	N/A	N/A	N/A	121.5221	N/A	N/A	N/A	93.3	43.7844
66	Fiji	1243824	0.16061	N/A	N/A	9078240	101.1222	46.445	N/A	N/A	37.4	8.74254
67	Finland	10992792	0.220369	3.16931	7011.462	N/A	139.2058	73.849	N/A	0.01956	86.53039	11.69661
68	France	63434263	0.121705	2.27592	4233.83	N/A	101.9183	76.621	N/A	0.000106	83.75	60.45
69	French Polynesia	N/A	N/A	N/A	N/A	N/A	93.89706	74.661	N/A	N/A	60.68	22.43058
70	Gabon	N/A	0.165978	N/A	N/A	94732950	155.6817	51.492	N/A	0.003144	38.07121	0.981951
71	Gambia, The	151776	0.115096	N/A	N/A	42895530	112.8282	54.198	N/A	N/A	15.56	2.758885
72	Georgia	196589	0.263254	0.1849	1070.877	340283660	133.8377	39.587	N/A	0.020915	44	27.19404
73	Germany	1.12E+08	0.204472	2.87289	4318.622	N/A	122.1971	70.52	N/A	0.095804	86.19	57.72963
74	Ghana	407544	0.140156	N/A	N/A	386614230	111.5201	43.356	N/A	N/A	25.51774	0.956518
75	Gibraltar	N/A	N/A	N/A	N/A	N/A	112.6761	N/A	N/A	N/A	N/A	69.38473
76	Greece	11152236	0.256641	0.8333	2652.27	N/A	113.4855	71.451	N/A	0.017362	63.21	49.705
77	Greenland	N/A	N/A	N/A	N/A	N/A	107.8377	N/A	N/A	N/A	66.7	30.50673
78	Grenada	N/A	0.189017	N/A	N/A	6787240	107.5747	N/A	3.7	N/A	51.6	25.04913
79	Guam	N/A	N/A	N/A	N/A	N/A	N/A	84.896	N/A	N/A	69.27	41.85919
80	Guatemala	69768	0.161034	0.02905	20.28441	28766710	106.2084	49.008	0.6	N/A	23.4	10.79114
81	Guinea	N/A	0.119612	N/A	N/A	44621110	77.87207	25.905	N/A	N/A	6.4	0
82	Guinea-Bissau	N/A	0.112455	N/A	N/A	3843670	65.48527	22.7	N/A	N/A	3.32	0
83	Guyana	0	0.380917	N/A	N/A	20269450	74.26249	55.124	1.6	N/A	32	20.92392
84	Haiti	N/A	0.163701	N/A	N/A	156393460	64.17012	39.645	N/A	N/A	11.4	0.388662
85	Honduras	239124	0.25411	N/A	N/A	244651340	86.26001	49.142	0.7	N/A	19.08	5.888379
86	Hong Kong SAR, China	37933773	0.121115	0.74014	3312.362	N/A	237.7048	87.737	N/A	N/A	79.86627	61.92096
87	Hungary	16482060	0.176113	1.35339	2671.161	N/A	119.5972	64.822	N/A	0.087206	75.6532	30.71143
88	Iceland	3035883	0.141664	1.99923	N/A	N/A	112.6153	77.034	3.2	N/A	98.16	52.20272
89	India	82718883	0.321254	N/A	N/A	4.066E+09	72.86262	29.548	N/A	0.022134	21	2.083983
90	Indonesia	85215880	0.18188	N/A	N/A	1.119E+09	127.6154	44.322	N/A	0.002868	17.14	10.27914
91	Iran, Islamic Rep.	16825261	0.489419	N/A	N/A	1618590	88.93109	48.35	1.5	0.005255	39.35	37.9214
92	Iraq	476484	0.324283	0.03733	68.38812	170978530	95.89692	55.606	1.4	0.005459	13.21	5.659952
93	Ireland	98449140	0.150374	1.50172	5237.128	N/A	106.1765	77.265	N/A	0.021164	83.49172	43.71278
94	Isle of Man	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
95	Israel	5886728	0.246502	4.19741	N/A	N/A	120.9542	81.059	N/A	0.055176	75.01775	43.63263
96	Italy	27193939	0.154827	1.34301	1983.413	N/A	148.8415	69.455	N/A	0.056853	55.63846	34.06978
97	Jamaica	76244	0.321909	N/A	N/A	72562080	104.5337	66.639	N/A	N/A	40.40274	8.851746
98	Japan	1.11E+08	0.255474	3.40022	5328.649	N/A	123.1632	70.262	N/A	0.045817	89.10683	49.58887
99	Jordan	3211795	0.343416	N/A	N/A	266243410	124.3706	71.36	1.9	N/A	46.2	4.210004
100	Kazakhstan	4918608	0.608936	0.16722	790.209	1.164E+09	165.2675	58.097	N/A	0.00547	66	25.16036
101	Kenya	4448531	0.11275	N/A	N/A	883099280	72.0184	34.368	N/A	N/A	16.5	0.385417
102	Kiribati	N/A	0.314021	N/A	N/A	1162830	27.42456	N/A	N/A	N/A	12.25	1.828304
103	Korea, Dem. People's Rep.	90335.88	N/A	N/A	N/A	35154000	11.17417	22.446	N/A	N/A	N/A	4.709114
104	Korea, Rep.	58289180	0.346151	4.28874	6856.397	N/A	113.2044	69.646	N/A	0.037651	87.55683	58.25419
105	Kosovo	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
106	Kuwait	3530851	0.356106	0.42705	605.1633	N/A	205.9095	72.203	2	N/A	78.7	13.38412
107	Kyrgyz Republic	712284	0.518239	0.12536	N/A	6.003E+09	129.4106	47.98	N/A	0.002211	28.3	7.582883
108	Lao PDR	1310124	0.054668	N/A	N/A	7.332E+09	69.55957	21.804	N/A	N/A	14.26	13.86732
109	Latvia	2636613	0.157563	0.6893	1859.012	N/A	117.9486	68.649	N/A	0.029897	75.83	19.79004
110	Lebanon	2419476	0.311247	N/A	N/A	66562500	70.07258	64.161	2.9	N/A	73	15.42431
111	Lesotho	N/A	0.429397	N/A	N/A	5098110	104.6658	22.261	N/A	N/A	22	2.432852
112	Liberia	N/A	0.170554	N/A	N/A	154089060	73.98219	42.706	N/A	N/A	5.41	0.230301
113	Libya	2391856	0.561135	N/A	N/A	2380770	133.5591	65.033	3.7	N/A	17.76	14.37419
114	Liechtenstein	N/A	N/A	N/A	N/A	N/A	109.212	N/A	N/A	N/A	95.21	48.47272
115	Lithuania	1274911	0.166895	1.03048	3063.968	N/A	143.6176	66.11	N/A	0.028204	72.13	19.74405
116	Luxembourg	1710624	0.188005	1.25978	4725.731	N/A	144.7028	87.591	4.9	0.113169	94.67	48.88948
117	Macao SAR, China	2078758	0.016671	0.08705	1033.967	N/A	314.5422	80.382	N/A	N/A	69.78	26.02252
118	Madagascar	520421	0.081364	0.0155	N/A	50360150	41.17816	23.761	N/A	0.001157	3.7	0.62974
119	Malawi	5856	0.068567	N/A	N/A	74935830	34.57746	19.414	N/A	N/A	5.83	0.116412
120	Malaysia	49673884	0.332015	1.26275	2029.607	10864840	150.4309	59.746	N/A	N/A	63.66543	14.76633
121	Maldives	1024694	0.238004	N/A	N/A	4517910	153.0563	70.473	N/A	N/A	49.28	5.183499
122	Mali	0	0.044623	N/A	N/A	102570560	138.8051	25.302	N/A	N/A	7	0.911864
123	Malta	1588165	0.168725	0.71499	1851.634	N/A	126.9718	77.725	4.7	N/A	73.17	53.54779

NO	Country	SDG						RM				
		9.1.2	9.4.1	9.5.1	9.5.2	9.a.1	9.c.1	1	6	11	15	16
124	Marshall Islands	N/A	0.551108	N/A	N/A	38209710	27.10785	N/A	N/A	N/A	16.8	4.129138
125	Mauritania	271212	0.182421	N/A	N/A	108266080	95.48281	32.701	N/A	N/A	10.7	1.308404
126	Mauritius	1354388	0.183673	N/A	N/A	235326950	131.3869	64.894	N/A	N/A	44.80328	29.60182
127	Mexico	39570522	0.232682	0.53044	N/A	642678610	87.19889	61.42	N/A	0.006117	44.39	15.42077
128	Micronesia, Fed. Sts.	N/A	0.459881	N/A	N/A	1.351E+09	N/A	N/A	N/A	N/A	29.65	6.538168
129	Moldova	692496	0.242823	0.37055	746.802	149641160	91.769	51.626	N/A	0.035169	67	29.90799
130	Monaco	64188	N/A	N/A	N/A	N/A	90.22828	N/A	N/A	N/A	92.4	135.6037
131	Mongolia	683254	0.628033	0.2234	N/A	194853730	102.9637	51.304	N/A	0.001173	19.94245	7.765939
132	Montenegro	503040	0.24033	0.3632	670.7304	16937730	161.7018	76.764	N/A	0.018513	61	26.2782
133	Morocco	6976810	0.242777	N/A	1020.601	1.645E+09	129.0187	39.674	1.1	0.004726	56.8	7.275714
134	Mozambique	739636.7	0.262242	N/A	N/A	367877090	70.31311	19.887	N/A	N/A	9.236315	0.330424
135	Myanmar	1926969	0.087338	N/A	N/A	98788790	55.52579	31.202	N/A	N/A	11.52	1.00762
136	Namibia	522216	0.164673	0.33996	143.3155	62821560	117.4873	55.847	N/A	N/A	14.84	8.031633
137	Nauru	34572	0.320174	N/A	N/A	1311280	N/A	N/A	N/A	N/A	N/A	0
138	Nepal	517548	0.125117	N/A	N/A	200163670	85.56218	16.329	N/A	N/A	15.44	3.111821
139	Netherlands	33956338	0.214544	2.00116	4513.445	N/A	115.8027	81.481	N/A	N/A	91.66667	41.11878
140	New Caledonia	N/A	N/A	N/A	N/A	N/A	90.79738	74.823	N/A	N/A	70	33.05458
141	New Zealand	13618712	0.222104	N/A	N/A	N/A	111.6578	72.927	N/A	N/A	85.5	40.50332
142	Nicaragua	N/A	0.168976	0.08935	N/A	126342110	115.0605	50.892	0.9	N/A	17.6	5.528958
143	Niger	13227.5	0.122807	N/A	N/A	70705600	42.80833	15.701	N/A	N/A	1.248676	0.547292
144	Nigeria	4462002	0.095962	N/A	N/A	835796440	78.77349	50.509	N/A	0.003874	21	0.103903
145	North Macedonia	N/A	0.293935	0.51646	837.6916	2380770	107.0587	51.178	N/A	0.027716	68.06	18.46158
146	Northern Mariana Islands	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	40.50267
147	Norway	N/A	0.146395	1.71187	5687.788	N/A	111.5843	77.311	N/A	0.011555	96.3	21.01932
148	Oman	5051804	0.382585	0.21253	180.8921	N/A	153.806	58.616	1.6	N/A	70.22	9.316409
149	Pakistan	7670348	0.195852	N/A	N/A	2.033E+09	69.51282	34.894	0.6	0.010107	12	2.507777
150	Palau	N/A	0.963783	N/A	N/A	3430620	108.4421	N/A	N/A	N/A	N/A	40.42324
151	Panama	11812713	0.112614	N/A	N/A	592202470	177.0196	64.217	N/A	N/A	44.92	15.08202
152	Papua New Guinea	2074020	0.223259	N/A	N/A	178181160	42.2677	26.572	N/A	N/A	6.5	1.825908
153	Paraguay	608844	0.079482	0.10331	153.2983	140588650	110.694	58.783	N/A	N/A	43	5.635284
154	Peru	12284677	0.172618	0.10789	N/A	250244560	105.9477	55.601	1.6	N/A	40.2	10.07816
155	Philippines	34897404	0.16026	N/A	N/A	704576040	110.7577	53.645	N/A	N/A	49.6	3.077444
156	Poland	5038745	0.308644	0.94014	2053.163	N/A	149.3927	57.967	N/A	0.061864	66.6	25.54913
157	Portugal	12635439	0.166381	1.28973	3643.856	N/A	114.181	67.494	N/A	0.027793	64.59	44.04365
158	Puerto Rico	N/A	N/A	N/A	N/A	N/A	92.9105	81.071	N/A	N/A	N/A	23.84497
159	Qatar	21425066	0.375833	N/A	N/A	N/A	134.4268	45.649	1.2	N/A	91.49	16.9807
160	Romania	3067724	0.177566	0.3825	906.686	N/A	114.3945	42.724	N/A	0.04681	54.08	22.75911
161	Russian Federation	72189961	0.461587	1.07011	3094.468	N/A	152.7879	65.759	N/A	0.005206	70.52	26.41456
162	Rwanda	626928	0.045434	N/A	N/A	127536670	69.89604	23.634	N/A	N/A	10.6	0.447615
163	Samoa	76944	0.195409	N/A	N/A	23781970	55.41746	79.858	N/A	N/A	21.2	6.127322
164	San Marino	N/A	N/A	N/A	N/A	N/A	114.1192	N/A	N/A	N/A	N/A	56.45259
165	Sao Tome and Principe	N/A	0.204755	N/A	N/A	4894510	65.65267	57.43	N/A	N/A	24.41	3.474227
166	Saudi Arabia	32269452	0.39091	N/A	N/A	N/A	170.5718	71.707	2.7	N/A	64.71366	N/A
167	Senegal	131964	0.215248	N/A	N/A	318280260	101.4462	52.365	N/A	N/A	17.7	2.200711
168	Serbia	2187144	0.376635	0.76972	1830.992	610689970	105.0199	55.48	N/A	0.043551	62.07508	32.09756
169	Seychelles	407280	0.223717	N/A	N/A	5677820	160.6284	N/A	N/A	N/A	51.2547	22.51022
170	Sierra Leone	N/A	0.109285	N/A	N/A	47720830	67.78822	36.28	N/A	N/A	6.057299	0.235138
171	Singapore	33643518	0.12574	2.15996	6729.68	N/A	146.6585	82.31	N/A	N/A	79.02924	36.13527
172	Sint Maarten (Dutch part)	N/A	0.578504	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
173	Slovak Republic	29031.6	0.206971	0.88008	2713.534	N/A	117.4862	61.058	N/A	0.075439	79.98	16.922
174	Slovenia	916981	0.217851	2.3667	4140.339	N/A	112.5223	59.441	N/A	0.060032	71.59	37.22788
175	Solomon Islands	330456	0.163795	N/A	N/A	27328380	64.16445	28.87	N/A	N/A	9	1.28177
176	Somalia	251652	N/A	N/A	N/A	33040520	40.97271	20.961	0.9	N/A	1.63	0.426116
177	South Africa	17026643	0.724804	0.77115	432.1981	1.16E+09	145.3514	71.929	N/A	N/A	49	6.687734
178	South Sudan	N/A	0.077987	N/A	N/A	29649890	27.24889	33.726	N/A	N/A	4.516154	0
179	Spain	53069339	0.16198	1.23535	2627.485	N/A	108.6116	76.307	N/A	0.030999	76.19	41.12307
180	Sri Lanka	4756131	0.083147	0.09989	99.74028	544821600	106.4194	45.045	N/A	N/A	25.8	13.03532
181	St. Kitts and Nevis	N/A	0.172263	N/A	N/A	N/A	128.0183	N/A	N/A	N/A	68	38.20853
182	St. Lucia	N/A	0.194279	N/A	N/A	N/A	105.6395	66.506	N/A	N/A	39.7	18.41432
183	St. Martin (French part)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
184	St. Vincent and the Grenadines	N/A	0.18532	N/A	N/A	N/A	105.6549	65.459	2.6	N/A	47.4	21.95736
185	Sudan	501864	0.097209	N/A	N/A	30535780	73.19202	40.959	N/A	N/A	24.64	1.093027
186	Suriname	269148	0.237414	N/A	N/A	24682900	167.693	68.088	N/A	N/A	40.08	15.34505
187	Sweden	N/A	0.100043	3.14587	6877.945	N/A	127.0364	79.422	N/A	0.023788	92.52	38.98595
188	Switzerland	27923164	0.075353	N/A	N/A	N/A	135.8762	75.134	N/A	0.101699	87.4	53.31098
189	Syrian Arab Republic	475932	N/A	N/A	N/A	71320	75.03589	55.914	1.5	N/A	28.09	19.39556
190	Tajikistan	1064176	0.24367	0.11468	N/A	141084630	96.9255	31.681	N/A	0.004302	17.49	5.339984
191	Tanzania	1124913	0.093971	N/A	N/A	604866580	63.77562	25.696	N/A	N/A	7	0.302787
192	Thailand	46546612	0.311085	0.47988	964.1642	383264550	141.8729	43.045	N/A	N/A	34.89	8.314004
193	Timor-Leste	N/A	0.061808	N/A	N/A	48791060	117.1517	39.871	N/A	N/A	17.5	0.302896
194	Togo	426344	0.258028	0.27166	37.56995	82930060	63.26862	44.986	N/A	N/A	5.7	0.746862
195	Tonga	N/A	0.227355	N/A	N/A	27026080	67.30807	39.249	N/A	N/A	35.95444	11.8779
196	Trinidad and Tobago	2732100	1.089708	0.08297	N/A	N/A	145.3792	68.266	3	N/A	65.1	21.2077
197	Tunisia	4628511	0.240276	0.65484	1800.984	595656720	129.1094	51.583	2.2	0.014444	46.16	8.581558
198	Turkey	84574844	0.200496	0.86077	1163.917	3.713E+09	93.08443	51.057	N/A	0.013106	51.04	16.22295
199	Turkmenistan	579715.7	0.873359	N/A	N/A	21759130	131.8271	42.882	N/A	0.006629	12.2	11.42266
200	Turks and Caicos Islands	N/A	0.294067	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	11.59207
201	Tuvalu	N/A	0.319206	N/A	N/A	15253430	34.63361	N/A	N/A	N/A	39.2	13.67116
202	Uganda	163824	0.082244	0.17043	26.46695	290487200	55.17502	21.275	N/A	N/A	16.9	0.878972

NO	Country	SDG						RM					
		9.1.2	9.4.1	9.5.1	9.5.2	9.a.1	9.c.1	1	6	11	15	16	
203	Ukraine	4503610	0.641222	0.65034	1029.13	1.443E+09	144.2788	59.084	N/A	0.037332	46.23598	24.67398	
204	United Arab Emirates	75608196	0.364817	0.6936	N/A	N/A	182.5342	72.324	N/A	N/A	90.4	22.82392	
205	United Kingdom	1.25E+08	0.167919	1.66568	4254.109	N/A	119.9282	79.781	N/A	0.068342	91.61	50.80485	
206	United States	7.63E+08	0.31687	2.73389	4217.349	N/A	111.5562	78.657	N/A	0.016719	73	40.32185	
207	Uruguay	N/A	0.099516	0.33579	504.1605	191004940	161.6585	69.853	2.8	0.008559	61.46	31.846	
208	Uzbekistan	2545935	0.526416	0.19644	500.0391	286447870	71.11985	35.888	N/A	0.009878	35.5	8.241895	
209	Vanuatu	320232	0.205713	N/A	N/A	20739170	59.13531	31.95	N/A	N/A	18.8	2.170239	
210	Venezuela, RB	7888722	0.35985	0.33713	266.5072	65819510	101.6145	71.356	0.8	N/A	57	25.99119	
211	Vietnam	23826013	0.342569	N/A	N/A	3.463E+09	148.4488	32.218	2.6	0.010275	41	7.332948	
212	Virgin Islands (U.S.)	N/A	N/A	N/A	N/A	N/A	N/A	72.699	N/A	N/A	50.07	72.39759	
213	West Bank and Gaza	N/A	N/A	N/A	N/A	N/A	72.20164	61.241	N/A	N/A	53.67	9.102526	
214	Yemen, Rep.	1665552	0.229594	N/A	N/A	221222980	66.21879	56.274	0.7	N/A	22.55	4.525338	
215	Zambia	8592	0.079359	N/A	N/A	179374720	65.68186	34.471	N/A	N/A	19	0.742997	
216	Zimbabwe	301260	0.352972	N/A	N/A	26432470	86.83967	25.398	N/A	N/A	16.36474	2.424981	

Appendix 3. BRF indicators to measure resilience. Highlighted rows show the resilience variables that SDGs do not have any available indicators for measuring. The proposed indicators (that can be added from BRF to SDGs) along with the relevant target/goals have been defined in the table.

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
Social		Education level & quality (E&K.1)	Ratio of the population with college education to the population with less than high school education		+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Cutter, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Frazier et al., 2014),(Singh-Peterson et al., 2014),(Jacob et al., 2013),(Hiete et al., 2012),(Fu & Wang, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population finished secondary level		+	(Kaye-Blake et al., 2019),(Kliskey et al., 2019),(Li, Lam, et al., 2016),(Hung et al., 2016),(Kotzee & Reyers, 2016),(Cutter, 2016),(Burton, 2015),(Frazier et al., 2014),(Jacob et al., 2013),(Ainuddin & Routray, 2012),(Yoon et al., 2016)
			% Population finished tertiary education		+	(Kaye-Blake et al., 2019),(Araya-Muñoz et al., 2016)
			% Population who are illiterate		-	(Hu et al., 2018),(Wu et al., 2016),(Araya-Muñoz et al., 2016),(Yenneti et al., 2016),(Ainuddin & Routray, 2012),(DasGupta & Shaw, 2015),(Shukla et al., 2016),(Yoon et al., 2016)
			Pupil-to-teacher ratio at public schools		-	(Links et al., 2018)
			School dropout rate of children		-	(DasGupta & Shaw, 2015)
			Average years of education attainment of population 15 years and up		+	(L. Siebeneck et al., 2015)
			Adult education and training program per 1,000 persons		+	(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Traditional knowledge (E&K.3)	No. of people 50 +years old and indigenous per capita	T 8.9, T 12.b	+	(Kliskey et al., 2019)
			No. of people with 30 +years residence per capita	T 8.9, T 12.b	+	(Kliskey et al., 2019)
	Population and	Public expenditure on education (E&K.2)	Per capita expenditure on education		+	(Manyena et al., 2019),(Hu et al., 2018),(González et al., 2018)
		Population structure (P&D.4)	% Population that is of working age (15-59)	G 1	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kim & Park, 2018),(J. Song et al.,

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
						2017),(Araya-Muñoz et al., 2016),(Kotzee & Reyers, 2016),(L. Siebeneck et al., 2015),(Burton, 2015),(Frazier et al., 2014),(Singh-Peterson et al., 2014),(Jacob et al., 2013),(Ainuddin & Routray, 2012),(Hiete et al., 2012),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Li, Lam, et al., 2016),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019) (Moghadas et al., 2019),(J. Song et al., 2017),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Li, Lam, et al., 2016),(Asadzadeh et al., 2015),(Shukla et al., 2016),(Yoon et al., 2016)
			Ratio of men to women	G 1	+	(Kim & Park, 2018),(Asadzadeh et al., 2015),(J. Song et al., 2018),(Mihunov et al., 2018),(Links et al., 2018),(Hung et al., 2016),(DasGupta & Shaw, 2015),(Yoon et al., 2016)
			% Population of elders (above 65)	G 1	-	(J. Song et al., 2018),(Mihunov et al., 2018),(Links et al., 2018) (Hu et al., 2018)
			% Children in population	G 1	-	(Kaye-Blake et al., 2019),(Scherzer et al., 2019),
		Population change (P&D.3)	Total no. of population	G 1	-	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Annual population change	G 11	-	(Abdrabo & Hassaan, 2015),(DasGupta & Shaw, 2015)
			Population change over the last five years	G 11	-	(Scherzer et al., 2019),(Mihunov et al., 2018),(L. Siebeneck et al., 2015),(Frazier et al., 2014),(Jacob et al., 2013),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Yoon et al., 2016)
			Population growth rate	G 11	-	(Mihunov et al., 2018),(Links et al., 2018)
		Household features (P&D.2)	% Households that are not single parents	G 1	+	(Abdrabo & Hassaan, 2015),(DasGupta & Shaw, 2015)
			Average number of people per household	G 1	-	(Hu et al., 2018),(C. Zhang et al., 2016),(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Li, Lam, et al., 2016)
			Household density	G 1	-	(J. Song et al., 2018),(Fu & Wang, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Tumini et al., 2017),(Li, Lam, et al., 2016),(Hung et al., 2016)
		Urbanisation and density (P&D.5)	% Population living in urban areas	G 11	+	(DasGupta & Shaw, 2015)
			People per sq. km of land area	G 11	-	(Hu et al., 2018),(Li, Lam, et al., 2016),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Hung et al., 2016),(Abdrabo & Hassaan, 2015)
		Workforce (P&D.6)	% Rural population	G 11	-	(Mihunov et al., 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Labour force employed		+	(Scherzer et al., 2019),(Yenneti et al., 2016),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Luh et al., 2015)
			Female workforce participation		+	(L. Siebeneck et al., 2015),(Fu & Wang, 2018),(Araya-Muñoz et al., 2016),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Links et al., 2018),(DasGupta & Shaw, 2015)
		Equality (P&D.1)	Gender Index		-	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Links et al., 2018)
			% Population whose income is below minimum wage		-	
			Absolute difference between male and female median income		-	

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
Health (He.)	Health (He.)	Health status (He.3)	Ratio of nonminority population to minority population		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population without sensory, physical, or mental disability		+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Links et al., 2018),(Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012),(Mihunov et al., 2018),(Kim & Park, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Mihunov et al., 2018),(Hung et al., 2016),(Yoon et al., 2016)
			All-cause mortality per 100k population		-	(Links et al., 2018)
			3-year total low birthweight babies per 10,000 individuals		-	(Mihunov et al., 2018),(Mihunov et al., 2018)
		Health services (He.2)	Average life expectancy		+	(Links et al., 2018),(C. Zhang et al., 2016),(Yenneti et al., 2016),(Luh et al., 2015)
			% Coverage among 1 –year olds		+	(Manyena et al., 2019)
			Distance to nearest health facility (e.g. health post, hospital, clinic)		-	(J. Song et al., 2018),(Tumini et al., 2017),(Araya-Muñoz et al., 2016),(DasGupta & Shaw, 2015)
			*% Population with health insurance		+	(Cutter et al., 2014),(Cutter et al., 2010),(Asadzadeh et al., 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
			% Uninsured adults		-	(Links et al., 2018)
			Psychosocial support facilities per 10,000 persons		+	(Cutter et al., 2014),(Links et al., 2018)
			Child/elderly care program per 10,000 persons		+	(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Physicians/ nurses/ midwives per 10,000 persons		+	(Manyena et al., 2019),(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Links et al., 2018),(Wu et al., 2016),(Araya-Muñoz et al., 2016),(Cutter, 2016),(Burton, 2015),(Mihunov et al., 2018),(Mihunov et al., 2018),(DasGupta & Shaw, 2015)
			Hospital beds per 1,000 people		+	(Manyena et al., 2019), (Hu et al., 2018),(Links et al., 2018),(J. Song et al., 2017),(Araya-Muñoz et al., 2016),(Li, Lam, et al., 2016)
			Expenditure on health (He.1)		+	(Manyena et al., 2019),(Hu et al., 2018),(González et al., 2018)
		Sanitation (He.4)	% Population with access improved sanitation facilities		+	(Manyena et al., 2019)
			Distance to nearest sanitation		-	(J. Song et al., 2018),(Tumini et al., 2017)
		Social welfare capacity (He.5)	Number of social welfare home beds per 10,000 persons (including homeless shelters and nursing homes)	T 1.5, T 1.3	+	(Li, Lam, et al., 2016)
Community Strength (CSt.)	Community Strength (CSt.)	Land (CSt.2)	% Area of urban green space		+	(Hu et al., 2018),(J. Song et al., 2018)
			Per capita expenditure on urban green space		+	(González et al., 2018)
			% Land area set aside in protected area status		+	(Kliskey et al., 2019),(Tumini et al., 2017),(Alessa et al., 2008)
		Social engagement (CSt.5)	Area of public open space		+	(Fu & Wang, 2018),(Tumini et al., 2017)
			Distance to open space		-	(Fu & Wang, 2018)
			The ratio of the sidewalk length over total area		+	(Fu & Wang, 2018)
			% Population involved in Red Cross volunteering activities		+	(Kaye-Blake et al., 2019),(Cutter et al., 2014),(Kim & Park, 2018),(Singh-Peterson et al., 2014)
			Budget of volunteer organisations		+	(Yoon et al., 2016)
			No. of registered volunteer/ volunteer organisations		+	(Yoon et al., 2016)
			% Voting age population participating in presidential election		+	(Kliskey et al., 2019),(Fu & Wang, 2018),(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Kotzee & Reyers,

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
						2016),(Mihunov et al., 2018),(L. Siebeneck et al., 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Mihunov et al., 2018),(L. Siebeneck et al., 2015)
			Less than 3 parties are involved in the decision-making process		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			*Park/Sports facilities/Cinemas persons/ Museums/libraries/zoos/ botanical gardens/ youth centres/clubs/child care centre per 1,000 persons		+	(Tumini et al., 2017),(Scherzer et al., 2019),(Burton, 2015),(Moghadas et al., 2019),(L. Siebeneck et al., 2015),(Frazier et al., 2014)
			Ratio of entertainment and recreation land uses/ Areas of public open spaces		+	(Asadzadeh et al., 2015),(Fu & Wang, 2018),(Tumini et al., 2017)
			Persons affiliated with a religious organisation per 10,000 persons		+	(Cutter et al., 2014),(Cutter et al., 2010),(Links et al., 2018),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018),(Cutter, 2016),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Kaye-Blake et al., 2019),(Frazier et al., 2014)
			Places of worship per 1,000 persons		+	(Scherzer et al., 2019)
			No. of religious organisations		+	(Cutter, 2016),(Asadzadeh et al., 2015)
			% Population that is not minority		+	(Burton, 2015)
			No. of registered non-profit organisations		+	(Cutter, 2016)
		Communication (CSt.1)	% Population with access to phone		+	(Kaye-Blake et al., 2019), (Cutter et al., 2014),(Moghadas et al., 2019),(Wei et al., 2017),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			% Population with access to internet/TV/radio		+	(Kaye-Blake et al., 2019),(Scherzer et al., 2019),(Links et al., 2018),(Wei et al., 2017),(Burton, 2015),(Luh et al., 2015)
			% Population proficient English speakers		+	(Cutter et al., 2014),(Cutter et al., 2010),(Burton, 2015),(Singh-Peterson et al., 2014),(Jacob et al., 2013),(Hiete et al., 2012),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Mobility (CSt.3)	% Households with at least one vehicle		+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Links et al., 2018),(Kotzee & Reyers, 2016),(L. Siebeneck et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018),(Araya-Muñoz et al., 2016),(L. Siebeneck et al., 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Who walk or cycle to work		+	(Links et al., 2018)
			Mode Diversity (fixed-wing air, road, boat, ATV/trail)		+	(Kliskey et al., 2019),(Yenneti et al., 2016)
			Regulation of transportation options		+	(Kliskey et al., 2019)
			Roads network density		+	(Hu et al., 2018),(J. Song et al., 2018),(Araya-Muñoz et al., 2016),(Kotzee & Reyers, 2016)
			No. of traffic accidents		-	(Hu et al., 2018)
			Distance to nearest transport network		-	(J. Song et al., 2018)
			Walkways length per total street length		+	(Tumini et al., 2017)
		Place attachment (CSt.4)	*% Population born in country of current residence		+	(J. Song et al., 2018),(Fu & Wang, 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Moghadas et al., 2019),(Mihunov et al., 2018),(L. Siebeneck et al., 2015),(Hung et al., 2016),(Kaye-Blake et al., 2019)
			% Population who migrated to country within previous five/ten years		-	(Cutter et al., 2014),(Kotzee & Reyers, 2016),(Burton, 2015),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P.,

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
Economic	Social Protection (SP)	Net in and out migration			-	Mahin, 2019),(L. Siebeneck et al., 2015), (Cutter et al., 2010),(Scherzer et al., 2019),(Kim & Park, 2018),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
					+	(Manyena et al., 2019)
		Expenditure (SP.3)	Public spending on social assistance as % of GDP		+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Kotzee & Reyers, 2016),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018),(Cutter, 2016)
		Organisations (SP.5)	Civic organisations per 10,000 persons		+	(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Fu & Wang, 2018),(Links et al., 2018)
		Community disaster preparedness (SP.1)	No. of social advocacy organisations per 10,000 population		+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Red cross training workshop participants per 10,000 persons		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Innovation (SP.4)	No. of courses in disaster risk reduction as part of the educational curriculum per schools and colleges		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			No. of education programs on DRR and disaster preparedness per each local community by local government per year		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Percent population employed in creative class occupations (ex. architects, engineers, and scientific researchers)		+	(Cutter et al., 2010),(Scherzer et al., 2019),(Tan et al., 2017),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Research & development firms per 1,000 persons		+	(Scherzer et al., 2019),(Araya-Muñoz et al., 2016),(Burton, 2015)
		Cultural heritage (SP.2)	Business and professional organisations per 1,000 persons		+	(Burton, 2015)
			National Historic Registry sites area per population		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	Economic Capacity (EC)	Household economy (EC.2)	Median household income		+	(Alessa et al., 2008),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Hung et al., 2016),(Abdrabo & Hassaan, 2015)
			% Owner-occupied housing units		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Food capacity (EC.1)	Households saving value in bank		+	(Hung et al., 2016)
			Food security rate		+	(Cutter et al., 2014),(Tumini et al., 2017)
			Kg per capita of subsistence harvest		+	(Alessa et al., 2008)
			% Farm managers with full agricultural training		+	(Williges et al., 2017)
			No. of scientists working in agricultural sector		+	(Williges et al., 2017)
			% Voting age population participating in presidential election		+	(Mihunov et al., 2018),(L. Siebeneck et al., 2015)
			% Employees not in farming, fishing, forestry, extractive industry, or tourism		+	(Hung et al., 2016),(DasGupta & Shaw, 2015),(Shukla et al., 2016)
			Area of commercial establishment per 10,000 persons		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	Household Capacity (HC)	Household assets (HC.1)	% Owner-occupied housing units		+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Mihunov et al., 2018),(Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Frazier et al., 2014),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
			% Households with at least one vehicle		+	(Cutter et al., 2014),(Cutter et al., 2010),(Mihunov et al., 2018)
			% Households with telephone service available		+	(Cutter et al., 2014),(Cutter et al., 2010),(Kotzee & Reyers, 2016)

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
	Employment (E)	Workforce (E.2)	Households saving value in bank		+	(Fu & Wang, 2018),(Hu et al., 2018),(Tan et al., 2017),(C. Zhang et al., 2016)
			% Labour force employed		+	(Kaye-Blake et al., 2019),(Cutter et al., 2014),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018),(Kim & Park, 2018),(J. Song et al., 2018),(Mihunov et al., 2018),(Links et al., 2018),(Wu et al., 2016),(Araya-Muñoz et al., 2016),(Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(L. Siebeneck et al., 2015),(Burton, 2015),(Frazier et al., 2014),(Singh-Peterson et al., 2014),(Jacob et al., 2013),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
			% Employees not in farming, fishing, forestry, extractive industry, or tourism		+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018),(Tan et al., 2017),(Asadzadeh et al., 2015),(Burton, 2015),(Frazier et al., 2014),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Mihunov et al., 2018)
			% Labour force employed by federal government		+	(Cutter et al., 2014),
			No. physicians/ nurses/ midwives per 10,000 persons		+	(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Both parents in workforce		+	(Jacob et al., 2013)
	Equality (E.1)		% Workers who are self-employed		+	(Jacob et al., 2013)
			% Female labour force participation		+	(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kotzee & Reyers, 2016),(Burton, 2015),(Hiete et al., 2012)
	Income (I)	Income features (I.2)	Average annual income per capita		+	(Kaye-Blake et al., 2019),(Fu & Wang, 2018),(Hu et al., 2018),(Mihunov et al., 2018),(Cutter, 2016),(Asadzadeh et al., 2015),(Shukla et al., 2016)
			Median household income		+	(Mihunov et al., 2018),(Links et al., 2018),(Chu et al., 2017),(Wu et al., 2016),(Cutter, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Jacob et al., 2013)
			Minimum wage rate per day		+	(L. Siebeneck et al., 2015)
			% Population with multiple sources of income		+	(Ainuddin & Routray, 2012)
			Disposable income per capita		+	(Hu et al., 2018),(Toubes et al., 2017),(C. Zhang et al., 2016)
			Income tax per capita		+	(Hu et al., 2018),(González et al., 2018)
		Equality (I.1)	% Population living below poverty		-	(Mihunov et al., 2018),(Asadzadeh et al., 2015),(Frazier et al., 2014),(Jacob et al., 2013),(Ainuddin & Routray, 2012),(Luh et al., 2015)
			Cost of living index		-	(Jacob et al., 2013)
			Gini coefficient		-	[1],[2],[43],[7],[8],[10]
			Absolute difference between male and female median income		-	[1],
			Ratio income of top quintile to lowest quintile			(Araya-Muñoz et al., 2016),(Brenkert & Malone, 2005)

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
	Business Activity & Production (BA&P)	Business features (BA&P.1)	Ratio of large to small businesses		+	(Cutter et al., 2014),(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(D. Wang et al., 2017b)
			Large retail stores per 10,000 persons		+	(Cutter et al., 2014),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Links et al., 2018),(Burton, 2015)
			No. of business per capita		+	(González et al., 2018)
			No. of grocery stores per 100 square miles		+	(Links et al., 2018)
			No. of banks per 1,000 persons		+	(Scherzer et al., 2019),(Links et al., 2018)
			No. of enterprises per 1,000 persons		+	(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015)
		Commercial activities (BA&P.2)	Area of commercial establishment per 10,000 persons	G 8	+	(Moghadas et al., 2019)
			Density of commercial infrastructure in each district	G 8	-	(Moghadas et al., 2019),(J. Song et al., 2018),(Burton, 2015)
			Research & development firms per 1,000 persons	G 8	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Commercial establishments outside of high hazard zones ÷ total commercial establishment	G 8	+	(Burton, 2015)
		Income and expenditure (BA&P.4)	Total financial revenue from business		+	(Hu et al., 2018),(González et al., 2018),(Tan et al., 2017),(Burton, 2015),(Frazier et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Ratio of public finance income and expenditure (%)		+	(Tan et al., 2017),(Shukla et al., 2016)
			Total amount (\$) of imported and exported goods		+	(Hu et al., 2018),(Tan et al., 2017)
			% GDP from primary industry (farming, fishing, etc)		-	(Li, Lam, et al., 2016),(G. Song et al., 2015)
			Amount of tax collected per capita			(Yoon et al., 2016)
			Net per capita spending for mitigation projects		+	(Yoon et al., 2016)
		Economy diversity (BA&P.3)	TRESS index	G 8	-	(Kotzee & Reyers, 2016)
	Cost and revenue of development (C&R)	Land (C&R.2)	Ratio of business (CBD centres) within build-up area	G 8	+	(J. Song et al., 2017)
			Price of land (RMB) per square meter	G 11	-	(J. Song et al., 2018)
		Urbanisation and density (C&R.4)	% Population living in urban areas	G 11	+	(J. Song et al., 2017)
			Cost of road construction	G 11	-	(Fu & Wang, 2018)
		Energy/water (C&R.1)	Energy use for residential, commercial and industrial land use		-	(Fu & Wang, 2018),(J. Song et al., 2018)
			Water use by households in the area		-	(Fu & Wang, 2018),(J. Song et al., 2018)
		Renewable energy (C&R.3)	Types of renewable sources		+	(Fu & Wang, 2018)
	Financial Services (FS)	Insurance (FS.1)	Crop insurance policies per square mile	T 8.10, T 1.5	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Housing units covered by disaster insurance	T 8.10, T 1.5	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	Production (Pr.)	Production type and features (Pr.1)	Food security rate		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Gross regional domestic product per capita		+	(Kim & Park, 2018),(Hu et al., 2018),(Chu et al., 2017),(J. Song et al., 2017),(Tan et al., 2017),(D. Wang et al., 2017b),(C. Zhang et al., 2016),(Li,

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
Institutional	Preparedness (P)	Mitigation (P.2)	Total farm cash flow		+	Lam, et al., 2016),(L. Siebeneck et al., 2015),(Brenkert & Malone, 2005),[33]
			Ratio of assets to liabilities		+	(Williges et al., 2017),[33]
			Farm fixed assets investment density (amount of investment per area)		+	(Williges et al., 2017)
			Farms marketing products through Community Supported Agriculture per 10,000 persons		+	(Tan et al., 2017),(D. Wang et al., 2017b)
			Density of manufacturing within built up area		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Proportion of cultivated land area		+	(J. Song et al., 2017)
			Proportion of non-resource-based industrial output in total industrial output (%)		+	(Li, Lam, et al., 2016)
			Net per capita spending for mitigation projects		+	(D. Wang et al., 2017b),(C. Zhang et al., 2016)
					+	(Cutter et al., 2014),(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Cutter, 2016),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
			% Population within 10 miles of nuclear power plant		-	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	Disaster experience (DE)	Accessibility (DP.1)	% Governmental financial resources to carry out risk reduction activities		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population covered by a mitigation plan		+	(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018),(Burton, 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
			% Population living in hazardous area		-	(Asadzadeh et al., 2015)
			Existence of government plans (i.e. disaster, climate adaptation)		+	(Chu et al., 2017),(Luh et al., 2015),(Burton, 2015)
			Net operating surplus as a percentage of gross operating revenues		+	(Scherzer et al., 2019)
			% Employed persons working in public administration, defence, social security or municipal activities		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(C. Zhang et al., 2016),(Burton, 2015)
			Average number of early warning centres per each independent zone		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018)
			No. of fire/ police/ambulance stations and shelters per 1,000 people		+	(Fu & Wang, 2018),(Kim & Park, 2018),(DasGupta & Shaw, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Mean distance in meters from denser settlement areas to nearest county capital	G 11	-	(Scherzer et al., 2019),(De Sherbinin et al., 2015)
			Presidential disaster declarations divided by number of loss-causing hazard events	T 1.5	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Cutter, 2016)
		Disaster aid experience (DE.1)	Emergency coordination time	T 1.5	-	(Luh et al., 2015)
			No. of paid disaster declarations	T 1.5	+	(Cutter et al., 2010),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			% Local schools, hospitals and health facilities that remained operational during emergencies in past events	T 1.5	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population with access to local disaster training	G 4	+	(Cutter et al., 2014),(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Shukla et al., 2016),(Wu et al., 2016),(Burton, 2015),(Singh-Peterson et al., 2014),(Ainuddin & Routray, 2012),(Hiete et al., 2012)
		Disaster knowledge (DE.2)	Red Cross training workshop participants per 10,000 persons	G 4	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Fu & Wang, 2018)
			% Officials and leaders who are under regular training programs	G 4	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
			Per capita expenditure on education	G 4	+	(C. Zhang et al., 2016),(Mihunov et al., 2018),(Tan et al., 2017)
		Income and expenditure (G.4)	Net per capita general expenditures		+	(Mihunov et al., 2018),(Links et al., 2018)
			Total financial revenue from business		+	(Mihunov et al., 2018)
	Governance (G)	Performance regime (G.6)	Proximity of county seat to state capital	T 10.2, T 10.3	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Proximity of county seat to nearest county seat within a Metropolitan Statistical Area	T 10.2, T 10.3	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Governments and special districts per 10,000 persons	T 10.2, T 10.3	+	(Cutter et al., 2014),(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Singh-Peterson et al., 2014)
		Social (G.7)	Local court convictions per capita		-	(Kaye-Blake et al., 2019)
			% Voting age population participating in presidential election		+	(Kaye-Blake et al., 2019),(Hung et al., 2016)
			Population change over previous five year period		+	(Cutter et al., 2014),(Moghadas et al., 2019)
		Financial (G.3)	% Housing units covered by disaster insurance	T 8.10, T 1.5	+	(Cutter et al., 2014),(Cutter et al., 2010),(Burton, 2015)
			% Population under age 65 with health insurance	T 8.10, T 1.5	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Development (G.1)	Crop insurance policies per square mile	T 8.10, T 1.5	+	(Cutter et al., 2014),(Cutter, 2016)
			No. of building units constructed over the last ten years	G 11	-	(Moghadas et al., 2019)
			% Land area that consists of windbreaks and environmental plantings	G 11	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Percent of vulnerable shoreline protected by dykes/embankments	G 11	+	(DasGupta & Shaw, 2015)
			% Designed structural damage - % Actual structural damage	G 11	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Urban improvement (G.8)	Per capita expenditure on Urban improvement programs		+	(González et al., 2018)
			Area of residential, commercial, industrial and educational land uses (km2)		+	(Hung et al., 2016)
			Municipal budget per inhabitant in national currency		+	(Araya-Muñoz et al., 2016)
			Existence of a current development plan		+	(González et al., 2018)
			Year of current development plan		+	(González et al., 2018)
			Existence of a current land use policy		+	(González et al., 2018)
			Year of current land use policy		+	(González et al., 2018)
			Frequency of official reviews of master plan		+	(Araya-Muñoz et al., 2016)
		Infrastructure (G.5)	% Building infrastructure not in high hazard zones		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Essential infrastructures that are under regular assessment programs		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Population access to electricity/gas/safe water/radio/internet		+	(L. Siebeneck et al., 2015)
			Hospital/hotel beds per 10,000 persons		+	(L. Siebeneck et al., 2015)
			% Housing units that are not mobile homes		+	(L. Siebeneck et al., 2015)
			Principle arterial miles per square mile		+	(Fu & Wang, 2018),(L. Siebeneck et al., 2015),(Frazier et al., 2014)
			The ratio of the number of crossings over the length of roads (network connectivity)		+	(Fu & Wang, 2018)
			Daily average amount of marine cargo transported		+	(Kim & Park, 2018)
			Average size of registered fishery vehicles		+	(Kim & Park, 2018)
			No. of seamounts		+	(Kim & Park, 2018)
			% State owned and collective owned households		-	(Kaye-Blake et al., 2019),(Tan et al., 2017)
			No. of schools per 1000 students		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Frazier et al., 2014)
			No. of fire/ police/ambulance stations and shelters per 1,000 people		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
Infrastructure	Recovery response (RR)	Environmental (G.2)	*Existence of structural measures that physically prevent extreme events		+	(Toubes et al., 2017)
			% Municipal wastewater treatment		+	(C. Zhang et al., 2016)
			*Amount of solid waste by source		-	(C. Zhang et al., 2016)
			The GDP growth rate of environment administration (%)		+	(C. Zhang et al., 2016)
			Fixed assets investment density (amount of investment per area)		+	(C. Zhang et al., 2016)
		Financial support (RR.2)	Microfinancing, cash aid, soft loans, loan guarantees available to affected households after disasters to restart livelihoods		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Ecosystem support (RR.1)	Local government plan to support the restoration, protection and sustainable management of ecosystems services		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Availability of agriculture credit/marketing society		+	(Shukla et al., 2016)
		Psychosocial support (RR.3)	Coastal setback, shoreline restoration		+	(Cutter, 2016)
			Local government access to resources and expertise to assist victims of psychosocial impacts of disasters	G 3	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
Infrastructure	Energy, water & sanitation (EW&S)	Electricity (EW&S.1)	% Population with access to electricity		+	(Manyena et al., 2019)
			% Farms with power supply		+	(Shukla et al., 2016),
		Plumbing and sewage (EW&S.2)	% Households with access to plumbing/piped water/flush toilet		+	(Mihunov et al., 2018),(Links et al., 2018),(Araya-Muñoz et al., 2016),(Kotzee & Reyers, 2016)
		Public establishment (EW&S.3)	% Infrastructure area per area (transportation, park, power, water services (ha.))	T 9.1	+	(Hung et al., 2016)
	Housing (Ho.)	Housing features (Ho.1)	% Housing units that are not mobile homes	G 11	+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Mihunov et al., 2018),(Links et al., 2018),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Median number of room	G 11	+	(Moghadas et al., 2019),(Jacob et al., 2013)
			% Average housing age	G 11	-	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Links et al., 2018),(Burton, 2015),(Jacob et al., 2013),(Hiete et al., 2012)
		Temporary housing availability (H0.2)	% Vacant units that are for rent	G 11	+	(Cutter et al., 2014),(Cutter et al., 2010),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Hotels/motels per 10,000 persons	G 11	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(J. Song et al., 2018),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Hung et al., 2016)
			Distance to nearest public shelter	G 11	-	(J. Song et al., 2018)
		Health services (HI.1)	Hospital beds per 10,000 persons		+	(Cutter et al., 2014),(Cutter et al., 2010),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Singh-Peterson et al., 2014),(Hiete et al., 2012),(Hung et al., 2016)

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
			Senior centres per 1,000 persons		+	(González et al., 2018)
	Land (L)	Social engagement (L.3)	%Area of community services (recreational facilities, parks, historic sites, libraries, museums) total area Area of public open space		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Urbanisation and density (L.4)	% Population living in urban areas	G 11	+	(J. Song et al., 2017)
		Agriculture (L.1)	% Agricultural land to total land area		+	(Hung et al., 2016)
		Informal settlements (L.2)	Area of informal settlements (ha.)		-	(Hung et al., 2016),(Kotzee & Reyers, 2016)
	Economic infrastructure (EI)	Commercial establishment (EI.1)	% Commercial infrastructure area per area % Commercial establishments outside of high hazard zones ÷ total commercial establishment	G 8 G 8	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019) (Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
	Education infrastructure (Ed.)	School restoration potential (Ed.1)	Public schools per 10,000 persons/or per square mile	G 4	+	(Cutter et al., 2014),(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Kotzee & Reyers, 2016),(Asadzadeh et al., 2015),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
	Emergency Response (ER)	Emergency stations and shelters (ER.1)	No. of fire/ police/ambulance stations and shelters per 1,000 people		+	(Scherzer et al., 2019),(Moghadas et al., 2019),(Cutter, 2016),(Burton, 2015)
			Mean distance in meters from denser settlement areas (tettsted N50) to the nearest /hospital/fire/police station (log-transformed)		-	(Scherzer et al., 2019),(J. Song et al., 2018),(J. Song et al., 2017),(Asadzadeh et al., 2015)
		Emergency workforce capacity (ER.2)	No of firefighters/ police officers/ medical staff per 1000 population		+	(Kim & Park, 2018)
		Transportation access (ER.4)	No. of vehicle registrations per capita	G 9	+	(Kim & Park, 2018)
			Annual increasing rate of privately possessed cars (%)	G 9	-	(C. Zhang et al., 2016)
		Infrastructure (ER.3)	% Building infrastructure not in high hazard zones	G 9	+	(Burton, 2015)
	Transportation (T)	Industrial re-supply potential (T.3)	Rail miles per square mile area	G 9	+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Kim & Park, 2018),(Burton, 2015)
		Evacuation potential (T.1)	Principle arterial miles per square mile		+	(Cutter et al., 2010),(Scherzer et al., 2019),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015),(Singh-Peterson et al., 2014),(Hiete et al., 2012)
			Major road egress points per 10,000 persons		+	(Cutter et al., 2014),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(J. Song et al., 2017),(Tumini et al., 2017)
			Roads network density		+	(Manyena et al., 2019),(Scherzer et al., 2019),(Shukla et al., 2016),(Luh et al.,

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
		Road safety (T.4)	Traffic accidents per 1,000 persons	T 3.6	-	2015),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016) (Scherzer et al., 2019),(Delgado-Ramos & Guibrunet, 2017a)
		Accessibility (T.2)	Mean distance in meters from denser settlement areas to the nearest airport (only airports operated by Avinor or the military were included) No. of vehicle per 1,000 persons		-	(Scherzer et al., 2019)
					+	(Delgado-Ramos & Guibrunet, 2017a)
			Extra travel time invested yearly or daily		-	(Delgado-Ramos & Guibrunet, 2017a)
			Total cost of carbon for private and public transport		-	(Delgado-Ramos & Guibrunet, 2017a)
			Economic benefit of street provides cycling/walking (\$/year)		+	(Delgado-Ramos & Guibrunet, 2017a)
	Communication (Co.)	High speed internet (Co.1)	% Population with access to broadband internet service		+	(Cutter et al., 2014),(Moghadas et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Chu et al., 2017),(Shukla et al., 2016),
		Telecommunication (Co.2)	Average number of Internet, television, radio, telephone, and telecommunications broadcasters per household		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Mihunov et al., 2018),(Shukla et al., 2016),
	Infrastructure workforce (IW)	Public utility sector (IW.1)	Percent of employed persons working in public utilities (electricity, water, waste, transportation, communication)	T 11.1	+	(Scherzer et al., 2019),(Mihunov et al., 2018),(Hung et al., 2016)
	Efficiency (Ef)	Electricity (Ef.1)	Megawatt hours per energy consumer		-	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Water (Ef.3)	Ratio of water production to demand	T 6.4	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
		Gas (Ef.2)	Ratio of gas production to gas demand		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
Environmental	Agriculture (A)	Local food suppliers (A.5)	Farms marketing products through Community Supported Agriculture per 10,000 persons No. of farms per square mile		+	(Cutter et al., 2014),(Green et al., 2017),(Mihunov et al., 2018)
					+	(Mihunov et al., 2019),(Wei et al., 2017)
			% Cultivated grass land for animal husbandry			(Wei et al., 2017)
			% Agricultural land to total land area		+	(Hu et al., 2018)
			% Agricultural lands not treated with herbicide/pesticide		+	(Green et al., 2017),(Li, Philp, et al., 2016)
			*Area for wintering green house (for cattle and vegetation)		+	(Wei et al., 2017)
		Connectivity (A.6)	% Farm operations with internet access	T 9.c	+	(Green et al., 2017)
		Assets (A.1)	% Family and individual farm ownership		+	(Mihunov et al., 2019),(Wei et al., 2017)
			Total farm assets (e.g. non-breeding livestock, stores of agricultural products)		+	(Williges et al., 2017)
			Total breeding livestock assets		+	(Williges et al., 2017)
			Agricultural holdings per 1,000 persons		+	(Scherzer et al., 2019)
		Income (A.4)	% Farms paying interest (real estate/ non-real estate)		-	(Mihunov et al., 2019)
			% Farms with expenses (animal/ chemical/ labour/ feed/rent/tax/fuel/energy)		-	(Mihunov et al., 2019),(Li, Philp, et al., 2016)
			Per capita revenue/ farm products per square meter		+	(Wei et al., 2017),(Li, Philp, et al., 2016),(Mihunov et al., 2018)
		Self-organisation (A.6)	% Principal operators living on farm	G 2	+	(Green et al., 2017)
			% Operations with on-farm packing/ direct marketing to retail	G 2	+	(Green et al., 2017)
		Diversity (A.3)	Average % of operations producing across seven different row crop options	G 2	+	(Green et al., 2017)

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
Ecosystem functionality (EF)	Safe zones (EF.5)	% Land in wetlands (natural flood buffer zone)		T 2.4	+	(Cutter et al., 2014),(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Chu et al., 2017),(Burton, 2015)
			% Land in wetlands in not slide area	T 2.4	+	(Scherzer et al., 2019)
			% Land area with no wetland decline	T 2.4	+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015)
			% Land area that consists of windbreaks and environmental plantings	T 2.4	+	(Burton, 2015)
	Air (EF.1)	Air quality index (AQI)			-	(Kaye-Blake et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Abdrabo & Hassaan, 2015)
			No. of days per year with pollution concentration above the local norm or standard		-	(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
	Soil (EF.6)	Health cost of air pollution (\$/year)	% Acid rain per total precipitation		-	(Delgado-Ramos & Guibrunet, 2017a)
			Soil erosion ton/year/person		-	(C. Zhang et al., 2016)
			% Land that is not impervious		-	(Kaye-Blake et al., 2019)
					+	(Cutter et al., 2014),(Kaye-Blake et al., 2019),(Scherzer et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Chu et al., 2017),(Kotzee & Reyers, 2016)
	Land & Sea (EF.3)	% Availability of quality agricultural land			+	(Manyena et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Li, Philp, et al., 2016),(Williges et al., 2017)
			% People accessing quality agricultural land and forests		+	(Manyena et al., 2019),(Abdrabo & Hassaan, 2015)
			Normalized difference vegetation index (NDVI)		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			Ratio of land that turned to urban areas to total land area		-	(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016),(Moghadas et al., 2019)
			% Forest to total land area		+	(Manyena et al., 2019),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Chu et al., 2017),(Burton, 2015),(Hu et al., 2018),(Shukla et al., 2016)
			% Land area that is developed open space		+	(Scherzer et al., 2019),(Moghadas et al., 2019),(Burton, 2015)
			% Land area that is arable (cultivated) land		+	(Scherzer et al., 2019),(Burton, 2015)
			% Irrigated area		+	(Shukla et al., 2016),(Li, Philp, et al., 2016),(De Sherbinin et al., 2015)
			Ratio of built and unbuild spaces		-	(Moghadas et al., 2019)
			% Land area with no land-use change		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015)
			% Land area under protected status		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016),(Yoon et al., 2016)
			% Area of urban green space		+	(Kim & Park, 2018),(J. Song et al., 2017),(Delgado-Ramos & Guibrunet, 2017a)
			% Population with access to a green urban area less than 300 m away.		+	(Delgado-Ramos & Guibrunet, 2017a)
			% Area of beach		+	(Kim & Park, 2018),(Toubes et al., 2017)
			Average elevations in the area		-	(Mihunov et al., 2018),(Wei et al., 2017),(Yoon et al., 2016),(Hung et al., 2016),(J. Song et al., 2018)

Dimension	Subdomain	variable	Indicators	Potential Goal/Target	Impact	Justification
			Degree of slope		-	(J. Song et al., 2017),(Yoon et al., 2016),(J. Song et al., 2018)
			Areas of potential debris flow torrents and landslides		-	(Hung et al., 2016)
			Distance from rivers less than 100 m		-	(Hung et al., 2016)
			Height in digital elevation model (DEM)		-	(J. Song et al., 2017)
			% Land area that does not contain erodible soils		+	(Hu et al., 2018),(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(Burton, 2015)
			% Natural vegetation		+	(Kotzee & Reyers, 2016)
			% Species susceptible to extinction		-	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019)
			% Indigenous vegetation cover (protected biomass)		+	(Kaye-Blake et al., 2019),(Manyena et al., 2019)
			Animal/plants diversity		+	(G. Song et al., 2015)
			% Availability of quality water resources for agriculture		+	(Manyena et al., 2019),(Abdrabo & Hassaan, 2015)
		Water (EF.7)	No. of rainy days		+	(Yoon et al., 2016)
			Averaged annual rainfall more than 1000mm		-	(Hung et al., 2016),(C. Zhang et al., 2016)
			% People accessing quality water resources for agriculture		+	(Manyena et al., 2019),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
			% Dam capacity		+	(Manyena et al., 2019)
			Number of river miles whose water is usable		+	(Kammouh, O., Zamani Noori, A., Cimellaro, G.P., Mahin, 2019),(J. Song et al., 2017)
		Natural disasters (EF.4)	Frequency of natural disasters	G 11	-	(Yoon et al., 2016)
	Environmental policies (EP)	Efficiency (EP.1)	Megawatt hours per energy consumer		-	(Cutter et al., 2014),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
			% Heating fuel		-	(Mihunov et al., 2019)
			Annual crude oil withdrawals, bbl per capita		-	(Mihunov et al., 2019)
			Annual natural gas withdr., 1000 ft3 per capita		-	(Mihunov et al., 2019)
			% Renewable energy to total energy production		+	(Manyena et al., 2019)
			Degree of resource depletion		-	(Tan et al., 2017),(Abdrabo & Hassaan, 2015)
			Water supply stress index		-	(Cutter et al., 2014)
			Total water consumption		-	(Hu et al., 2018),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
			% Total renewable water resources		+	(Mihunov et al., 2019), (Manyena et al., 2019)
		Recycling (EP.3)	% Ground water withdrawals (agriculture, public supply, industry)		-	(Mihunov et al., 2019),(Núñez et al., 2017)
			No. of ground water users		-	(Núñez et al., 2017)
			Recycling ratio of wastes		+	(Kim & Park, 2018)
		Emission (EP.2)	NO/SO2 emission		-	(Hu et al., 2018),(C. Zhang et al., 2016),(Yoon et al., 2016)
		Swage & waste (EP.4)	GHG emission per capita per year		-	(Delgado-Ramos & Guibrunet, 2017a)
			Amount of daily sewage treatment		+	(Hu et al., 2018),(Delgado-Ramos & Guibrunet, 2017a)
			*Amount of solid waste by source		-	(Hu et al., 2018),(Delgado-Ramos & Guibrunet, 2017a),(C. Zhang et al., 2016)
Social impact (SI)	Crime (SI.1)	Environmental violations case	G 15	-	(C. Zhang et al., 2016)	
	Gross production (SI.2)	Gross regional domestic product per capita		+	(Delgado-Ramos & Guibrunet, 2017a)	
	Population (SI.3)	Population density	T 11.7	-	(Yoon et al., 2016)	

Appendix 4. SDG indicators and their relevance to resilience dimensions.

Dimension	Sub-domain	SDGs	Indicators
Social	Community Strength	G2	2.1.2, 2.4.1., 2.5.1, 2.a.2
		G3	3.6.1
		G5	5.b.1
		G9	9.1.1, 9.c.1
		G10	10.7.4
		G11	11.7.1
		G15	15.1.2, 15.4.1
		G17	17.6.1, 17.8.1
	Economic capacity	G1	1.4.2
		G2	2.1.2, 2.4.1, 2.5.1, 2.a.2
	Education & Knowledge	G1	1.a.2
		G4	4.1.1, 4.1.2, 4.2.2, 4.3.1, 4.4.1, 4.6.1, 4.b.1, 4.c.1
	Health	G1	1.a.2
		G2	2.1.1, 2.1.2, 2.2.1, 2.2.2, 2.2.3
		G3	3.1.1, 3.1.2, 3.2.1, 3.2.2, 3.3.1, 3.3.2, 3.3.3, 3.3.4, 3.3.5, 3.4.1, 3.4.2, 3.5.1, 3.7.1, 3.8.1, 3.9.1, 3.9.2, 3.9.3, 3.b.2, 3.c.1, 3.d.1, 3.d.2
		G5	5.2.1, 5.2.2, 5.3.1, 5.3.2
		G6	6.2.1
		G11	11.5.1
		G13	13.1.1
		G16	16.1.2
	Population & Demographics	G1	1.1.1, 1.2.1
		G8	8.5.2
	Social Protection	G1	1.3.1, 1.a.2
		G9	9.5.2
		G11	11.3.2, 11.4.1, 11.b.2
Economic	Business activity	G8	8.1.1, 8.9.1, 8.10.1
		G16	16.6.1
	Cost and revenue of development	G12	12.a.1
		G7	7.3.1
	Employment	G5	5.5.1, 5.5.2
		G8	8.5.2, 8.7.1
		G9	9.2.2
		G16	16.7.1
	Financial Services	-	-
	Household Capacity	G1	1.4.1, 1.4.2
	Income	G1	1.1.1, 1.2.1, 1.2.2
		G2	2.3.2
		G5	5.4.1
		G8	8.5.1
		G10	10.1.1
	Production	G2	2.3.1, 2.3.2, 2.4.1
		G9	9.3.1, 9.b.1
Institutional	Disaster Preparedness	G1	1.5.3, 1.5.4

Dimension	Sub-domain	SDGs	Indicators
	Governance	G11	11.b.2
		G13	13.1.3
		G5	5.b.1
		G11	11.6.1, 11.a.1
		G 16	16.1.1, 16.1.2, 16.1.3, 16.2.1, 16.2.3, 16.3.1
		G17	17.1.1, 17.1.2
	Disaster experience	-	-
	Recovery response	G1	1.3.1
		G2	2.4.1
Infrastructural	Communication	G17	17.6.1, 17.8.1
	Economic infrastructure	-	-
	Education infrastructure	-	-
	Efficiency	G7	7.3.1
	Emergency response	G3	3.8.1, 3.c.1
	Energy, water & sanitation	G1	1.4.1
		G6	6.3.1
		G7	7.1.1
	Health infrastructure	G 3	3.8.1
	Housing	-	-
	Land	G2	2.4.1
		G11	11.1.1, 11.7.1
	Transportation	G9	9.1.1
		G11	11.2.1
	Infrastructure workforce	-	-
Environmental	Agriculture	G2	2.3.2, 2.4.1
		G5	5.a.1
	Ecosystem functionality	G2	2.5.2
		G3	3.9.1
		G6	6.1.1, 6.3.2, 6.6.1
		G11	11.7.1
		G14	14.5.1
		G15	15.1.1, 15.1.2, 15.3.1, 15.4.1, 15.5.1, 15.8.1
	Environmental policies	G6	6.6.1, 6.a.1
		G7	7.1.2, 7.2.1
		G12	12.5.1, 12.a.1
		G13	13.2.2
		G14	14.1.1
	Social Impact	G8	8.1.1

Appendix 5:

Overlap coefficient (Vijaymeena & Kavitha, 2016) is calculated by dividing the size of the intersection by the minimum size of the two sets in a cluster:

$$Overlap(R_b, S_b) = \frac{\zeta R_b \cap S_b \zeta}{\min(\zeta R_b \zeta, \zeta S_b \zeta)}$$

Since the aim of this study is to measure to what extent resilience indicators are covered by SDGs, the irrelevant indicators have not included in the calculation. In this case, SDG indicators to measure resilience are always a subset of resilience indicators in a cluster based on the following equation:

$$S_b \subseteq R_b \text{ if } \forall x (x \in S_b \subseteq \rightarrow x \in R_b)$$

Consequently, the cardinality of the intersection of resilience and SDGs is equal to the cardinality of SDGs:

$$S_b \subseteq R_b \hat{U} \zeta R_b \cap S_b \zeta = \zeta S_b \zeta$$

Also $\min(\zeta R_b \zeta, \zeta S_b \zeta) = \zeta S_b \zeta$. Therefore, the overlap of the two frameworks is always 1 and so the method has not been considered in this research.

The second popular method is the Jaccard coefficient (Alqadah & Bhatnagar, 2010). The Jaccard coefficient measures similarity between two sets in a cluster, and is formally defined as the size of the intersection divided by the size of the union of the sets:

$$J(R_b, S_b) = \frac{\zeta R_b \cap S_b \zeta}{\zeta R_b \zeta + \zeta S_b \zeta - \zeta R_b \cap S_b \zeta}$$

The Jaccard Index is a value between 1 (objects are the same) and 0 (objects are indefinite).

The third method is Cosine similarity (Vijaymeena & Kavitha, 2016), which measures the similarity of vectors as the cosine of the angle between two vectors:

$$Cosine(\vec{R_b}, \vec{S_b}) = \frac{\vec{R_b} \cdot \vec{S_b}}{|\vec{R_b}| |\vec{S_b}|} = \frac{\sum_{i=1}^N r_{bi} \times s_{bi}}{\sqrt{\sum_{i=1}^N r_{bi}^2} \sqrt{\sum_{i=1}^N s_{bi}^2}}$$

Where r_{bi} and s_{bi} are respectively the components of $\vec{R_b}$ and $\vec{S_b}$, and i is the number of vectors' components.

Both Jaccard and Cosine can be employed to measure the similarity of the frameworks but generate a different level of similarity. For instance, the similarity of SDGs with RVF to measure social resilience has been 67.86% and 82.38%, respectively, based on the Jaccard and Cosine methods. To explore the importance of $\vec{R_b}$ and $\vec{S_b}$, or R_b and S_b , which have resulted from the coding process, in the similarity of frameworks, initially, a sensitivity analysis has been conducted applying the following formula (Jorgensen, 1994; Liu, 2008)

$$Sensitivity = \frac{dx}{dp} \frac{p}{x}$$

Where x is one of the methods to measure similarity and p is either $\overrightarrow{R_b}$ or $\vec{S_b}$ when calculating the sensitivity of Cosine, or R_b and S_b for Jaccard.

Sensitivity analysis in this case reveals the impact of uncertainty that may have occurred through the coding process (in this case, selected indicators) on the output (similarity of frameworks) where lower sensitivity means the input (lower bias) yields less impact. Nonetheless the results of this test showed equal sensitivity for both and therefore equal validity.

After obtaining similar sensitivity ([Appendix 4](#)), the literature on the intersection of Jaccard and Cosine similarity has been explored and, based on research conducted by Zahrotun (2016) (Zahrotun, 2016), Cosine was selected to measure the similarity. Zahrotun has compared the validity of Jaccard, Cosine, and their combination when measuring the similarity obtained from the NN method. The research has concluded that the best accuracy can be achieved employing Cosine similarity. Matching their approach to defining similarity (NN method) with the method applied here, Cosine has been selected here as the method to measure the similarity of frameworks.