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Measuring Social Vulnerability to Environmental Hazards in the Dutch Province of Zeeland

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MEASURING SOCIAL VULNERABILITY TO ENVIRONMENTAL HAZARDS IN THE DUTCH PROVINCE OF ZEELAND

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ABBREVIATIONS

BBC = Bogardi/Birkmann Framework (2006)
BeVI = Built Environment Vulnerability Index (Norway)
CBS = Centraal Bureau voor de Statistiek (Statistics Netherlands)
CRED = Centre for Research on the Epidemiology of Disasters
DP = Delta Programme
FA = Exploratory Factor Analysis
EM-DAT = International Disaster Database
EPA = US Environmental Protection Agency
ESRI = Provider of GIS software (ArcMap)
EU = European Union
FEMA = United States Federal Emergency Management Agency
GDI = (UN) Gender Disparity Index
HDI = (UN) Human Development Index
HVRI = Hazards and Vulnerability Research Institute
KMO = Kaiser-Meyer-Olkin Measure of Sampling Adequacy
KWB = (CBS) Kerncijfers wijken en buurten (Key Figures and Neighborhoods)
PCA = Principal Components Analysis
PRTR = Rijksoverheid Emissiergistratie (Pollutant Release and Transfer Register)
RWS = Rijkswaterstaat
SIFVI = Social and Infrastructure Flood Vulnerability Index
SeVI = Socioeconomic Vulnerability Index (Norway)
SoVI = Social Vulnerability Index (United States Counties)
SPSS = Statistical Package for the Social Sciences (IBM Software)
SVI = Social Vulnerability Index
SWD = Southwest Delta
TRI = (US EPA) Toxic Release Inventory
UN = United Nations
UNDP = United Nations Development Programme
UNU-EHS = United Nations University Institute for Environmental and Human Security
US = United States
VNK/VNK2 = Veiligheid Nederland in Kaart (Safety in the Netherlands)

ABSTRACT

The Netherlands is a kingdom known for resisting the perils of natural disaster and keeping records of how these great feats were accomplished. The Dutch have measured physical risk through methods such as the intricate VNK models to predict flood scenarios, but little research has been conducted to examine how the people living in affected areas could be impacted from a natural disaster event. This study employs fine-scale data to construct a social vulnerability index for the 164 districts of the low-lying delta province of Zeeland. The methodology used to measure social vulnerability is built on recent social vulnerability and resilience research that has been conducted in North America, Asia, and Europe. Specific attention is paid to methods used previously and how they can be improved from a statistical standpoint. Factor Analysis of 35 variables selected from the resilience and social vulnerability literature results in nine factors explaining about 72% of the total variance. The factors of vulnerability in Zeeland include *Density of the Built Environment and Public Support, Reduced Wealth and Single Households, Infrastructure Accessibility and Career Qualifications, Recovery Capacity and Female Gender, Personal Wealth, Occupation, Residential Quality, Access to Healthcare, and Evacuation Potential.* The index is constructed using data for all 35 variables with weight decided by the variance explained by each factor. Relative index scores range from a low social vulnerability score of 0.248 in the district Kattendijk, Goes, to the highest social vulnerability score of 0.458 found in Oudelandse Hoeve, Ternuezen. The highest-scoring districts are located towards the South of Zeeland. Eight of the ten most vulnerable districts located in Terneuzen. The Municipality of Goes contains more low-scoring districts than any other municipality. The majority of low scoring, less vulnerable districts are located on the Central lobe of Zeeland. The results of the social vulnerability analysis provide new insights for policy makers, researchers, and community stakeholders that could be combined with Dutch flood-scenario models to guide planning efforts in the Netherlands to mitigate the damaging impacts of future floods. The study provides an example for adaptation of a social vulnerability index for a fine level of analysis.

CHAPTER 1: INTRODUCTION

1.1 Problem Statement

The Netherlands is a region where social vulnerability has not been quantified. The uniqueness of the region suggests that methods for measuring social vulnerability may require special attention. Influence of the governmental structure of the Kingdom and uniqueness of the Water Boards and Delta Works have aided in resistance from disaster in recent history despite high exposure to hazards. To raise risk awareness in the face of climate change and relative sea level rise, a social vulnerability index can provide insight on the spatial distribution of vulnerability. Geographic, cultural, institutional, and scale differences can add difficulty when adapting indicators of social vulnerability across spatial levels and boundaries.

1.2 Research Objective

Analysis at a fine geographic scale provides important information to the residents, planners, business owners, and other stakeholders of the low-lying and fragmented Province of the Netherlands. When combined with flood modeling or other hazards assessment, the findings within this analysis can help guide the on-going planning efforts to mitigate the damaging impacts of future natural disaster events. The objective of this analysis is to provide a method for measuring social vulnerability in the Dutch province of Zeeland that considers geographic and cultural uniqueness for assessment of Dutch social vulnerability. Figure 1 illustrates the Province of Zeeland in Red, which is the southernmost province of the Netherlands. The study seeks to create and demonstrate a method to construct a social vulnerability index using blended frameworks, concepts, and methods from related studies to develop a new, more flexible measurement method geared for small-scale analysis.

Figure 1: Reference Map

1.3 Procedure of Analysis

In the first chapter, the purpose of the study and the objectives of the analysis are introduced. The second chapter provides discussion on the evolution of social vulnerability measurement and frameworks applied to measuring social vulnerability in the Netherlands. Also covered in the second chapter are the decision tools for model planning, development, and assessment based on a content review of methods for measuring vulnerability and statistical procedure. The third chapter introduces the study area and sheds light on the hazards specific to the Netherlands. An introduction to the data sources and types are also included in the third chapter. Methods explored and developed for the Zeeland SVI are discussed in the fourth chapter. Specific implications for analysis design are discussed to determine the best procedure for the study area. Methods for the construction of the Zeeland SVI are presented, including specific procedure developed for this study. The fifth chapter lists the criteria of the statistical analysis and results of the Factor Analysis including a map displaying relative vulnerability in for the districts of Zeeland and discussion for naming the factors of social vulnerability in Zeeland. In addition, a discussion about the spatial distribution of social vulnerability in Zeeland is discussed in the fifth chapter. The sixth chapter contains limitations of the analysis and conclusions of the study. The method for Statistical analysis is located in Figure 2.

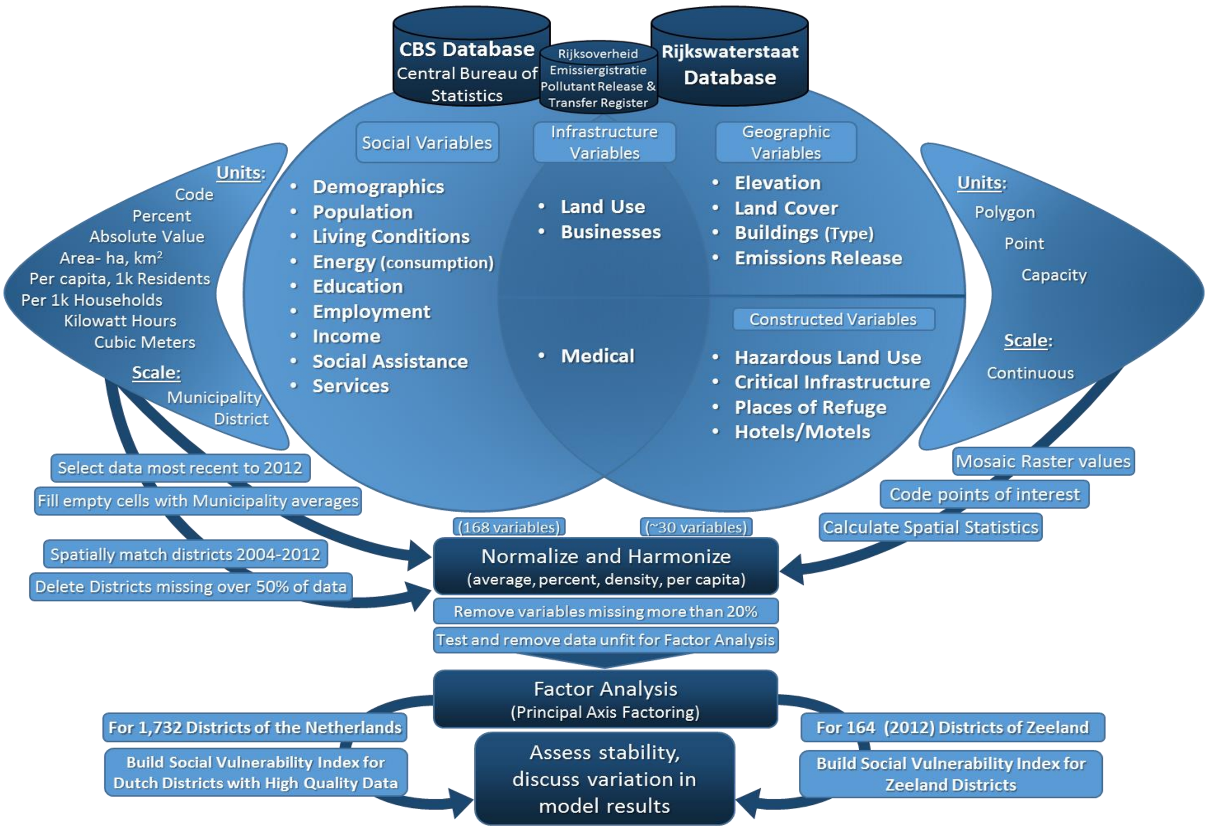


Figure 2: Zeeland Analysis Design

CHAPTER 2: BACKGROUND

2.1 Measuring Social Vulnerability

Social vulnerability is a concept that identifies the susceptibility involved with inequalities of populations, and in this case, their vulnerability to natural hazard events. Mapping social vulnerability reveals areas that may require extra aid whether planning for disaster mitigation before an extreme event, or extra relief efforts after the impact of a disaster. Planning efforts and public policy can benefit from social vulnerability mapping, which may reveal areas not thought to contain a higher rate of vulnerable residents.

In terms of natural or environmental hazards, exposure events may occur in a wide range of magnitude, duration, and frequency. An earthquake or tsunami may occur in seconds with little warning. These events are high-magnitude and rapid due to a sudden onset hazards. Storm, wildfire, or flooding occurs with some warning, and presents a longer residence time (duration), but also falls under the classification of fast-moving events of high magnitude. Fast-moving events pose the greatest level of threat to communities by imposing immediate tests of coping and evacuation efficiencies while gauging a level of resilience, and tend to be the focus of for similar indexes.

The results of a social vulnerability analysis on the Southwest Delta can benefit Dutch planners and officials, providing geographic insight on social inequalities. It is important to note that the majority of constituents have lived free of the need to evacuate or recover from a disaster event, which presents a large unknown and possibly distorted risk perception for responding to disaster among the citizens of Zeeland. This study provides a measurement tool for modeling social conditions in a region lacking damage from catastrophic natural disasters in recent years. Perhaps the best-known disaster impact assessment in the Netherlands is the *Flood Risk in the*

Netherlands, or VNK, which provides scenarios and risk calculation of the probability and consequences of dike ring, dune, or hydraulic structure failure. VNK takes into account failure mechanism, damage, and fatalities, based on environmental factors. The current, second generation VNK2 provides an in-depth analysis for multiple dimensions of potential flood propagation events including flood pattern, water depth, water velocity, and rise rates at the time of failure (VNK2, 2012). When layered over an existing risk model such as the VNK analysis, an additional dimension of social vulnerability provides an argument for planning for disaster management at a sub-municipal level.

In 2005, the National Institute of Building Science's Multihazard Mitigation Council (MMC) investigated the consequences of disaster mitigation investments. The MMC concluded that from 1993 to 2003, the United States Federal Emergency Management Agency's (FEMA) benefits in ratio to costs of hazard mitigation investments for earthquake, flood, and wind preparation amounted to 4.0, or the equivalent of spending $1 in hazard mitigation investment to save $4 after a disaster (MMC, 2005). When planners have a better idea of where the vulnerable populations reside, a higher rate of efficiency in disaster management is achievable.

Social vulnerability is an increasingly important topic for disaster management and planners. Social vulnerability indexes have been included in many studies to examine community susceptibility to natural disaster and climate change, community recovery capacities, cumulative risk evaluations, elderly vulnerability, public safety assessments, terrorism vulnerability, pollution vulnerability, and other community attributes (Cutter et al., 2003; Cutter & Finch, 2008; Dwyeret al., 2004; Fekete, 2010; Finch et al., 2010; Ge et al., 2013; Holand & Lujala, 2013; Holand et al., 2011; Huang & London, 2012; Kaushik, 2013; Luers et al., 2003; O'Brien et al., 2004; Rubin, 2014; Tapsell et al., 2010; Tate, 2013; Vincent, 2004; Yusuf & Francisco, 2009; Zhang & Huang,

2013). Literature relevant to vulnerability measurement has existed for decades. Still, of the most prominent flaws with hazard measurement research is the general non-replicability of geographic vulnerability analyses (Holand & Lujala, 2013). While some concepts of vulnerability are accepted commonly across scales and boundaries such as age and socioeconomic status, others require case-by-case validation. Replication of methods are less of a problem when reproducing a study domestically, but problems arise when methods for measuring social vulnerability are applied to measure conditions outside the target region, including cultural and exposure differences and data availability.

In the context of natural disasters, social vulnerability has been defined to include the social, economic, demographic, and built characteristics that influence a community's ability to respond to, cope with, recover from, and adapt to environmental hazards (Cutter, 1996; Cutter et al., 2003; HVRI, 2013). This definition of social vulnerability presented by the Hazards and Vulnerability Research Institute (HVRI) is a product of Professor Susan Cutter's research group at the University of South Carolina. The team is responsible for development of the 2003 United States (US) Social Vulnerability Index (SoVI), a pioneering study for social vulnerability research for attempts at quantitative validation.

Since the 1970's, attention has been turned to the advancement of understanding concepts related to resilience and vulnerability, largely influenced by Buzz Holling's (1973) *Resilience and Stability of Ecological Systems*, in which he examines the cycles and patterns existing within populations and ecosystems. Holling's work encouraged researchers to pull concepts including resilience and vulnerability into a social context, inspiring researchers to blend the concepts of systems theory and ecology as groundwork for disaster management research (Holling, 1973). A wealth of literature published on the complexion and evolving concepts of resilience, vulnerability,

robustness, and panarchy, evolved the concepts to fit descriptive analysis in the social context. The era of descriptive studies lead researchers to qualitative analysis of spatially distributed vulnerability. Once the utility of qualitative measurements plateaued for assessing vulnerability, researchers advanced the field through the development of quantitative indicators for measuring community trends. Defined by the HVRI, indicators are "quantitative measures intended to represent a characteristic or a parameter of a system of interest" through the application of a single value (Cutter et al., 2008). The use of social and economic indicators dates back to the 1940s (Cutter et al., 2009), however early indicators were not intended for sub-nation spatial analysis in the field of disaster management.

The use of indicators for quantitative analysis is a growing trend of disaster management, but indicators also present certain limitations with no transparent solutions. Conditions within social-ecological systems are determined though synergistic interactions which can be obscured by complex processes. The reduction of real-world interactions to single quantifiable traits leaves room for over simplification, fragmented sampling practices, and criticism. For Example, Putnam (2001) points out that some criticized the US Social Capital Index for including abstract concepts including social trust, altruism, and reciprocity to determine proxies, which some fear lack clear connections with real-world conditions (Putnam, 2001). Reliance on informal data such as social attendance rates and survey responses are less favorable for indicator construction when the condition being measured is abstract. The selection of indicators are supported more when re-occurring institutional population-level data such as US Census data is employed for analysis, which favors future analysis replication.

Following Cutter's (1996) *Vulnerability to Environmental Hazards,* the art of constructing models to measure social vulnerability has been attempted on six of the seven continents with the

guidance of the Hazards-of-Place Framework (Cutter, 1996) for measuring social vulnerability, illustrated in Figure 3. The framework for measurement rippled through hazards literature following a 2003 publication, when a method of model validation were proposed to assess the accuracy of a model for measuring social vulnerability in the United States (Cutter et al., 2003). Results of the model validation were not statistically significant; however, the general acceptance of the methods presented by Cutter et al.'s (2003) SoVI has led many researchers to echo the methods elsewhere. Much of the popularity of the SoVI lies in the aggregation of seventeen concepts and metrics of social vulnerability listed in the SoVI overview discussed in the next chapter, which have proven endurance for vulnerability measurement. The 2003 US SoVI has

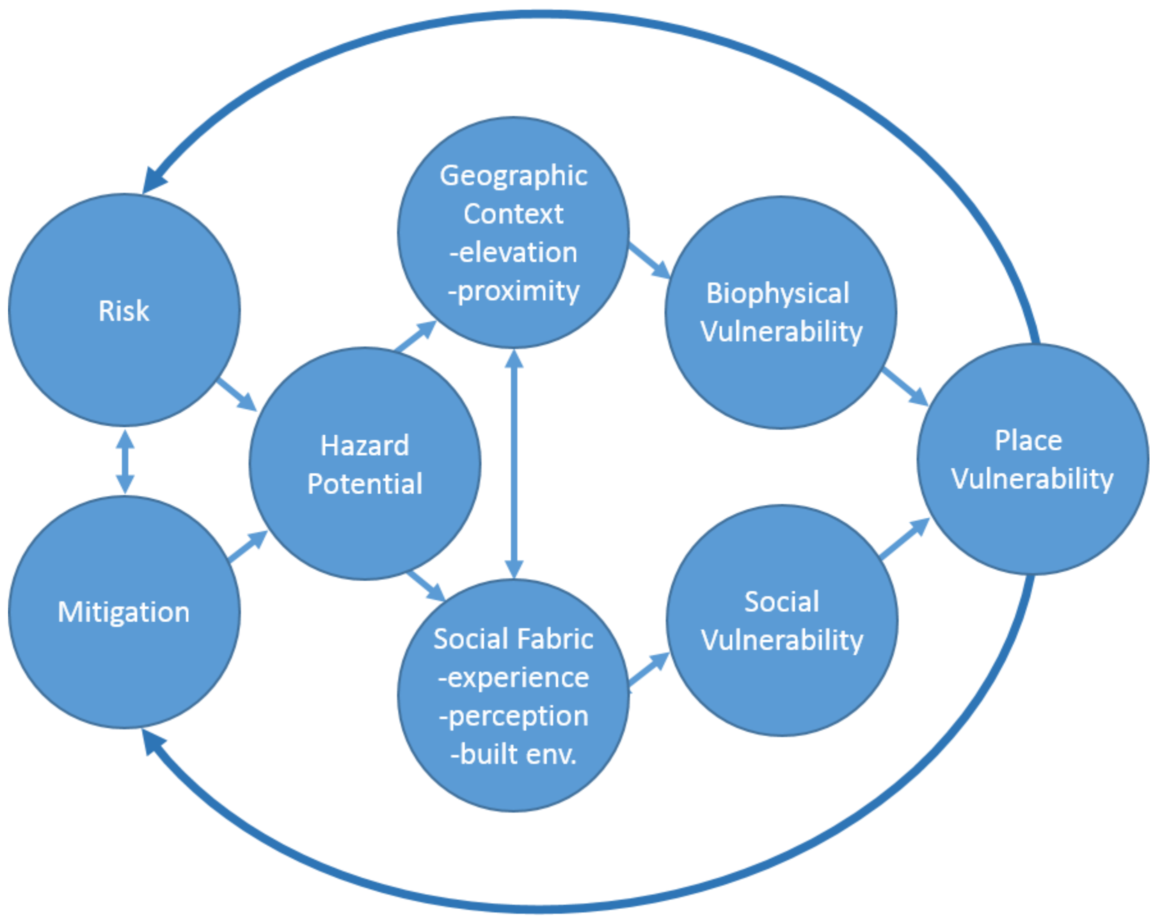


Figure 3: Hazards-of-Place Framework for Measuring Social Vulnerability (Source: Cutter, 1996)

proven useful for aiding framework development, but the Zeeland analysis relies more on recent adaptations of the concepts of vulnerability and aggregation methods to develop a fresh method for measuring social vulnerability.

In the years since the development of the US SoVI, researchers have updated techniques to improve methods for framework development, concepts adaptation, data processing, statistical procedure, index aggregation, and methods assessment techniques (Cutter & Finch, 2008; Doba et al., 1999; Fekete, 2010; Finch et al., 2010; Holand & Lujala, 2013; Reams et al., 2012; Schmidtlein et al., 2008; Sherrieb et al., 2010; Tapsell et al., 2010). Advancements of the US SoVI methods are demonstrated across spatial scales and political boundaries, resulting in a growing knowledge bank testing the sensitivity, robustness, and validity of social vulnerability measurement procedure. Holand and Lujala (2013) consider US SoVI methods and concepts to guide replication and adaptation of the SoVI framework across national and cultural boundaries. Alexander Fekete (2010) expresses attention to detail for methodological decisions, exposure-based validation of for concepts selection and model assessment in the multiple index analysis, *Assessment of Social Vulnerability for River-Floods in Germany*. In addition, Reams, Lam, and Baker (2012) developed methods to measure resilience capacities of Gulf of Mexico Coastal US Counties using Exploratory Factor Analysis to guide data reduction for the aggregation of an additive average-weighted index, contributes statistical improvements to the vulnerability measurement framework based on the work of Ariele Baker (Baker, 2009).

Among early social vulnerability analysis methodology, data reduction with Principal Components Analysis (PCA) became popularly accepted. Researchers seek to identify methods of higher statistical reliability and reduced subjectivity through methodological standardization, but a growing database of procedures complicates efforts of determining best practice methods.

The need for more precise planning tools and hazard mitigation techniques have been requested by the United Nations, the European Floods Directive, and the IPCC (Tsakiris et al., 2009). In addition, the US *Disaster Mitigation Act* of 2000 requires regular submission of multi-hazard mitigation planning for local governments to qualify for disaster relief and mitigation funding. A more flexible framework for fine scale analysis can contribute to each of these.

2.2 Selecting Indicators of Social Vulnerability

An appropriate framework to measure social vulnerability must respect the geographically and temporally unique hazards including exposure, magnitude, and adaptive capacities by which regional communities resist hazards and the institutional influences supporting communities in response to and recovery from natural hazards. Decades of related research have led researcher to develop many frameworks to guide social vulnerability measurement. Although social vulnerability measurement was not central to Cutter's (1996) Hazards-of-Place framework, the model has guided the development of many similar indexes. Related literature contains a host of frameworks for measuring vulnerability in many contexts. A second popular method for measuring social vulnerability is the BBC-Framework (Birkmann, 2007) illustrated in Figure 4, which provides an added dimensions of vulnerability and paths related to its measurement. Blended representation of multiple frameworks is commonly found in similar analyses. Framework development for the Zeeland SVI relies on the Hazards-of-Place and the BBC-Frameworks to blend broad concepts of measuring vulnerability. Although many concepts of vulnerability are general, some concepts are context-specific. Concepts for measurement of social vulnerability guiding this analysis draw from both frameworks above used for data selection are listed in Table 1.

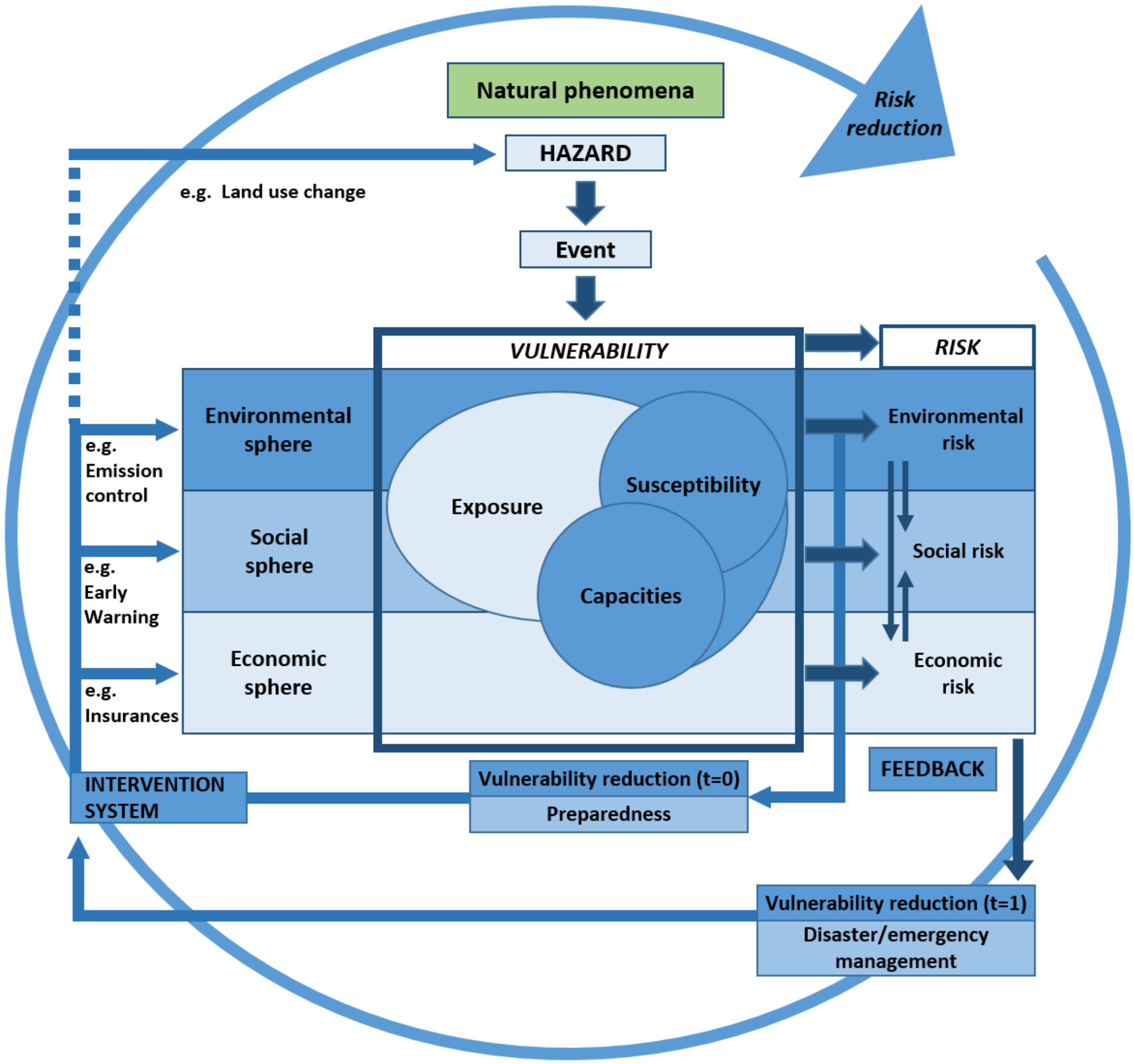


Figure 4: BBC-Framework for Measuring Social Vulnerability (Source: Birkmann, 2007)

This analysis aims to provide specific methods decisions for data analysis using that popular IBM's popular software, SPSS 22. It is important to understand the process to obtain the best results, but the scarcity of instructional resources for model optimization hinders researchers from understanding the consequences of their methods selection (Costello & Osborne, 2005). The following methods identify options available to the researcher within SPSS and reasoning for decisions made for the Zeeland SVI.

Table 1: Common Concepts for Measuring Social Vulnerability

Hazards-of-Place Vulnerability	US SoVI Metrics (Cutter et al., 2003)	Norway SoVI Adapted Metrics (Holand & Lujala, 2013)	*
Socioeconomic Status Status	High status (+/–)	High status (–)	C
	Low income or status (+)	Low income or status (+)	N
		Good public finances (–)	C
		Civic involvement (–)	C
Gender	Gender (+)	Gender equality (–)	C
Race and ethnicity	Non-white (+)	Non-Western immigrants (+)	T
	Non-Anglo (+)	Western immigrants (–)	T,C
Age	Elderly (+)	Elderly (+)	N
	Children (+)	Children (+/–)	C
Comm. & Ind. Development	High density (+)	High density (+)	T,C
	High value (+)	High value (+)	T
Employment Loss	Employment loss (+)	Employment loss (+)	N
Rural/Urban	Rural(+)	Rural(+)	G,C
	Urban (+)	Urban (+)	G,C
Residential Property	Mobile homes (+)	House value (–)	T
		Old houses (+)	T
Infrastructure and lifelines	Extensive infrastructure (+)	Extensive infrastructure (+)	N
		Old infrastructure (+)	C
		Evacuation possibility (–)	C
Renters	Renters (+)	Renters (+)	N
Occupation	Professional or managerial (-	Professional or managerial (–)	N
	Clerical or laborer (+)	Clerical or laborer (+)	N
	Service sector (+)	Service sector (+)	N
Family Structure	High birth rates (+)	Positive birth rates (–)	C
	Large families (+)	Large families (+)	N
	Single-parent households (+	Single-parent households (+)	N
Education	Little education (+)	Little education (+)	N
	Highly educated (–)	Highly educated (–)	N
Population Growth	Rapid growth (+)	Rapid growth or decline (+)	C
		High outmigration (+)	C
Medical Services	Higher density (–)	Higher density (–)	N
		Distance to med. services (+)	C
Social Dependence	High dependence (+)	High dependence (+)	N
	Low dependence (–)	Low dependence (–)	N
Special needs	Large special needs pop. (+	Large special needs pop. (+)	N

(Table 1 continued)

Concepts Unique to Germany SVI (Fekete, 2009), BBC Framework	
Potential for the	Tourist overnight stays (+) Municipality debts per resident (+) Key funds allocation (+) Fixed investments (-) Day-care centre (+) Rehabilitation centres per Resident (+) Elementary Schools per Resident (+) Population projection age 60+ (+) New apartments (-) One and two family homes (-) Small apartments (+) Living space pp (-) New residents (+)

Legend		
Source: US SoVI	Source: Norway SoVI	Source: Germany SoVI
*Adaptation Issue: C-conceptual, G-geographic, N-none, T-technical		

Once a dataset of raw information is assembled, it should be verified that assumptions for measurement with Factor Analysis are met. For index construction with Exploratory Factor Analysis (FA), data should be of a large sample, free of missing values, interval or ratio level measurement, normally distributed, and should pass select quality standards. While fulfillment of all these conditions are not all mandatory for SPSS to return output results for PCA data reduction, more problems can occur when FA Principal Axis Factoring extraction is selected for low quality data. If FA assumptions are ignored, problems including un-proportional index score contributions, over-representation of concepts, and a reduced ability to determine a numeric solution may occur.

An appropriate Factor Analysis should be designed as a large-sample study. With a suggested minimum of 100 subjects, sample size requirement is a potential limitation of Factor Analysis (Suhr & Shay, 2008). It is argued that the number of variables included should depend

on the size of the sample, although there is a broad width of disagreement on the correct ratio. Costello and Osborne (2005) present survey results revealing that a surprising 15% of recent studies accept a subject to item ratio of 2:1 or less, although a generally-acknowledged limit of ≤ 10:1 is accepted by 63% of recent factor analyses architects, with 97% accepting ≤ 100:1 as an adequate FA sample. Depending on the size of the sample, the presence of conceptually redundant, low loading, or values with low communalities can be identified and trimmed from the dataset.

Social vulnerability analyses were reviewed globally at scales ranging from US Census Block to national level analysis, considering vulnerability to natural disasters across the spectrum to gain an understanding of the effects scale plays on the project design (Cutter et al., 2003; Cutter & Finch, 2008; Fekete, 2009; Fekete, 2010; Finch et al., 2010; Ge et al., 2013; Holand & Lujala, 2013; Holand et al., 2011; Huang & London, 2012; Rubin, 2014; Tapsell et al., 2010; van Beuningen & Schmeets, 2012; Vincent, 2004; Yusuf & Francisco, 2009; Zhang & Huang, 2013). The selection of scales play a large role in the data availability for the social vulnerability index, and can enhance or suppress problems including data scaling, averaging, and data availability (Fekete, 2010; Schmidtlein et al., 2008). The problem of scale is one that exists throughout vulnerability literature. Although scale is an issue of both spatial and temporal consideration, complications of scale are most common to the spatial context. Problems of scale can influence the quality of methods in many ways. A common issue when considering analysis scale is influence on project design by the data available in the area of interest. Some researchers utilize data inappropriately across scales. Tapsell et al. (2010) of the *Flood Hazard Research Centre*, Citing Green and Penning-Roswell (2007), recognize that the "level at which we can measure individual or social characteristics will (then) dictate how we can relate those characteristics in the form of some measure of vulnerability" (Green & Penning-Rowsell, 2007; Tapsell et al., 2010).

Analysis level choice is important for assigning appropriate concepts and proxies to measure social vulnerability. Variables measuring national vulnerability may not be appropriate for measuring conditions at a sub-national level. An example of this phenomenon is visible when assessing spending on education or pollution release across scales. Spending on Education is most valuable for large-scale analysis, where a national trend is observed. It is unlikely that Gross Domestic Product will be included to measure a vulnerability at a sub-national scale such as county. On the other hand, pollution release at a small scale does a fine job for identifying fenceline communities and industrial fallout zones, but is not a valid indicator of exposure at the national level.

Multi-scale or cross-scale considerations may be necessary for multiple reasons. Besides the notion that place-based analysis of vulnerability requires selection of a unit of analysis, Fekete (2009) asserts that scales are important because the systems of interest operate across a variety of spatial and temporal scales, and that cross-scale interaction by these systems influences the model results at a given scale (Fekete et al., 2009). Given the holistic consideration of community systems and interactions and the arbitrary nature of a community, scale considerations are a crucial aspect for defining methods for measuring social vulnerability in Zeeland. It is important to define the scale(s) of analysis before analysis. The consideration of cross-scale interactions requires concern prior to conceptualization of analysis design.

The notion that vulnerability differs across space and time requires careful consideration for the selection of indicators that accurately measure these changes at a scale common the study. To address the viability of the data available for measuring vulnerabilities researchers identified the need for cross-scale and multi-scale indicators (Birkmann, 2007; Fekete, 2010; Fekete et al., 2009; Tapsell et al., 2010; Varma & Mishra). Data upscaling is a common practice easily achieved

with GIS technique. Upscaling is necessary to fit continuous, usually environmental variables such as elevation or building density to common level of analysis, for example finding district average elevation. Contrarily, the practice of downscaling data beyond its lowest level observed has proven problematic. The problems posed by downscaling is most commonly encountered with economic or government-related data, has previously been dealt with by dividing the respective indicator by the total population or total land area of interest (Fekete et al., 2009). The Zeeland analysis requires multi-level data observation to include governmental data, which is available at the municipal level.

Data availability from spatially discrete information may play the largest role in variable selection, but temporal scale should also be considered when selecting proxies. Although it is often necessary to increase temporal width of data collection, the effects of opening temporal scale has burdening effects on coupled systems in the consideration of processes such as defining complex feedback loops, which are further burdened by uncertainty of reliance on institutional organization and efficiency (Anderies & Janssen, 2013; Fekete et al., 2009; Gall, 2007; MEA, 2003; Robards et al., 2011; Varma & Mishra). Most reviewed data sources such as the US Census or Statistics Netherlands (CBS) do not collect the same discrete variables at each collection, often resulting in the need to expand data collection to previous years when conditions may have not been the same within the study area.

The accuracy of an index of any measurement is dependent on the agreement between the perceived and actual local traits. Concepts of Vulnerability based on the 2003 US SoVI have been adapted to measure many social vulnerability, resilience, recovery, and other trends on different scales and discrete locations within the US (Cutter et al., 2003; Cutter & Finch, 2008; Doba et al., 1999; Finch et al., 2010; G. Huang & London, 2012; Reams et al., 2012; Schmidtlein et al., 2008).

The framework of the US SoVI (Figure 5**)** applies the work of several authors for identification of the primary factors that influence social vulnerability, including: “lack of access to resources (including information, knowledge, and technology); limited access to political power and representation; social capital, including social networks and connections; beliefs and customs; building stock and age; frail and physically limited individuals; and type and density of infrastructure and lifelines” (Cutter et al., 2003). Many of the above concepts stem from un-published and international documents, although many recognize the broad collection of general concepts of social vulnerability acceptable for US social vulnerability research through a consensus of literature.

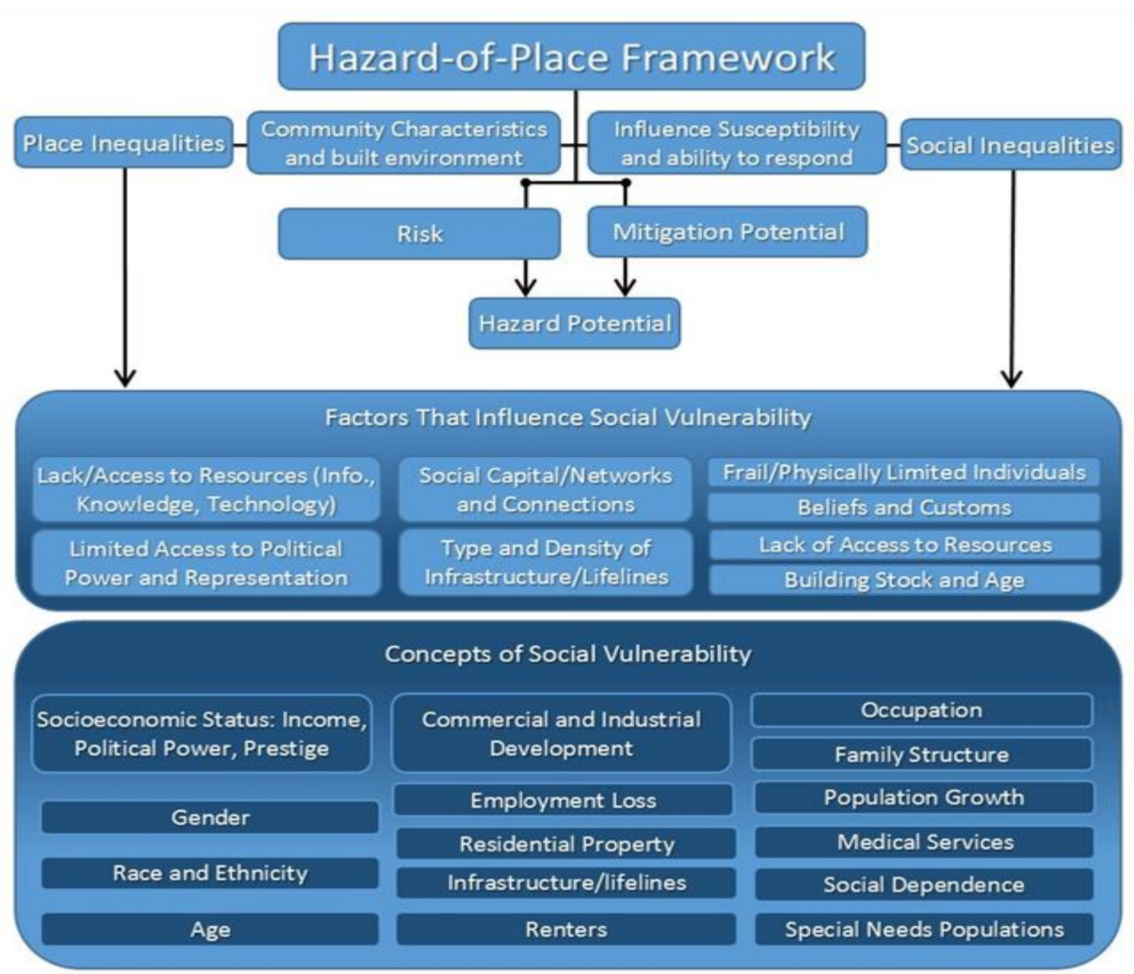


Figure 5: US Social Vulnerability Index 2003 Overview (Adapted from Cutter et al., 2003)

An indicator represents a community attribute that contributes to or mitigates the average social vulnerability in an area. Many of the metrics found in reviewed literature share a common agreement to the concepts of vulnerability, but some conditions that disagree geographically were investigated to determine validity of application in the Netherlands to avoid making false assumptions. For example, US studies accept a positive relationship between the portion of female population and social vulnerability with the inclusion of *Percent females* as a proxy for gender-induced vulnerability. Cutter et al. (2003) cite seven sources when defining the role that gender plays in determining social vulnerability, claiming that “women can have a more difficult time during recovery than men, often due to sector-specific employment, lower wages, and family care responsibilities” (Cutter et al., 2003). In the sixth factor of the US SoVI, race (African American) correlates highly with percent female-headed households, leading researchers to conclude that African-American, female-headed households are among the most vulnerable. As expressed in the previous chapter, race and gender are found to hold cultural deviation from US assumptions. German researcher Alexander Fekete (2010) found that females in Germany possess a higher capacity for risk perception and preparedness for action in disaster situations based on the findings published from local flood survey, weakening the argument that more females lead to more vulnerability (Fekete, 2010). The German metric for gender remains positively related with vulnerability due increased family responsibilities, although holds less of an argument for conceptual validity.

In Norway, researchers recognize that females tend to be more highly educated, are more likely to move to seek diverse employment and education opportunities, and that common female occupations in healthcare and education provides better shelter in disaster situations, and thus, omit the percent of females as an indicator of social vulnerability from selected proxies (Holand

& Lujala, 2013). The UNUDP 2012 *Gender Disparity Index* recognized that that Norway contains the lowest level of gender disparity in the world (Malik, 2014). Norwegian researchers reverse the direction of the influence females have on social vulnerability on the argument that females possess higher education and are more likely to move for education and employment opportunities (Holand & Lujala, 2013).

An absence of large-scale disaster exposure records in current Dutch history shades potential for real world concept validation for female capacities or vulnerabilities in terms of disaster preparation as noted in the German SVI. While it may be the case that women may bear more responsibility for raising young, the 2014 UNDP *Human Development Report* ranks the Netherlands as having the fourth highest gender equality in the 187 measured nations, resting above the US and Germany at fifth and sixth respectively (Malik, 2014). Many conceptual parallels are drawn from the Norwegian analysis, but the country profile on gender equality in the Netherlands, although exceeds the EU average, indicated that female gender contributes to vulnerability. Although Dutch females contain only slightly higher rates of unemployment from a gender perspective, lower average employment in many professional fields including teaching, social science, business, law, science, computing, engineering, and health are reduced for Dutch females in respect to the EU average (European Commission, 2013). Besides shedding light on a reduced portion of females in professional careers, the report also identifies that Dutch children possess part-time childcare rates much higher than the EU average. Without services of childcare the many part-time Dutch women (and men) could be burdened during recovery from disaster.

A second example of vulnerability concept validity in the Netherlands is found in the common US concept of spending on education. While US county level indexes are often aggregates of multiple school districts with performance-based funding, the Netherlands has a

different method for allocating funds for education. The amount of funding for Dutch schools are decided on a standard per-student basis at the national level of government with more funding allocated in cases such as special needs students. In this case, it could be argued that higher spending on education (per student) is associated with elevated social vulnerability due to an increased amount of special needs youth within a population group.

The Netherlands differs from the US in many cultural channels. The availability of undeveloped space, poor zoning practices, and uneven urbanization found in many of the United States are factors that influences US culture in ways not observed in the Netherlands. Development in the US commonly leads to the occurrence of spatial sprawl before adequate infrastructure is planned and installed. One commonly accepted US variable for proxy structural vulnerability and affordability is mobile homes (Cutter et al., 2008; Cutter et al., 2003; Cutter et al., 2000; Deyle et al. 2008; Finch et al., 2010; Flanagan et al., 2011; McGuirk & O'Neill, 2012; Reams et al., 2012; Rygel et al., 2006; Schmidtlein et al., 2008; Sherrieb et al., 2010; Tapsell et al., 2010). Topping the charts for EU population density (behind the small island nation of Malta), the Netherlands has a history of dense population, forcing planners to make the most of the available space. Thus, the Netherlands and much of Western Europe lacks a presence of mobile homes. Norwegian researchers have addressed solutions for geographic and cultural issues such as housing quality and other US Conceptual dissimilarities. A product of the Built Environment Vulnerability Index (BeVI), Norwegian housing quality is determined by the age of residential construction (Holand et al., 2011; Holand & Lujala, 2013).

Norwegian researchers Holand and Lujala stress the requirement of local concern for concepts validity. Holand and Lujala apply the concepts and methods of the 2003 US SoVI directly to measure social vulnerability in Norway. Researchers also present a method to measure

social vulnerability in Norway with the application of concepts adapted from the US SoVI, split into the Socioeconomic Vulnerability Index and a Built Environment Vulnerability Index developed for localized validity developed by Holand et al. (2011). Authors compare the results of direct migration of US SoVI variables to a dataset of conceptually, technically, and geographically adapted variables based on the US vulnerability concepts. Upon comparison of the two indexes, moderate correlation of r=0.44 and only 19% variation in the adapted model explained by the SoVI replication, indicating a necessity for conceptual adaptations when building an index from concepts developed elsewhere (Holand & Lujala, 2013). After providing a template of model adaptation, authors stress the conclusion that “a model for one location should not be applied to other locations without thorough contextualization” (Holand & Lujala, 2013). These findings are supported by O’Brien et al. (2004), who declare that different concepts of vulnerability returns vary with different results when quantified.

One problem that arises when adapting methods from foreign studies is the availability of data. Each nation gathers data on its citizens to measure culturally relevant trends of domestic interest. These institutions often differ in the way information is collected, altered for privacy, and its availability for public acquisition. Holand and Lujala’s (2013) adaptation of the US SoVI contributes as a template for effective methods application in Norway and other Western Coastal European nations by providing technique for conceptual, technical, and geographic adjustments of indicators to provide added value for measurement in Norway (Holand & Lujala, 2013).

One problems encountered within related literature is the growing list of methods for analysis without comparisons made to previous studies to present variation in the model results. The ability to assess the accuracy of measurement technique is important for the advancement of the process. Researchers seek methods that prove reliability to support methods replication for the

advancement and improved awareness of social vulnerability and related concepts. Similarly, the ability to distinguish the validity of a study is important to confirm its reliability. Citing the work originally presented by Campell and Fiske (1959), Hammersley adds clarity for distinguishing the concepts, stating, "Reliability is the agreement between two efforts to measure the same trait through maximally similar methods. Validity is the agreement between two attempts to measure the same trait through maximally different methods" (Hammersley, 1987). In the context of social vulnerability measurement, proving reliability is difficult due to dynamic temporal and spatial variation of indicators of social vulnerability. Proving reliability is not easily achieved, but the ability to claim validity for a method may be assessed to a degree on a case-by-case basis.

Model validation assesses the quality of an index. Validation is performed qualitatively with the acquisition of descriptive support such as expert opinion, or empirically with secondary statistical analysis. Supported by the BBC Framework (Birkmann, 2007) validation can be accomplished with assessment of feedback of real-world exposure situations as a form of *in situ* comparison from a source other than data used for primary analysis **(**Figure 4). Few related literature contains methods for validation and less present successful findings. Validation relying on expert decision presents questionable efficacy, and cannot be recycled across scales of analysis. Proposed methods to assess model quality include the application of simple correlations, logistic regression, comparison to annual economic loss, comparison to recovery, and comparison to previous studies (Cutter et al., 2003; Fekete, 2010; Finch et al., 2010; Ge et al. 2013; Sherrieb et al., 2010). Of the validation techniques reviewed, the most logical and effective quantitative validation was developed for Alexander Fekete's (2010) assessment of social vulnerability to river floods in Germany.

Fekete considers locally validated concepts and metrics of social vulnerability is found in the German SVI, with consultation of a household survey of flood victims in three German states for the 2002 multi-river disaster. The survey was designed to collect characteristics of property damage, but value was placed in the survey's dimensions of preparedness and recovery to help validate the social vulnerability index (Fekete, 2010). The household survey provides support for the construction of a logistic regression of to validate PCA results of German social vulnerability.

The straightforward approach of the US SoVI provides methodological simplicity, but contains some rigidity hindering effectiveness of aggregation of index scores. Following a Principal Components Analysis with Varimax rotation, factor scores are retained to build the index. Factor retention is decided, then the general influence a factor has on relation to vulnerability is considered. If the factor tends to increase vulnerability, the direction of the factor is left alone. If the factor represents a general capacity to decrease vulnerability, the directions of the signs of the individual factor scores are reversed. In the case that the factor has arbitrary contribution to concepts of vulnerability, the absolute values of the scores are added to the index. The sum of the factor scores is thought to represent the social vulnerability without assumption about the importance of each factor on the overall measured vulnerability. This method is accepted among many researchers, but not selected for application to the Zeeland SVI. Baker (2009) suggests that the practice of selecting factor scores for index construction is a method the indexes an index. In addition, the index treats all variable in the dataset as if they contribute to social vulnerability equally. The Factor Analysis offers a solution to determine how important each factor is for explaining variance within the dataset. When a dataset has been constructed with thorough consideration to the study area, it seems sensible to allow the model to decide the importance a factor has on the model at a whole. The method selected for index aggregation for

the Zeeland index draws from Baker's (2009) weighted-average technique. Later included for indexing the Gulf of Mexico Counties Resilience Capacities by Reams et al. (2012), this method builds weighted index scores based on the actual data for the dominant variables of each factor, which are added for a total score. The weighted method is selected for its use of real data rather than factor score, and reduced generalizations of factors.

Principal Components Analysis (PCA) is prevalent for data reduction in similar studies, but was more commonly accepted for use in early social vulnerability indexes. PCA has been questioned for seeking maximizing variations, which may distort real-world representation perceived conditions (Reams et al., 2012; Sarkar et al., 2008). Selecting PCA as the primary reduction tool can result in falsely inflated variance and communalities due to the consideration of both unique and common variance when determining a solution. Recent literature shows a shift towards the employment of Exploratory Factor Analysis (FA) with Principal Axis Factoring also known as Iterative Principal Factoring. FA methods are considered superior for measuring vulnerability due to a focus placed on correlations rather than variance (Reams et al., 2012). FA methods target pattern in the data by ignoring unique variances in the solution (Holand et al., 2011). Targeting patterns in the data results in reduced total explained variance, suggesting less distortion.

To assess the quality of input data and model results, several quality tests must be acknowledged. Bartlett's Test of Sphericity is a test to determine homogeneity (or redundancy) in the dataset. Bartlett's statistic tests the correlation matrix against the identity matrix, checking if all diagonal values are 1, and off-diagonal values equal 0. A significance value less than 0.05 indicate that a Factor Analysis may be suitable for the dataset on hand (IBM, 2014). Similar to Bartlett's Test, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) is the final test

of data quality. KMO tests the quality of the dataset by observing partial correlations between two variables. A KMO score of 1.0 indicates optimal suitability for Factor Analysis. A lower limit for the KMO Test is often cited as 0.6, which indicates that a proportion of variance among the variables might be caused by underlying factors (IBM, 2014). If previously identified precautions and assumptions of FA are met, the KMO Test should present a statistic well above 0.6.

CHAPTER 3: STUDY AREA AND DATA

3.1 Study Area

The Netherlands is a relatively small nation nestled between Germany and Belgium on the North Sea. Twelve provinces make up 33,718 square kilometers of land mass, which is just larger than the US State of Connecticut. In 2012, Centraal Bureau voor de Statistiek, or Statistics Netherlands (CBS) counted 16,730,350 inhabitants distributed at an average 496 persons per square kilometer (CBS, 2014). The area of interest for this analysis is the Southwest Delta (SWD) of the Netherlands, which is located where the Rhine, Meuse, and Scheldt Rivers meet the North Sea to form a historically tide-dominated delta with relatively low river discharge. The Rhine and Meuse empty into estuaries closed from the sea with average annual discharge rates of 2,300 and 230 cubic meters per second respectively (Delta Alliance, 2014). The Scheldt River flows through the Westerschelde into the North Sea with an average discharge rate of 104 cubic meters per second (Baeyenset al., 1998), although discharge is not the factor of vulnerability for the Scheldt River. Vulnerability in terms of flooding may be greatest on the banks of the Westerschelde, which is the only Dutch estuary with un-managed tidal influence common in excess of four meters (Van den Berg et al., 1995).

The Southwest Delta was the initial scope for the analysis, although due to a large portion of the eastern boundary decided by a soil transition, it was decided that the extent of Zeeland, the southernmost province of the Netherlands would serve as the extent of the study area. The fragmented province of Zeeland contains less than half the landmass of Rhode Island, totaling 1,835 square kilometers with a 2012 population of 381,400, or about 214 persons per square kilometer (CBS, 2014). Zeeland is a province vulnerable to coastal and river flooding among other disasters. It consistently contains some of the lowest elevation for the Netherlands. With almost

one-third of the province resting below sea level, the average elevation for the districts is 1.1 meters above sea level (Rijkswaterstaat, 2014). The land below sea level in Zeeland is illustrated in orange in Figure 6.

Public CBS records were observed between years 2003 and 2013 to develop a broad understanding of the data available in Zeeland and shifts in political boundaries. The detail of shorelines and the differentiation between surface covered by soil and water improved greatly over the observed decade. Spatial scale of wijk (districts) was essential to process the data with adequate spatial variation while retaining a high level of data richness. In 2013, a consolidation of districts mainly within the municipality of Terneuzen led to a reduction from 164 to 141 districts in Zeeland, resulting in dismissal of 2013 data for analysis purposes. District boundaries for 2012 provide 164 high-resolution geographic units for spatial analysis and validate data for years prior to 2012. The small area per case is advantageous for defining spatial variation, but limits the data available for analysis. District boundaries for 2012 are mapped respective to their municipalities in the Figure 7, Zeeland Reference Map.

Much of the CBS data is collected at the levels descending from province, municipality, district, and neighborhood. As the size of the political area decreases, so does the amount of available data. District level data is a good fit for this study because it contains a high level of detail for the relatively small area. The CBS defines a wijk (district) as “Part of a municipality where a specific form of land use or building is predominating e.g. Industrial, Housing with high or low building” (CBS, 2014). Zeeland is an agricultural province with larger districts and lower population density than the Dutch national average. In Zeeland, there is an average of 12.6 districts in 13 municipalities. The national average for district land mass is just under 7 square kilometers,

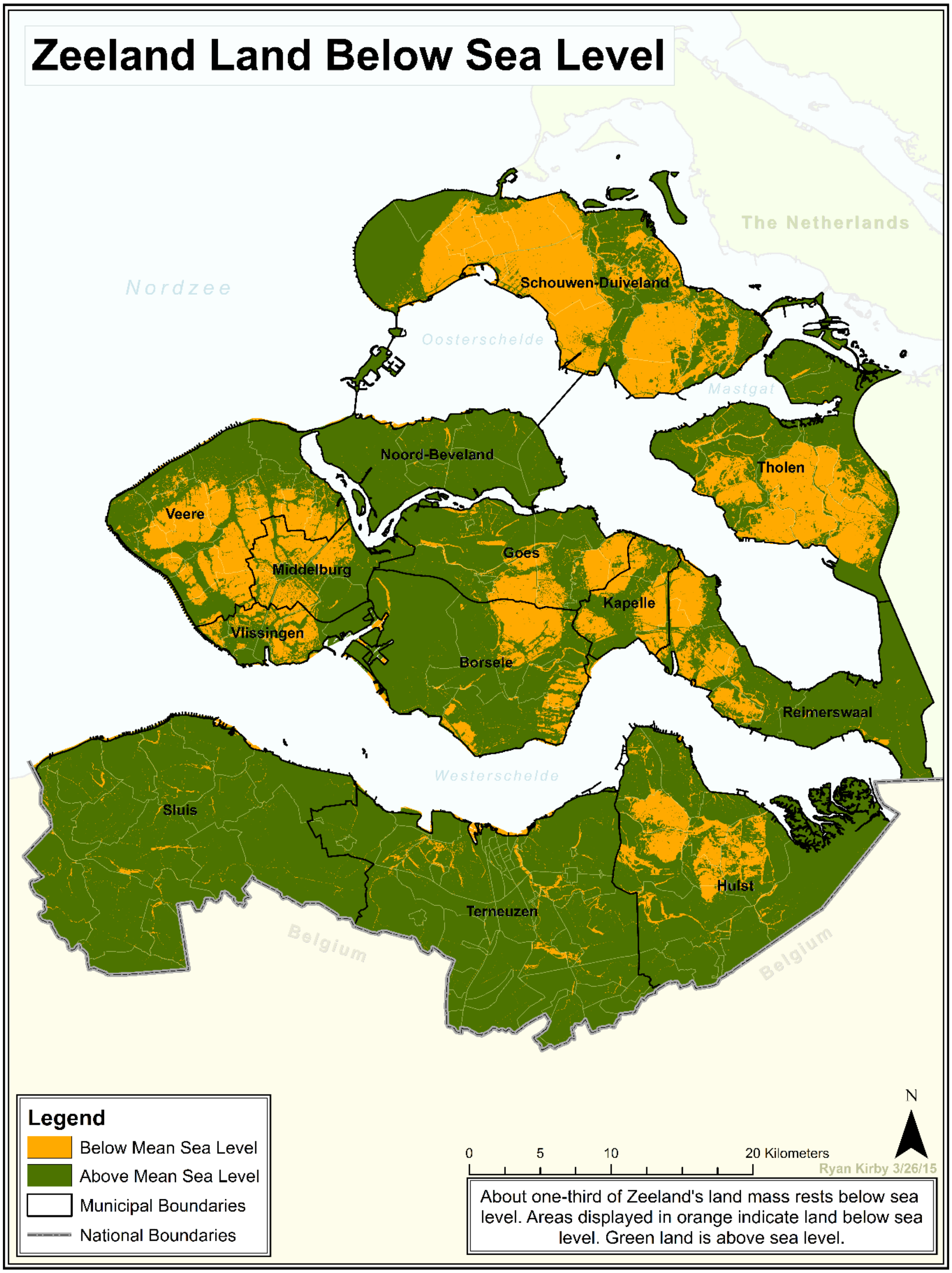


Figure 6: Zeeland Land Below Sea Level

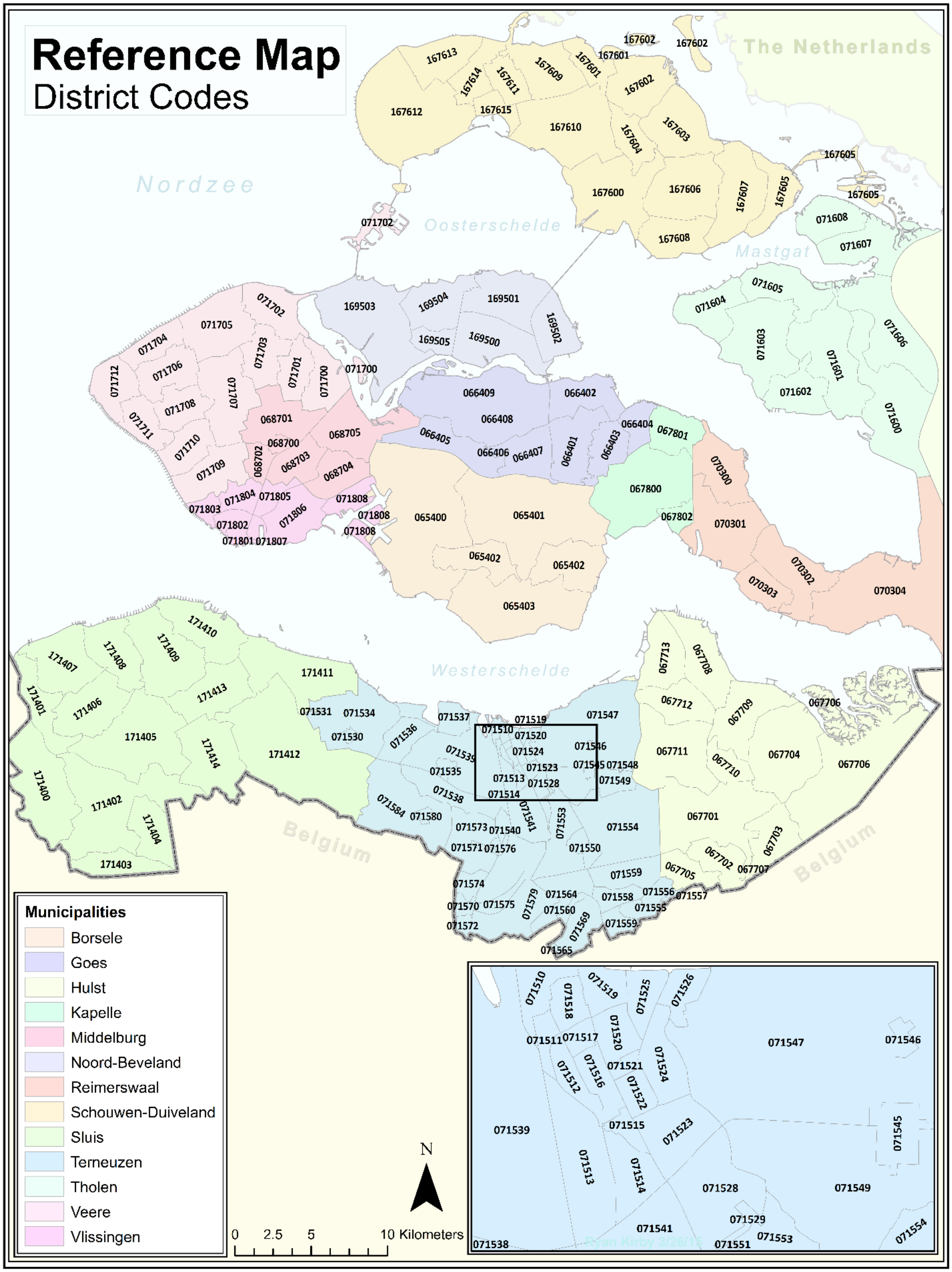
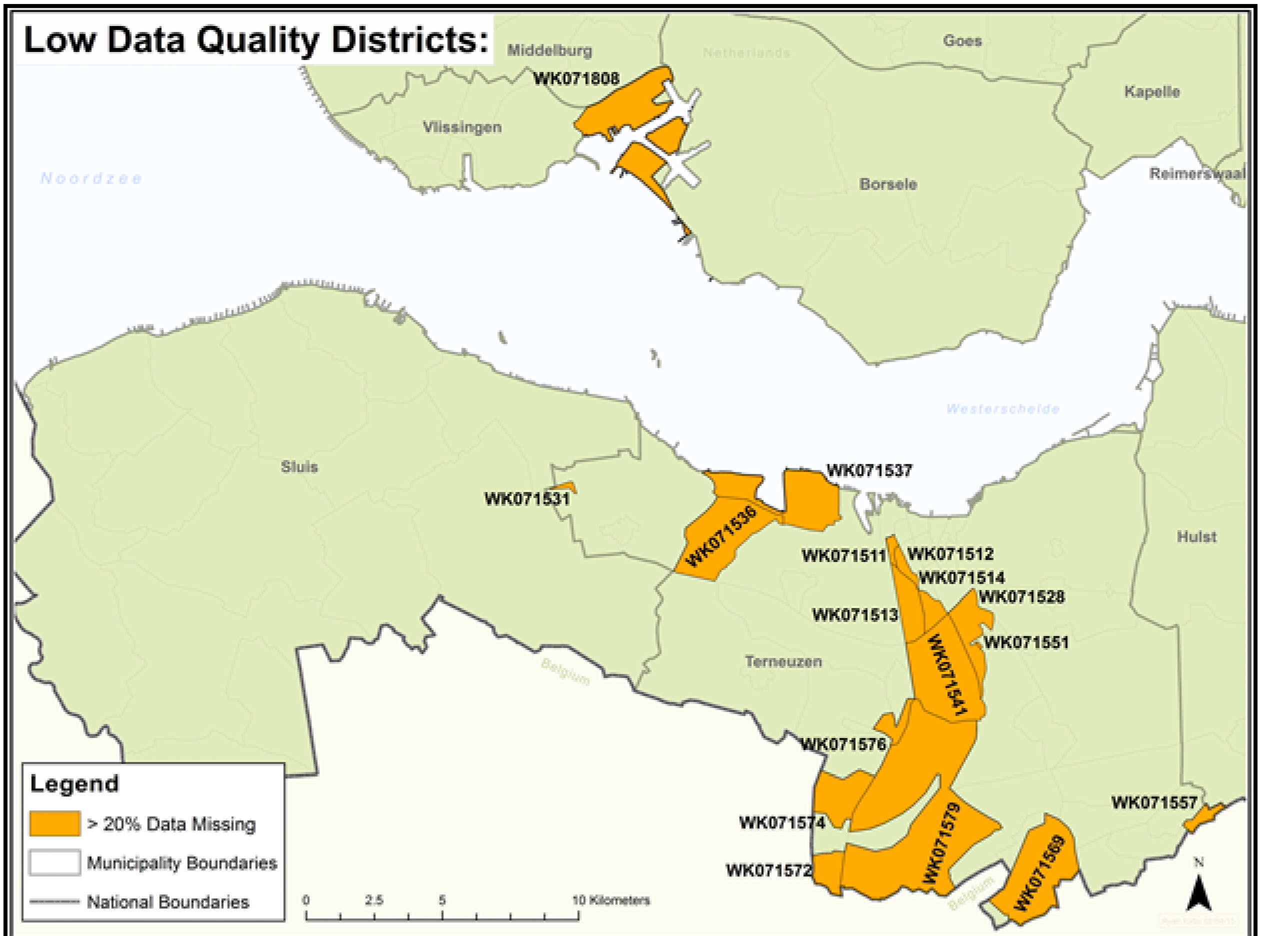


Figure 7: Zeeland Reference Map

but Zeeland contains larger districts, with an average district land mass just under 11 square kilometers (CBS, 2014). Areas that lack sufficient population or development density are problematic in Zeeland at the district level. Data suppression recoding values to "secret" is common to all KWB human information if a neighborhood contains less than 50 total residents, but ranges to a minimum of 200 for income-related data. Only two districts in the municipality of Terneuzen rest below the 50 resident population threshold, but all but one district of Terneuzen contains less than 200 inhabitants in 2011 after 2012 data was collected. Household data undergoes suppression relative to sensitivity at a threshold of 20, 50, or 70, depending on the variable. Terneuzen contains 25 districts that fall below the highest threshold of threshold of 70 housing units per district. Districts identified for containing low data quality are flagged for reliability and mapped in Figure 8, paired with a brief description of dominant land use(s), although remain included in the study with limited utility. It is understood that the nature of the wijk considers the inclusion of similar land-use types. The case of the Vlissingen district 71808 is a fine example of land-use consideration for boundary decision, where the harbor makes up the entire district. The districts identified as low data quality are mostly industrial and the remaining simply lack in stature.

3.2 Environmental Hazards and the Netherlands

The Kingdom of the Netherlands is a coastal nation with high exposure to natural hazards. The type of hazard posing the most threat to human life through history is transparent through the name the "Netherlands," or lowlands. Modern Dutch owe about half of their landmass to an ongoing victory against the sea through the construction of polders, but flooding in the Netherlands wreaked havoc throughout history, even becoming part of the Dutch culture with the erection of Terps, or elevated land to serve as community safe havens. The earliest known reports of flooding



WK Code	WK Name	GM Name	Total Pop	Primary Land Use
WK071511	Noorderdokken	Terneuzen	0	Commercial/Industrial
WK071512	Haarmanweg	Terneuzen	35	Commercial/Industrial
WK071513	Zevenaar	Terneuzen	0	Chemical Industry/Industrial/Shipping
WK071514	Handelspoort	Terneuzen	40	Industrial
WK071528	Buitengebied Zuid	Terneuzen	30	Agriculture
WK071531	Driewegen	Terneuzen	85	Residential/Agriculture
WK071536	Hoek-Braakman	Terneuzen	40	Wetlands/Residential
WK071537	Hoek-Dow-complex	Terneuzen	0	Chemical Industry
WK071541	Sluiskil-Buiten Oost	Terneuzen	25	Industrial/Agriculture
WK071551	Spui	Terneuzen	25	Residential (block)
WK071557	Emmabaan-Oost	Terneuzen	95	Residential/Agriculture
WK071569	Overslag-Buitengebied	Terneuzen	90	Agriculture
WK071572	Buitengebied-Zuid	Terneuzen	20	Industrial/Agriculture
WK071574	Buitengebied-Noord	Terneuzen	20	Chemical Industry/Agriculture/Residential
WK071576	Stroodorpe	Terneuzen	15	Commercial Shipping
WK071579	Buitengebied	Terneuzen	30	Agriculture/Commercial Shipping
WK071808	Sloegebied	Vlissingen	0	Harbor

Figure 8: Low Quality Data Districts

in the Netherlands date to the ninth century in 838, when Bishop Prudentius of Troyewhich recorded the effects of a flood that claimed a reported 2,437 lives (Deltawerken, 2004). Following bombing and German occupation during World War II, the Netherlands stood with crippled flood defenses. In 1953, a winter windstorm invaded from the North Sea at the time of a spring tide. During the first night of February, the combination of wind, water, and low barometric pressure produced a surge of seawater that overwhelmed dikes and flood defense structures in over 70 locations, leading to the most destructive event for human and economic loss in recent Dutch history. The devastating flood motivated formation of the Dutch flood defense program, “Delta Works.” The Delta Works developments have successfully reduced flooding to localized pockets since the 1953 flood by providing barriers to close off many of the nation’s estuaries. Flooding in the Netherlands carries the threat of large economic and human loss largely due to complex infrastructure and high density of development in many areas built over a flat deltaic landscape.

Hazard mitigation efforts have earned the Netherlands global recognition for disaster resistance. The 2012 United Nations (UN) World Risk Report recognizes the Netherlands for maintaining a high level of resistance to risk. “In terms of exposure, this country ranks 12th among the states most at risk worldwide. However, thanks to social, economic, ecological and institutional factors, the Netherlands has reduced its disaster risk enormously, and in terms of risk ranking worldwide, it is ranked 51st (globally for national risk)” (Shepard et al., 2012).

Between 1980 and 2010, the Netherlands has suffered from 27 events considered natural disasters (EM-DAT, 2010). The most common natural disaster events affecting the Netherlands during the 30 years is storm (18), followed by extreme temperatures (4), flooding (3), earthquake (1), and epidemic (1). These events varied greatly in magnitude, but together, the 27 natural disaster events resulted in 2,013 deaths and over $4.5 billion worth of damage (EM-DAT, 2010).

Storms may occur at the greatest frequency in recent Dutch history, but the largest threat to human health is a result of extreme temperatures. Since 1980, deaths have resulted from extreme cold and heat, but heat has proven a much larger threat to life. In 2003, a heat wave contributed to 965 deaths. Three years later, the Dutch suffered a second heat wave, resulting in 1,000 deaths (EM-DAT, 2010). Between 1980 and 2010, the death rate resulting from natural disasters averaged 1.3 persons per 10,000. Though this number is relatively low, the majority of deaths are overtly due to social vulnerabilities and inequalities. An optimistic result of this study is to provide technique and data that can deliver insight to reduce socially influenced mortality through identification of current pockets of socially vulnerable areas within the Netherlands with potential for monitoring though repetition for future years.

The Netherlands could endure some of the greatest potential climate change consequences in the EU. It is suggested that assessing vulnerability as an end point is useful for measuring the impacts of climate change and costs of adaptations for mitigation (O'Brien, 2004). Climate change projections lead researchers to believe that future populations will endure increased frequency of weather events on both the wet and dry side of the norm. While the recent record points to extreme temperatures posing the greatest threat to the Dutch, EU researchers expect future threat of increased winter precipitation in the European northwest. An increased input in the regional hydrologic budget could affect river flow rates in the winter and spring months thus increase potential for flood disaster events in the Netherlands and the surrounding northwestern nations (EAA, 2012). Most climate models forecast an additive trend of exposure for coastal nations, pairing the looming threat of sea level rise to potential for increased river discharge. Elevated sea level causes complications for not only flood defense planning and maintenance, but also unknown impacts due to altered hydraulic gradients at pump stations and drainage systems among other

complications for lowlands. One high-end scenario for sea level variation projects a range of 40 to 105 cm increase for year 2100. From a relative perspective, high waters will be witnessed lapping on the shores of a subsiding landmass largely due to the compression of peat soil in the Dutch polders (Katsman et al., 2011). Although the Dutch have proven to exhibit a capacity to prepare for disaster through engineered resistance, the Netherlands still possesses potential for large environmental impacts from climate change in the future.

In January 2014, residents in the provinces of Noord and Zuid Holland were under threat when, in some places, 15 cm of rain fell in less than 24 hours. Panicked citizens deluged first responders with calls of questionable emergency. Flooding forced closure of portions of Amsterdam's A10 ring highway. Other local arteries endured lane closures. The threat of dike failure in Alphen aan den Rijn caused localized road closures for travelers crossing the Noordzee Kanal. Closure of the Velser Tunnel provoked large traffic jams around the Velsen area. Station flooding and a lighting strike crippled public transportation and Amsterdam's Schiphol airport closed for nearly two hours, delaying flight traffic at Europe's fifth largest airport. Rijkswaterstaat made the decision to close Oosterschelde storm surge barrier twice within one year in December 2013 and October 2014, taxing the marine ecology with tidal stagnation in the mussel-rich Oosterschelde estuary. The high water events also threatened with closure of the Maeslantkering, which dams the Noordzee Kanal and results in a halt of goods transportation from the North Sea to inland harbors.

Recent exposure events are useful for the identification of indicators and metrics of local social vulnerability. Averting any fallacious assumptions, the consideration of public reaction to small-scale exposures such as the January 2014 flooding should be noted but disregarded for any model validation. It would be incorrect to assume that all of the Netherlands is capable of

responding to disaster in a homogenous manner based on a few cherry-picked data points. It is also incorrect to assume that the Dutch would react to an event in the same manner as to the Flood of 1953. Not only has the complexity of infrastructure and flood management grown far beyond those present in 1953, but also most of the current Dutch population has not lived through the damaging effects from a large-scale disaster.

When a community is impacted by a disaster event such as but not limited to the wet and dry events discussed above, demographic sub-groups will be impacted in differing magnitudes, thus setting the stage for varying responses among the different demographics. One of the best-known tools to mitigate disaster and decrease recovery time is wealth. Although, an excess of wealth may also provoke unsustainable building practices in areas with high potential for exposure such as the aesthetically valuable coastal fringe (Cutter et al., 2003). In the case of US disasters, the coastal fringe is responsible for some of the costliest recovery zones due to the increase of assets of wealth found in vulnerable areas. However, with wealth comes stability and often the construction of social capital and greater safety nets (Cutter et al., 2000). On the other side of the coin, one commonly acknowledged attribute of a vulnerable sub-population is the large presence of foreign individuals. Foreign persons often exhibit a reduced ability to understand and communicate changing threat levels and lack a social support group (Cutter et al., 2003; Fekete et al., 2009; Holand & Lujala, 2013). When attributes influencing vulnerability such as wealth or foreign populations occur in small or large ratios in a study area, it is assumed that the geographic unit contains a reduced or increased capacity to mitigate disaster. While the persons within an area exhibit a certain level of vulnerability, the collective product of their actions builds a capacity to handle the burden disaster events. When a burden of natural disaster is placed on a society inexperienced with disaster events, the reaction may be different from one that, for example, is

impacted by hurricanes every few years. Without a dimension of exposure to large-scale disaster events, the capacity of collective action within a society remains largely unknown. A concept closely related with collective action is social capital.

Social capital is one capacity resulting from collective action that can be observed and measured without the requirement of a shock to the system. The level of social capital in a community is an important indicator for vulnerability and resilience research, and is a common concept for measurement in the Netherlands (Bekkers & Veldhuizen, 2008; Kunst et al., 2013; van Beuningen & Schmeets, 2012). In his 2003 publication *Social Capital, Collective Action, and Adaptation to Climate Change*, Neil Adger dissects the meaning of social capital. Adger explains that social capital "describes relations of trust, reciprocity, and exchange; the evolution of common rules; and the role of networks" (Adger, 2003). Asserting the role social capital plays in society, Adger claims, "Social capital is a necessary glue for adaptive capacity, particularly in dealing with unforeseen and periodic hazardous events" (Adger, 2003). Social capital exists publically and privately, but most noticed as a product of the actions of the state. The presence of social capital is evident in many forms throughout the Netherlands. One of the most prominent examples of Dutch social capital is the long-lasting success of the Dutch Water Boards. Since the 13th century, the people of the Netherlands have enthusiastically fought for rights to their low-lying land with an army of Water Boards. In 1850, a mass of 3,500 Water Boards stretched across the flatlands. That number dropped to 2,500 in the late 1940's. The latest consolidation has brought the total number of Dutch Water Authorities to 23 Water boards across the Netherlands (Lazaroms & Poos, 2004; UVW, 2014). Some of the success of the Water Boards lies in their decentralized structure and independence from the central government. Dutch Water Boards are 95% self-supported financially through Water Board charges and a pollution levy to provide services of flood

protection, surface water quantity management, water quality management, as some infrastructure management including access roads and bike paths (Lazaroms & Poos, 2004). Historically, the Water Boards have provided a high success rate for defense against high water. The large number of water boards provided localized attention to detail. Currently, the Province of Zeeland is reliant on the Scheldestromen, or Scheldt flow board for water management.

Flood protection in the Netherlands exists in more places than the vast network of pump stations, dykes, sluices, and dams. Nationally, 26% of the Netherlands is below sea level. Creative and "non-structural projects," a concept of the Louisiana Coastal Master Plan, are widespread in the form of floating houses and flood-proof construction. The strategy of "living with water" has sparked the ignition of a knowledge program dedicated to using water as an opportunity and challenge rather than a threat. Self-organization and preparation is particularly necessary in the province of Zeeland due to low elevations.

Researchers have calculated flood risk and probability within the VNK analysis. Social capital and social cohesion has also been measured and mapped for Dutch municipalities (Bekkers & Veldhuizen, 2008; Schmeets & te Riele, 2013; van Beuningen & Schmeets, 2012; Vergolini, 2010). To my knowledge, there has not been an empirical assessment measuring the social vulnerability of the Dutch population. The VNK2 addresses risk to flooding and the financial implications for each flood scenario using probability and consequence data, but it does not provide area-specific implications of flooding in respect to the human-related susceptibilities after a disaster event. In respect to flood impacts, the ability to determine disaster impact from a human dimension is valuable information when observed at a scale that delivers variation within a municipality. Conceptually related previous social capital and social cohesion studies performed at a larger, municipal scale, fail to identify pockets of socially vulnerable citizens.

3.3 Data

Initial data collection was broad in order to capture any relevant attributes of community vulnerability. A majority of the data obtained was publicly available through several agencies. Statistics Netherlands (CBS) publishes district-level data in a document titled StatLinepublicaties Kerncijfers wijken en buurten (KWB). This public database provides information for all of the Netherlands at the spatial scales of the municipalities, districts, and neighborhoods, and reports on the subjects of demographics, employment, living conditions, income, business, work, energy, education, motor vehicles, local amenities, and land use. CBS StatLine also provides data for municipal budgets, which were collected in 14 categories. Specific emissions release data is available through the Rijksoverheid Emissiergistratie Pollutant Release and Transfer Register (PRTR). The Compendium vood de Leefomgeving, or The Environmental Compendium, provides data for highly educated individuals. By special request, Rijkswaterstaat (RWS) provided access to the *Top 10* database, which includes data for elevation, infrastructure, land cover, and administrative boundaries. Data including political boundaries, *mean district elevation* and *length of paved roads per vehicle* were extracted from the RWS database using ESRI ArcMap 10.2.2.

Data provided by the RWS made it possible to generate variables to represent geographic attributes. Some place-based attributes are mapped to represent land use combinations that affect recovery after a hazard event. It is noted that custom variable construction is not always a feasible route for large-scale modeling, but can aid in data interpretation and understanding of the model results even when not used for analysis. For example, in relation to the destruction in Germany caused by the 2002 Elbe River flood, the highest damage occurred to houses and infrastructure, economic values, contamination by fuel tanks, and proximity to chemical industry (Fekete, 2010).

To examine these spatial intersections in Zeeland, districts were identified based on proximity to combinations of these factors as a hazardous land-use combination layer, mapped in Figure 9.

Norwegian researchers include the *length of roads per capita* as a measure for evacuation potential. RWS data made replication of this concept possible by providing geodata for roads. In Zeeland, there is an average of 1.1 more persons than vehicles per household, which poses the concern of correct distance normalization for concept adaptation. The task was achieved by exporting highways, regional roads, and main local roads to a new layer, then using the "Identity" tool to count the length of the roads within each district. For a nation with more vehicles per length of road, less vehicles per capita, and a heavier reliance on public transportation (Ministry of Transport, 2010; Norway, 2014; World Bank, 2011), the limiting factor for evacuation in the Netherlands could be represented better by normalizing the length of road with the number of passenger cars in a district. Elevation data for the Netherlands is provided by RWS at a resolution of 5x5 meter grids. Again using ArcMap, 2012 raster image data was combined into a single map to represent an exposure potential and analysis device using the "Mosaic" tool. Elevation values were extracted for districts using the "Zonal Statistics as Table" tool. Variable generation with GIS proved to be successful for increasing the amount of data valuable to the study area by filling gaps where data is not provided by CBS documents. Most of the data used for analysis represented 2012 conditions, although cases were observed from 2003 to 2012 to build a KWB dataset for 180 fields. When 2012 data was unavailable, the previous nearest year was selected. All data besides the population change information included in the final model is from 2008 to 2012. Variables were observed at the municipal level when district level data was unavailable. This information includes municipal budgets, emissions release, and highly educated individuals. The complete initial database contained over 200 community attributes in over 20 analytical categories.

Figure 9: Hazardous Land Use Combinations

CHAPTER 4: METHODS

4.1 Data Preparation

The initial raw data pool contains over 200 variables for consideration. Once data is screened to recommend deletion of variables containing more than 20% non-number values, the subset is assessed for quality and relevance with consideration of ability to measure vulnerability. Data is normalized to convert absolute or continuous variables to functions of percent, per capita, or density. The normalized dataset is assessed statistically for problems with correlation, low communalities, and high cross loadings to shed redundancy and improve the dataset for analysis. As variables are removed from the dataset, the KMO Test is observed to confirm data improvement. Following the reduction for quality, a subset of 44 variables containing a KMO statistic of 0.754 was left for further investigation.

To reduce this dataset to a more manageable input for size of the sample of 147, a manual reduction tests conceptual, technical, and geographic ability to measure vulnerability in Zeeland. In addition to removing less important data, manual data reduction aims at targeting over-representation of concepts of vulnerability and proxies of unclear concepts, with the added benefit of achieving a more acceptable subject to item ratio. Variables that require an argument for the reader to understand the conceptual link should be considered for elimination for the reason that they could complicate interpretation of factors. Within the 2003 US SoVI, when sorting the 42 variables into the 17 concepts of vulnerability, the placement of *"Vote cast for president, 1992—percent voting for leading party (Democratic)"* does not appear to represent any of the listed concepts of social vulnerability. A link may be apparent to the authors, but may be considered subjective to the reader.

To guide the process, Factor Analysis helps to support decisions for manual reductions of the dataset. Variables that load similarly within a factor are considered for removal due to redundancy. Variables found loading significantly across two or more factors are considered for removal to clarify factor arguments. Variables with insignificant loadings are considered unrelated, and flagged for removal. Communalities are sorted, and lowest values were marked for examination. In addition, linear regression helps to strengthen the argument for the exclusion in redundant variables using correlation statistics. To determine the appropriate variables to remove from the dataset, VIFs are consulted to determine cases of extreme collinearity among variables. Inflated VIFs shared among conceptually related variables required examination of each variable's ability to represent vulnerability in Zeeland. For example, *Dwelling density* and *Population density* presents extreme collinearity in the Zeeland dataset. Each variable is a clear indicator of vulnerability in an urban environment, but *Population density* is determined more valuable for measuring a social condition. Although the dataset has been screened previously for problems with correlation, regression is helpful for supporting means of deductive data reduction.

Manual data reduction involves methodical removal of variables while monitoring the quality of the dataset. The methods were responsible for narrowing the data for analysis from 44 to 35 variables. The remaining 35 variable dataset is considered suitable for Factor Analysis due to an acceptable KMO value of 0.757, with limited municipal influence and reduced conceptual redundancy.

One problem for Factor Analysis arises in the presence of missing values. The KWB documents did not contain any empty cells, but some cases were suppressed for various reasons. The greatest amount of suppressed data was coded as "secret", followed by "nil", and a small portion coded for "missing". The primary reason for missing values is due to a small population

within a district. A high level of data completeness is important for a quality analysis, so limits for data inclusion due to incomplete variable were set with an upper limit of 20% missing values. Initially, variables with a larger portion of missing data was included due to unique concept representation, although many of these variables were filtered from the input dataset due to failure to meet additional quality standards.

Non-number values were present throughout the CBS datasets. In the complete KWB dataset for the 164 districts of Zeeland, 13% of the data is coded as a non-number value at the district level. To filter away low quality data districts, those missing more that 20% of their data for 2012 were filtered from the dataset, resulting in 147 input districts. Low quality data districts listed in Figure 8 represent mostly industrial and heavy commercial land use, where little or no residents are contained in the districts. When authors of the 2003 US SoVI were faced with missing values, a zero value was substituted. It is important to note that a missing value is very different from a zero value, and the two must be handled with more care. Following this method could lead to inaccurate spatial representations in the Netherlands largely due to over 90% of the total missing values coded as secret information due to small district populations. In 2008, Cutter and Finch updated the US SoVI and added a dimension of temporal analysis. Instead of replacing missing values with a zero value for US counties as done previously, the average state value was calculated and substituted. The results of the method improvement accounted for a shift from 11 to 12 factors explaining a shift from 76.4% to 77.99% of the total variance for the 1990 dataset following identical analysis procedures (Cutter & Finch, 2008). Similarly, in the German SVI, Fekete replaced missing county averages with overall variable averages. For missing CBS values, it was decided that municipality averages would be substituted for district values. Based on the assumption that districts within a municipality are more closely related to each other than they are

to districts outside of the municipality, this method aims to retain maximum regional variation at the highest achievable level of accuracy. The province average substitutes one missing municipality value (for *% Highly educated individuals*).

One method to adjust data to compensate for completeness is to combine variables that explain the same concept of social vulnerability. Most researchers agree that foreign populations and minorities are vulnerable to disasters for reasons including unsupported social networks or unfamiliarity with the area and changing threat levels. Data suppression results in limited representation of western and non-western immigrants with 44% of foreign populations data suppressed at the district level in the 2012 KWB document. To boost the utility of data on foreign populations in Zeeland, all foreign classes were combined to express foreign population presence as a total single value, and named "*FOREIGN*."

Difference in the level of data observation and the level of analysis raises concern of cross-scale influence on factor groupings. Municipal level variables of interest including the percent of highly educated individuals, municipal budgets, and emissions release data. Experimental analysis explored interpolation for data downscaling to retain maximum spatial variation through discrete consideration of the district level. Testing various techniques suggested that scale manipulation results in unnecessary subjectivity, thus any municipal level variables are included in the input dataset as homogenously repeating municipal values for respective districts, and normalized as per-capita and density functions.

4.2 Factor Analysis

The selection of the correct extraction method is the first concern for statistical procedure. Principal Components Analysis (PCA) is popular among social vulnerability indexes (Cutter et al.,

2003; Cutter & Finch, 2008; Doba et al., 1999; Fekete, 2010; Finch et al., 2010; Holand & Lujala, 2013; Holand et al., 2011; Schmidtlein et al., 2008), although others consider PCA to be an incorrect method of primary analysis. Principal Axis Factoring extraction targets patterns in the data through consideration of only common variances. When correlations exist within the dataset, PCA method can present falsely inflated variances. FA Principal Axis Factoring should return stable results regardless of intercorrelation and multicorrelation, thus expanding the amount of appropriate data available to sample (Costello & Osborne, 2005). The Zeeland dataset is built using cited concepts of social vulnerability that tend to relate, therefore Principal Axis Factoring is identified as superior in regard to correct extraction method to build an index of social vulnerability.

Following Factor Analysis, rotation helps to clarify the output matrix by adjusting by strengthening loading values which the rotation methods finds more valuable. Rotation aims to "simplify and clarify" the model (Costello & Osborne, 2005) by increasing the distance between factors. Procedures for rotation are either orthogonal or oblique. While the commonly accepted default Varimax (orthogonal) rotation adds clarity to factor results, it possesses the potential for loss of detail. By definition, orthogonal refers to a situation involving right angles. Orthogonal rotation forces factors to 90° separation, which can distort results in a dataset of known correlation (Matsunaga, 2010), but the simplicity of interpretation offered by Varimax rotation may by responsible for its popular use in similar analyses. Experimental analysis considering both Varimax (orthogonal) and Promax (oblique) rotations identified only minor differences in the results. With little difference existing between rotation methods, Varimax rotation is selected for simplicity of interpretation and common acceptance in related studies.

Factor retention method can also play a large role in the outcome of an index. Additive factor score index aggregation developed for the US SoVI can produce a very different index depending on the number of factors selected to retain. Contrarily, weighting the index using eigenvalues helps build a more robust method for index aggregation when it comes to factor retentions. The most commonly accepted method for factor retention in vulnerability literature is the default application of the Kaiser Criterion that retains factors with eigenvalues greater than 1.0. Costello and Osborne (2005) warn of oversampling, which occurred in 36% of the test models when assessing the quality of the Kaiser Criterion rule (Costello & Osborne, 2005). An often-preferred method of factor retention is Cattell's (1966) Scree Test. Named for the way that waste piles up at the bottom of a hill after a landslide, a Scree plot is a visual method for differentiating between useful variable, and those that are less meaningful based on a point of inflection, or elbow, on the plot (Suhr & Shay, 2008). The Scree test is preferred for large datasets, while the Kaiser criterion is designed to handle small to moderate number of variables (10-30) containing high communalities greater than 0.70 (Stevens, 2012).

Effects of factor retention technique can be amplified by the choice for index aggregation method. For example, experimental testing on the Zeeland data employed for two SoVI methods replications resulted in an 11-factor (Kaiser Criterion) and 5-factor (Scree Test) index, which contained a Pearson's Correlation of 0.645. Factor retention is pivotal for valid index aggregation when following the SoVI technique, but less an issue for the weighted index presented for Zeeland, which can benefit from more factors retained. Therefore, Kaiser Criterion is selected for the method of retention for the Zeeland index to maximize factors for index contribution and explained variance to minimize weight distortions.

4.3 Social Vulnerability Index

Factors loading in the Rotated Factor Matrix confirm dominantly loading variables for each factor for index aggregation. Additional variables are included for factor representation based on qualification by the rules defined below. Variables are examined independently to determine a relationship with social vulnerability. For the purpose of this index, all factors must express a positive relationship with social vulnerability to construct an index of social vulnerability. Variables found containing a negative relationship to social vulnerability are inverted. For inverted variables, the presence of zero values posed the issue of index distortion. To solve this problem, zero density cells are reclassified as the minimum value for the variable to depict an increased vulnerability rather than complete absence.

Weighting is a technique that does not receive much common agreement, although the nature of Factor Analysis supports the application of weighting due to the amount of variance explained by factors. The method proposed for Zeeland introduces methodological subjectivity and suffers from averaging in attempt to improve existing methods for performance in the existence of non-normality in the data found more commonly at the fine scale. Each variable indicates a degree of vulnerability rather than a mixed dataset containing both capacities and vulnerabilities, as commonly observed in similar analyses. The Zeeland SVI is constructed based on the aggregation methods presented by Reams, Lam, and Baker (2012), which are valued for weighting based on rescaled explained variance per factor originally developed for the Master's Thesis of Ariele Baker (2009). The framework for the Gulf of Mexico (GOM) Index is conceptually rooted in the methods developed by Cutter et al. (2003), but researchers dissect statistical methods to improve the ability for the index to convey a condition presented by actual data rather than factor scores. The US GOM Index is valued for its additive average-weighted

index methodology and use of actual data for index construction. The method serves to strip the amount of insignificant data from consideration for the final index, then weights each factor by the variance it explains within the dataset rescaled to 100%. The GOM technique assumes factors contribute to the vulnerability depending on the variance explained by the factor. Thus, the sum of all district scores should mimic the shape of a Scree Plot when plotted per factor. Significance of factor loadings of the Rotated Matrix designates appropriate variables to represent factor contributions. Methods presented by Reams et al. (2012) include single-variable indicators for factors designated by the dominant variable per factor. Testing this method for used in Zeeland reveals un-proportioned factor contributions due to positive skew in the leading factor and negative skew later in the factors. The presence of positive skew suppresses the total amount of index contribution. Oppositely, negative skew distorts factors with large contributions to the index. Results of experimental tests suggest that reduction to single variables per factor may be appropriate for larger scale analyses such as US County level, but application for measurement in Zeeland requires revision to consider more data per factor. The use of multiple variables per factor aims to balance skew in the data to consider more homogenized land use at the Dutch district level.

The issue of non-normality is handled through revision of GOM methods with consideration of multiple variables making partial contributions per factor to the index score. Since the rotated matrix maximizes the representation of relation in variables within a factor, the method relies on significance of loadings for variables selection. The method for variable selection should consider the placement of a variable on both axes of the rotated matrix. Considerations for the effects of cross-loading data are most useful for this step of index aggregation. The rules listed below present criteria for data selection for index development to allow factors to qualify for index contribution.

1. Based on factor loading values of the Rotated Factor Matrix, a variable may only be considered for factor representation on the factor it loads with the highest magnitude.

2. Multiple variables may represent a single factor if they are found loading greatest on the same factor, but in the case that rule #1 is not satisfied, no additional variables may be considered for the observed factor.

Once variables are selected for factor representations, the variables of each factor are weighted and reduced to be considered as a single contribution to the index through partial factor scores. First, the explained variance is rescaled to represent 100%. Variables are normalized to range from 0 to 1. Normalized variables are weighted according to the rescaled variance of the respective factor. For multivariate factors, each variable within the factor is reduced to represent a portion of the factor. For example, if a factor contains three variables, each variable's partial contribution is determined by multiplying its weighed value by 1/3, partial factor contributions are summed for a total factor contribution. Factors represented by a single variable are considered 1/1 of the total factor contribution. The result of the proposed weighting method offers a more general representation of factors, and allows each variable to represent the factor it loads greatest. This method is considered acceptable due to the scrutiny of the quality and manual data reductions previously addressed to determine the input dataset (Table 2). Results also indicate a significant amount of weighting shifted to form scree-like factor contributions (Figure 10), thus improving the weighting assumption of the GOM index that would be observed if all indicators are normally distributed. This adjustment is most applicable when variables are included for conceptual importance rather than quality of data distribution.

Table 2: Zeeland SVI Input Variables

Description	Mean	Std. Dev.	N	Source	Level
(km2) Population Density	792.97	1378.25	147	CBS-KWB	Wijk
% Female	0.49	0.03	147	CBS-KWB	Wijk
% Population Change 2003-2012	11.62	37.94	147	CBS-KWB	Wijk
% Population 65+	19.09	6.06	147	CBS-KWB	Wijk
% Foreign Population	16.31	11.20	147	CBS-KWB	Wijk
% Married	48.34	4.78	147	CBS-KWB	Wijk
% Single Person Households	29.41	7.99	147	CBS-KWB	Wijk
# Passenger Cars per Household	1.23	0.21	147	CBS-KWB	Wijk
# Average Household Size	2.30	0.26	147	CBS-KWB	Wijk
(1k €) Average House Value	207.80	47.26	147	CBS-KWB	Wijk
% Stacked Housing	5.60	10.50	147	CBS-KWB	Wijk
% Old Houses	90.86	8.95	147	CBS-KWB	Wijk
% Rental Housing	25.12	11.94	147	CBS-KWB	Wijk
% Unemployment	25.63	6.06	147	CBS-KWB	Wijk
% Low Income Households	37.97	8.64	147	CBS-KWB	Wijk
(1k € PP) Average Income	21.42	2.30	147	CBS-KWB	Wijk
(1k PP) Income Recipients	715.40	75.55	147	CBS-KWB	Wijk
% Employment Service Industry	62.68	10.88	147	CBS-KWB	Wijk
% Employment Agriculture	6.67	4.99	147	CBS-KWB	Wijk
% Self-employeed	12.03	5.49	147	CBS-KWB	Wijk
(km2) Total Active Businesses Jan.2011	44.66	91.03	147	CBS-KWB	Wijk
(km2) Industry & Energy Businesses	6.17	8.78	147	CBS-KWB	Wijk
(km2) Transport. Info. Comm. Businesses	4.56	7.96	147	CBS-KWB	Wijk
(1k HH) Relative Disability Benefits	66.99	24.33	147	CBS-KWB	Wijk
(1k PP) Health Care Workers	10.16	3.30	147	CBS-KWB	Wijk
(1k PP 3km) Near Hotels	12.88	23.30	147	CBS-KWB	Wijk
(3km) Number of Childcare(s)	3.01	3.66	147	CBS-KWB	Wijk
(km) Distance to Train Station	25.73	16.89	147	CBS-KWB	Wijk
(km) Distance to Medical Services	8.39	4.83	147	CBS-KWB	Wijk
(km PP) Distance Major Roads	75.60	835.62	147	RWS	Wijk
% Agricultural Area	69.40	25.30	147	CBS-KWB	Wijk
% Constructed Area	18.19	25.94	147	CBS-KWB	Wijk
% Highly Educated	19.75	3.21	147	CBS StatLine	Gem
(1k € PP) Spending, Public Order & Safety 2012	4200.06	2500.29	147	CBS StatLine	Gem
(1k € PP) Spending, Social Cons 2012	30641.16	17678.58	147	CBS StatLine	Gem

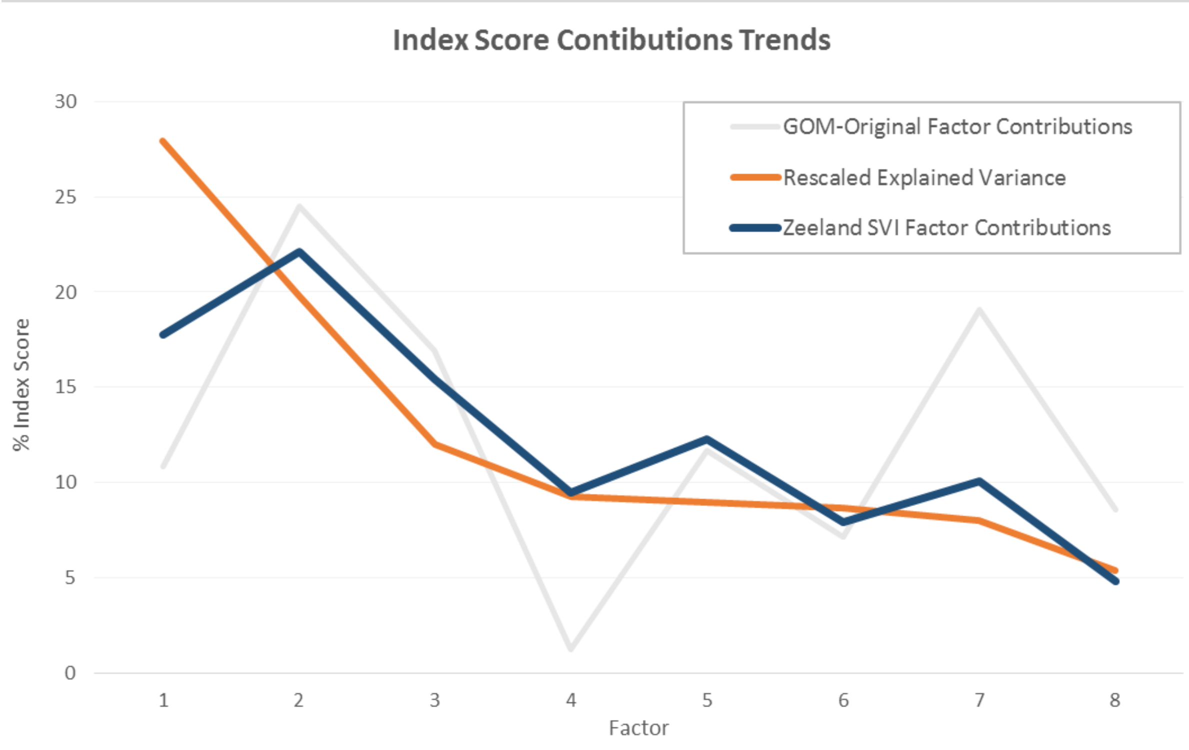


Figure 10: Weighting Trend of Factor Contributions

CHAPTER 5: RESULTS AND DISCUSSION

5.1 Factor Analysis

Statistical analysis methods development of the Zeeland Social Vulnerability Index (SVI) involved a wealth of experimental testing to determine the effects of data collection, processing, and analysis on the level of analysis and data quality. Deductive reasoning employed for methods development is based on literature for similar analyses and Factor Analysis technique. Methods analysis, literature review, and *in situ* investigation of the study area results in an analysis dataset of migrated, adapted, and new proxies of vulnerable populations, which is reduced by Factor Analysis, then aggregated with a new weighting technique based on the work of (Baker, 2009). This "from scratch" index aims to build the utility of the weighting scenario developed by Baker (2009), and practiced by (Reams et al. (2012) with extra consideration paid to the fine level of vulnerability in the districts of the Netherlands.

The input dataset (Table 2) contains 35 variables rooted in previously cited concepts of vulnerability. Data reduction for the Zeeland SVI elects Exploratory Factor Analysis (FA) Principal Axis Factoring to determine useful pattern within the dataset. Varimax Rotation with Kaiser Normalization provides a clear solution for factor assignment and a base for factor weights through perpendicular axis rotation. Factor retention using Kaiser Criterion retains all factors when eigenvalues greater than 1.00. The Total Variance explained is pictured in Table 3.

5.2 Results

Factor Analysis on the Zeeland dataset explains 72.28% of the total cumulative variance with nine factors (Table 4). Varimax Rotation with Kaiser Normalization converged in 10 inclusion of 8 factors, illustrated in Figure 11. This decision is confirmed upon observation of

Table 3: Total Variance Explained

Total Variance Explained									
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cum. %	Total	% of Variance	Cum. %	Total	% of Variance	Cum. %
1	9.964	28.468	28.468	9.752	27.862	27.862	6.880	19.657	19.657
2	4.323	12.352	40.821	4.094	11.697	39.559	4.641	13.260	32.917
3	3.366	9.619	50.439	3.055	8.728	48.287	2.690	7.685	40.602
4	3.021	8.630	59.069	2.795	7.986	56.273	2.571	7.346	47.948
5	2.145	6.129	65.199	1.871	5.345	61.618	2.453	7.008	54.957
6	1.505	4.300	69.499	1.218	3.479	65.097	2.036	5.819	60.775
7	1.269	3.625	73.124	1.000	2.856	67.953	1.839	5.255	66.030
8	1.173	3.350	76.474	.802	2.290	70.243	1.171	3.347	69.377
9	1.040	2.973	79.447	.713	2.037	72.280	1.016	2.903	72.280
10	.930	2.656	82.103						
11	.780	2.228	84.332						
12	.682	1.950	86.282						
13	.562	1.606	87.888						
14	.471	1.347	89.235						
15	.417	1.192	90.427						
16	.391	1.118	91.545						
17	.370	1.057	92.602						
18	.324	.926	93.529						
19	.274	.783	94.311						
20	.268	.767	95.078						
21	.227	.649	95.727						
22	.216	.616	96.343						
23	.196	.559	96.902						
24	.164	.470	97.372						
25	.147	.420	97.792						
26	.132	.377	98.168						
27	.124	.354	98.522						
28	.108	.308	98.830						
29	.101	.288	99.119						
30	.086	.246	99.365						
31	.072	.206	99.571						
32	.052	.149	99.721						
33	.049	.140	99.861						
34	.028	.080	99.941						
35	.021	.059	100.000						

Extraction Method: Principal Axis Factoring.

Table 4: Rotated Factor Matrix

Rotated Factor Matrix[a]									
	Factor								
	1	2	3	4	5	6	7	8	9
(km2) Population Density	.846	.264	.021	-.103	-.192	-.180	-.006	.113	.060
% Female	.013	.497	-.079	-.682	-.054	-.026	.100	.184	.197
% Population Change 2003-2012	.033	-.230	.040	.463	.060	-.037	-.701	.015	-.018
% Population 65+	-.062	.764	-.024	-.118	.053	-.044	.095	.234	.105
% Foreign Population	.279	.211	.594	.321	-.029	-.171	-.134	.084	-.066
% Married	-.364	-.309	.053	-.116	.522	.125	.326	.264	.155
% Single Person Households	.277	.818	.027	-.068	-.237	-.093	.169	-.291	-.121
# Passenger Cars per Household	-.260	-.648	.088	-.093	.423	.172	.199	.036	.069
# Average Household Size	-.196	-.854	-.148	.063	-.212	.087	-.296	.163	.172
(1k €) Average House Value	-.427	-.153	-.459	.028	.531	.125	-.083	.068	.160
% Stacked Housing	.548	.587	-.131	-.094	-.180	-.136	-.130	.032	-.087
% Old Houses	-.024	.107	.118	-.144	-.039	-.007	.776	-.001	-.006
% Rental Housing	.239	.599	-.150	.028	-.520	-.243	-.137	-.037	-.066
% Unemployment	.196	.237	.150	.668	-.330	-.291	-.229	.133	-.069
% Low Income Households	.236	.515	.309	.348	-.342	-.019	.245	-.163	-.051
(1k € PP) Average Income	.008	-.003	-.083	.012	.834	.058	-.135	.000	-.039
(1k PP) Income Recipients	-.006	.304	-.141	-.059	.198	.243	.225	-.079	.021
% Employment Service Industry	.211	.240	-.623	.088	.068	-.218	-.113	-.032	-.118
% Employment Agriculture	-.170	-.236	.184	.052	.021	.818	.003	.165	.069
% Self-employeed	-.438	-.001	-.029	.110	.287	.725	.014	-.044	.156
(km2) Total Active Businesses Jan.2011	.830	.218	-.116	.007	-.036	-.005	.007	-.267	.105
(km2) Industry & Energy Businesses	.876	.035	-.074	.079	-.098	-.081	.101	-.184	.066
(km2) Transport. Info. Comm. Businesses	.876	.014	.104	.021	-.023	-.049	.052	.061	.055
(1k HH) Relative Disability Benefits	.280	.368	.405	-.123	-.105	.009	.138	-.086	-.092
(1k PP) Health Care Workers	-.137	.173	.121	.677	-.025	.105	-.086	.113	.507
(1k PP 3km) Near Hotels	.010	-.222	-.159	.747	.074	.127	-.231	.018	-.039
(3km) Number of Childcare(s)	.695	.280	-.169	-.059	-.161	-.203	-.243	.026	-.146
(km) Distance to Train Station	-.098	.109	.789	.095	.245	.152	.103	.196	.020
(km) Distance to Medical Services	-.499	-.092	.053	.017	-.141	.099	.191	-.050	.356
(km PP) Distance Major Roads	-.016	.064	-.033	.028	-.048	-.069	.004	.031	-.453
% Agricultural Area	-.516	-.121	.157	-.163	.033	.457	-.017	-.168	.147
% Constructed Area	.858	.169	.030	.061	-.143	-.292	-.015	.161	-.070
% Highly Educated	.126	.136	-.685	.038	.185	-.002	.027	.065	-.095
(1k € PP) Spending, Public Order & Safety	.583	-.176	.274	.028	.150	.123	-.011	.589	-.096
(1k € PP) Spending, Social Cons	.666	-.075	.057	.160	.060	.019	-.092	.465	-.334

Extraction Method: Principal Axis Factoring.
a. Rotation converged in 17 iterations.

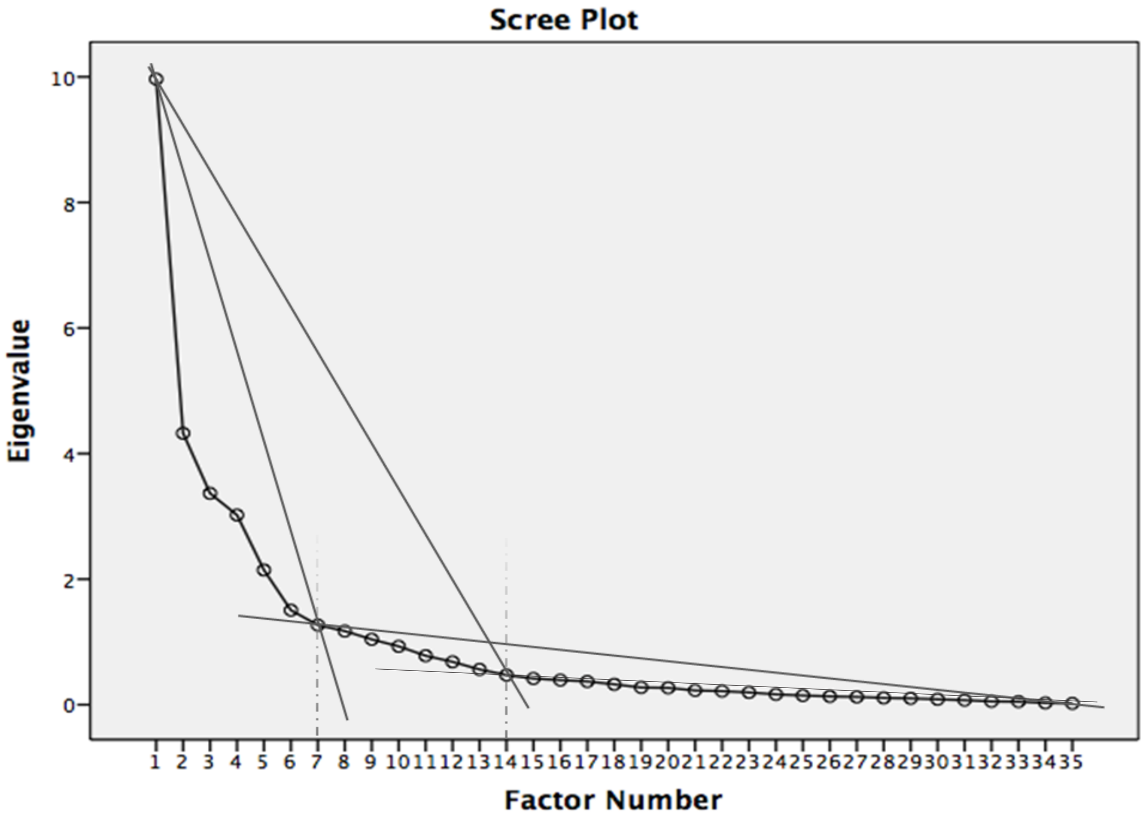


Figure 11: Scree Test

loadings in the Rotated Factor Matrix (Table 5). Factor loadings observed in the Rotated Factor Matrix are assessed to determine relationships among factors and metrics within factors. All variables are sorted by factor, loading value, and metric for index construction, listed in Table 6. The Zeeland SVI ranges from a district score of 0.248 in district Kattendijke of Goes indicating low social vulnerability, to a maximum score of 0.483 in Oudelandse Hoeve of Ternuezen. The average score is 0.318 found in Lamswaarde, Hulst.

5.3 Mapping Social Vulnerability

District scores are applied to 2012 district limits for the 147 districts of Zeeland using natural beaks (Jenks) divided into five classes of relative social vulnerability. Figure 12 illustrates social vulnerability ranging from a low level illustrated in green, to a high level of social

vulnerability in red. Generally, densely developed districts of city centers are found at the top of the Zeeland SVI, indicating a higher social vulnerability score.

Table 5**:** Variables for Index Construction

Factor 1	19.66%	Factor 2	13.26%	Factor 3	7.69%	Factor 4	7.35%	Factor 5	7.01%
(km2) Population Density	.846	% Population 65+	.764	% Foreign Population	.594	% Female	-.682	% Married	.522
(km2) Total Active Businesses Jan. 2011	.830	% Single Person Households	.818	% Employment Service Industry	-.623	% Un-employment	.668	(1k €) Average House Value	.531
(km2) Industry & Energy Businesses	.876	# Passenger Cars per Household	-.648	(1k HH) Rel. Disability Benefits	.405	(1k PP) Health Care Workers	.677	(1k € PP) Average Income	.834
(km2) Transport. Info. Comm. Businesses	.876	# Average Household Size	-.854	(km) Distance to Train Station	.789	(1k PP 3km) Near Hotels	.747		
(3km) Number of Childcare(s)	.695	% Stacked Housing	.587	% Highly Educated	-.685				
(km) Distance to Medical Services	-.499	% Rental Housing	.599						
% Agricultural Area	-.516	% Low Income Households	.515						
% Constructed Area	.858	(1k PP) Income Recipients	.304						
(1k € PP) Spending, Social Cons	.666								

Factor 6	5.82%	Factor 7	5.26%	Factor 8	3.35%	Factor 9	2.90%
% Employment Agriculture	.818	% Population Change 2003-2012	-.701	(1k € PP) Spending, Public Order & Safety	.589	(km PP) Distance Major Roads	-.453
% Self-Employed	.725	% Old Houses	.776				

Legend	Exp. Var%
Mitigates Vulnerability	Dominant Variable
Contributes to Vulnerability	Significant Variable

Table 6: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.772
Bartlett's Test of Sphericity	Approx. Chi-Square	4857.418
	df	595
	Sig.	0.000

This trend is visible in Figure 13, which contains the ten districts with the highest and top ten lowest index scores. This data is transparent over the location of building clusters in Zeeland, marked as gray clusters on the map.

5.4 Factor Discussion

Variables identified by the Rotated Factor Matrix are weighted and aggregated to develop the Zeeland Social Vulnerability index. Analyzing the Pattern of the data in the Rotated Matrix is helpful for understanding the relationships among vulnerable categories of grouped data. Understanding how the methods affect the factor loadings is necessary for a successful interpretation. Factors are named to represent the concepts of vulnerability they proxy rather than the variables they consist of. Table 5 illustrates factors included for index construction.

Factor 1: Density of the Built Environment and Public Support The highest loading variable on the first factor identifies *(km2) Transport. Info. Comm. Businesses*. This variable represents the complex infrastructure in city centers, and the businesses that maintain it. Loading closely to Infrastructure business is *(km2) Total Active Businesses Jan.2011, (km2) Industry & Energy Businesses,* and *(km2) Population Density*, which reinforce the density of the built environment. Cutter et al. (2003) cites the complications involved with evacuation in high-density

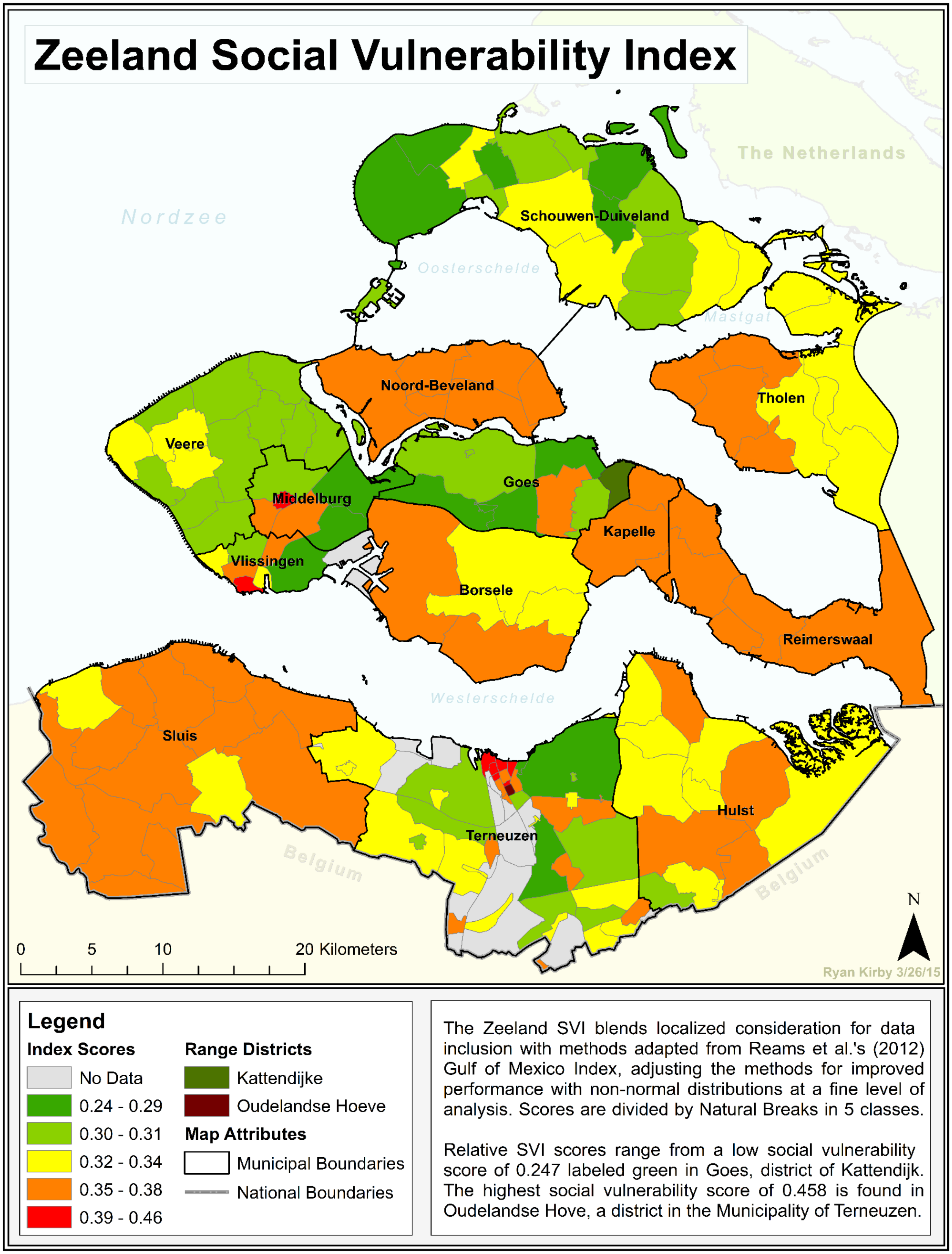
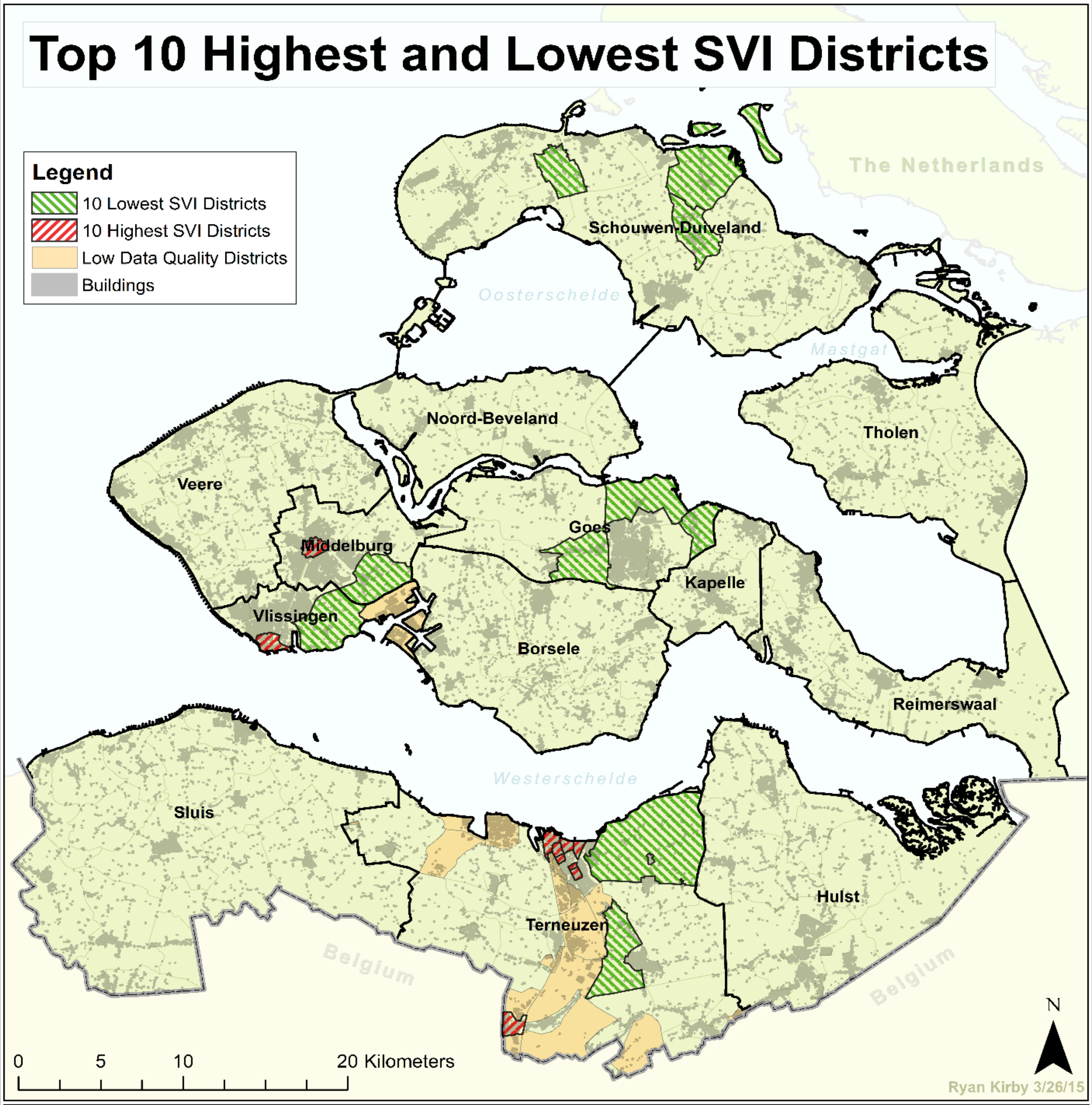


Figure 12: Zeeland Social Vulnerability Index



Top 10 SVI Districts, Descending

Rank	District	Code	Municipality	Score
1	Oudelandse Hoeve	WK071522	Terneuzen	0.463
2	Triniteit	WK071517	Terneuzen	0.443
3	Binnenstad	WK071510	Terneuzen	0.436
4	Middelburg-Centrum	WK068700	Middelburg	0.445
5	Zuidpolder	WK071521	Terneuzen	0.46
6	Serlippenspolder	WK071525	Terneuzen	0.45
7	Lievenspolder	WK071518	Terneuzen	0.408
8	Binnenstad	WK071801	Vlissingen	0.411
9	Noordpolder	WK071519	Terneuzen	0.412
10	Kern Sas van Gent	WK071570	Terneuzen	0.379

Lowest 10 SVI Districts, Ascending

Rank	District	Code	Municipality	Score
1	Kattendijke	WK066404	Goes	0.248
2	Zaamslag - Buiten Noord	WK071547	Terneuzen	0.248
3	's-Heer-Hendrikskinderen	WK066407	Goes	0.249
4	Verspreide huizen West Axel	WK071553	Terneuzen	0.251
5	Ritthem en omgeving	WK071806	Vlissingen	0.255
6	Noordgouwe	WK167604	Schouwen-Duiveland	0.265
7	Wilhelminadorp	WK066402	Goes	0.265
8	Ellemeet	WK167611	Schouwen-Duiveland	0.266
9	Nieuw - en Sint Joosland	WK068704	Middelburg	0.267
10	Zonnemaire	WK167602	Schouwen-Duiveland	0.268

Figure 13: 10 Highest & Lowest Scores vs. Buildings & Low Data Quality Districts

urban areas and the financial burden complex infrastructure repairs can put on recovering small towns. The John III Heinz Center for Science, Economics, and the Environment (2002) identifies the burden placed on families in a disaster situation when childcare centers close. The shifting of responsibilities to care for the young can slow recovery progress (Center, 2002). Researchers also identify high-density urban areas to contain a high level of vulnerability due to higher potential for economic and commercial loss. Figure 14 illustrates the connections between variables of Factor 1, representing Major roads, buildings clusters, and commercial density represented by five classes of Natural Breaks. Figure 14 also helps to convey the effects of negative skew on the index contributions. Instead of a normal distribution where variables related to built density load evenly across the five classes, the case positive skew is apparent through the large number districts with falling into the lowest class of density. In terms of contributions made on the index scores, the effect of skewed distribution for built density results in less total index score contributed by the fist factor than by the second regardless of the 8.85% difference in weighing values between the first two factors.

Factor 2: Reduced Wealth and Single Households. The second factor identifies vulnerability in family structure and support. The top loading variable for this factor is *% Single Person Households,* followed by an opposite (negative) loading for *# Average Household Size,* which helps target the group of Dutch citizens living alone. Also loading high on the second factor is *# Passenger Cars per Household,* loading negatively to indicate reduced mobility, *% Population 65+, % Rental Housing,* and *% Low Income Households.* With the addition of more variables, this factor indicates reduced wealth and elderly populations are also present on the second factor. Although these mixed attributes of vulnerability may be lumped into a single factor, it is noted that

the non-normality of the second factor helps to contribute to the factor's emergence as the highest contributing factor in the index, amounting to about 25% of the total weighted index score.

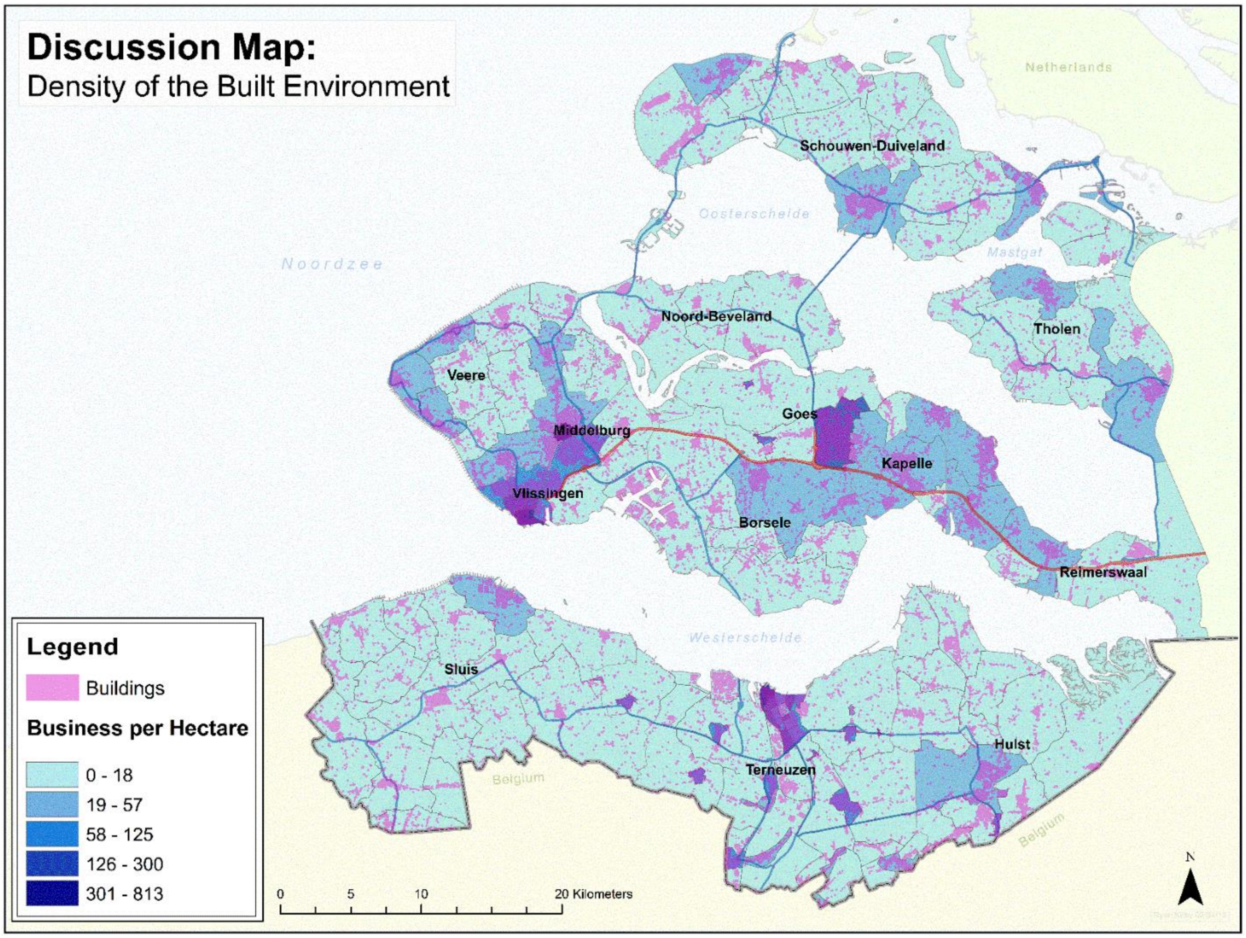


Figure 14: Density of the Built Environment

Fekete (2010) asserts that a single person has a reduced ability to protect themselves (Fekete, 2010). Fekete also finds that single households relate with high socioeconomic status and home ownership, but the same cannot be said for the Zeeland SVI. The points of interaction expressed on the second factor identify more than one of the most vulnerable demographic groups. Elderly residents exhibit reduced health and mobility which agrees with low passenger car ownership. These conditions paired with *% Stacked Housing* poses a vulnerability for a rapid

evacuation. Households with low income may have a difficulty recovering, and rental property is often associated with reduced financial stability and a transient population. This factor may be explained best with retired residents renting property in the beach communities such as Dieshoek or Zouteland of the central lobe of Zeeland. The beach communities of Zeeland and elderly populations are mapped in Figure 15, which illustrates large elderly and foreign populations relative to the highest and lowest SVI districts.

Factor 3: Infrastructure Accessibility and Career Qualifications. The third factor is led by *(km) Distance to Train Station*, a variable representing access to infrastructure necessary for daily transportation, and more importantly for rapid evacuation. In addition, *% Highly Educated* is

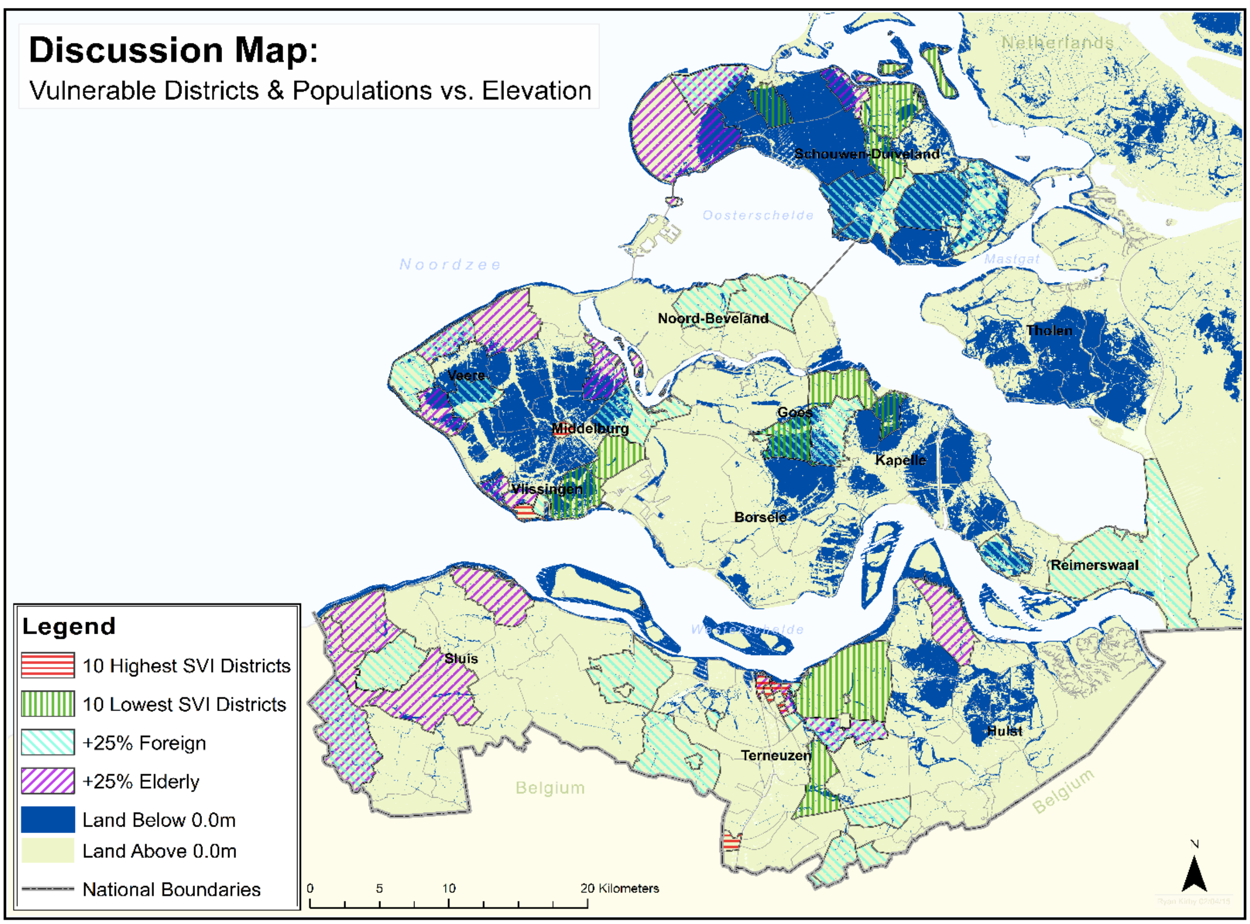


Figure 15: Zeeland Vulnerable Populations

related negatively to the distance to train stations and similarly with *% Employment Service Industry* in Zeeland, which indicates reduced career qualifications. Universities in Zeeland are found only near train stations. It is possible that the difficulty of getting to a university could possibly influence motivation for obtaining a degree in higher education. Without a doubt, Zeeland is a fragmented province, with 40% of its claimed total area made up by water, there is almost as much estuary as dry land. With a vehicle ownership rate similar to Zeeland's land rate, many people may rely on public transportation in the event of an evacuation. During an emergency evacuation, trains have a large capacity to move residents away from the coast, but only one passenger rail runs through the central lobe of Zeeland. To access the universities and rail offered by the central lobe, northern and southern citizens must cross water by tunnel, bridge, or ferry. This factor is next strongest with the polarization of foreign populations. While the Norwegian SVI found western immigrants to hold higher paying jobs, this is not the condition of factor three, which also shows relation between disability benefits, and low house value. A visual reference of Zeeland infrastructure and building clusters, Figure 16 and Figure 17 contains rail and roadways locations in Zeeland.

Factor 4: Recovery Capacity and Female Gender. Fewer hotel beds present a reduced capacity for recovery following a disaster event. Hotels serve as temporary housing for locals suffering from structural compromise, but also serve as a capacity to house temporary workers. It may be assumed that areas with a greater capacity to house workers will recover faster than an area far from temporary shelter. The second highest loading variable here is *(1k PP) Health Care Workers*. Much like temporary housing, the availability of healthcare workers is important after a disaster event. Access to health care providers following a disaster event is a major community

capacity. Areas containing less health care providers per capita may struggle to find appropriate professionals to facilitate and direct emergency medical decisions.

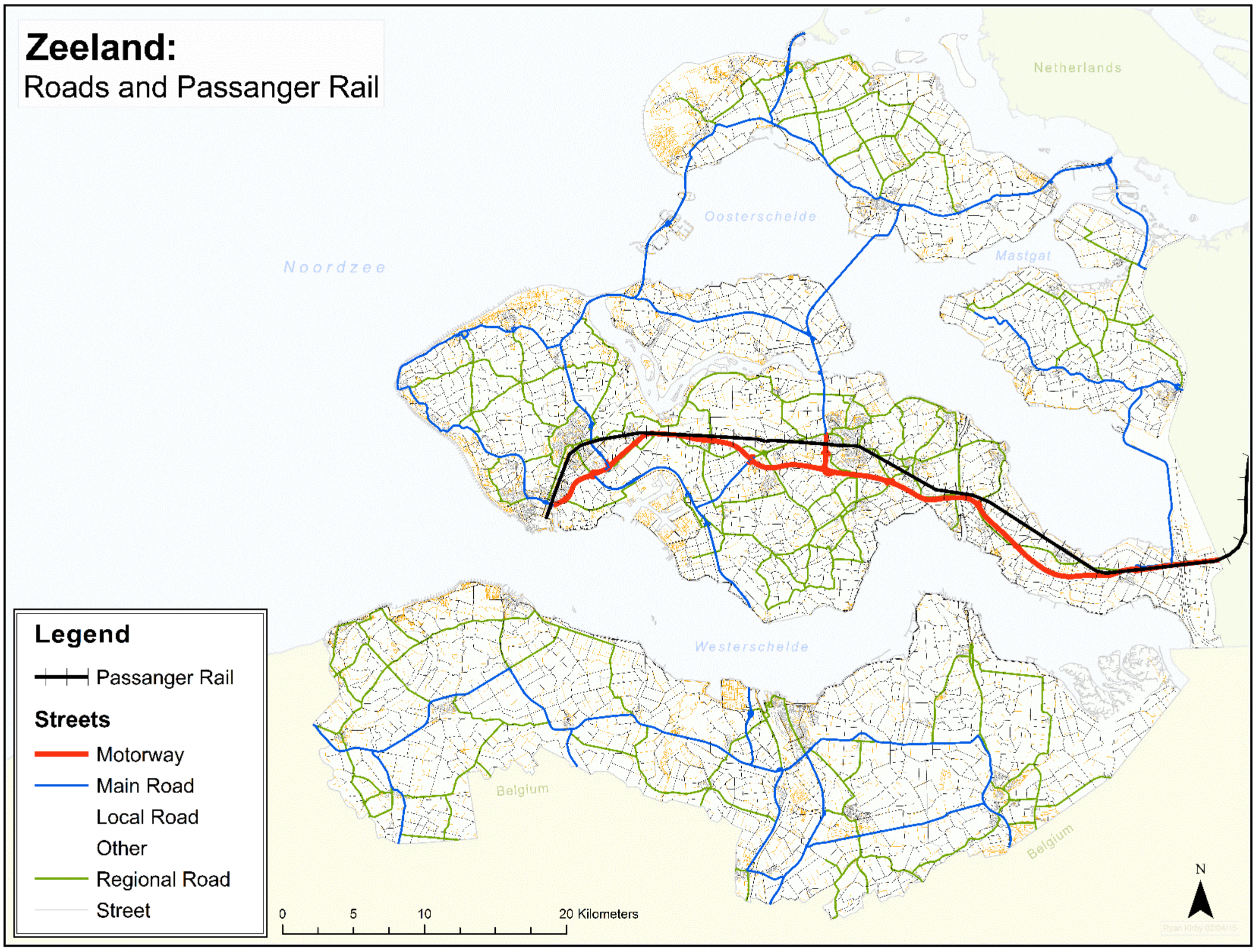


Figure 16: Zeeland Infrastructure

Also present on the fourth factor is female gender, which is oppositely related to the number of nearby hotels per 1,000 residents. Both of these variable load significantly on the seventh factor, but each variable represents different types of vulnerability. After inverting the proxy of shelter capacity, the presence of more females and less hotels agrees for contributing to vulnerability. Females are thought to express a more difficult recover process due to lower wages and family

care responsibilities (Cutter et al., 2003). Dutch females have less of a presence in the full time work place, possibly due to responsibility of raising children.

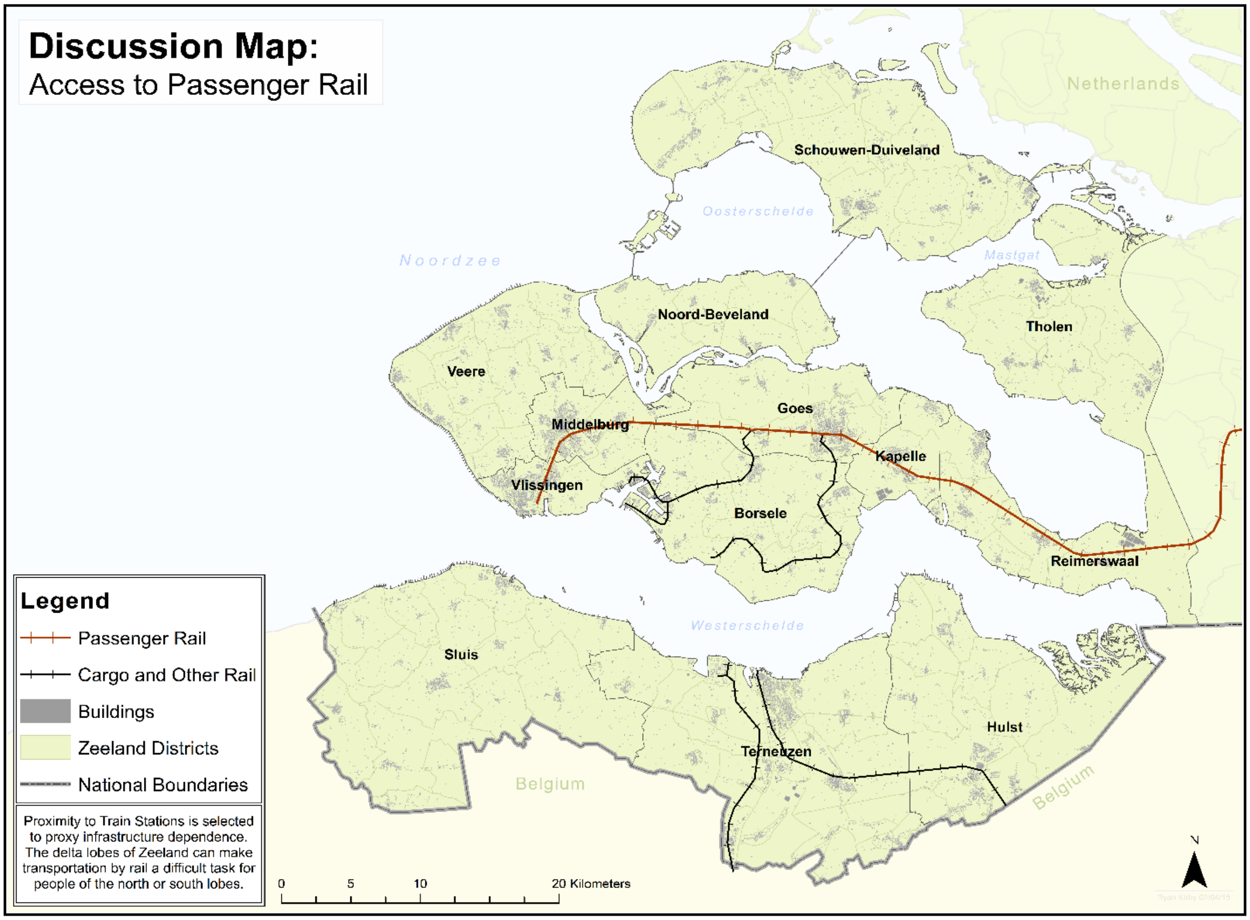


Figure 17: Access to Passenger Rail

Factor 5: Personal Wealth. The highest variable for the fifth factor is *(1k € PP) Average Income*, followed by *(1k €) Average House Value*, which are both indicators of wealth, and both widely accepted indicator of vulnerability. These variables are inverted to represent a positive relationship between low income and vulnerability. Also inverted, *% Married* is the second highest loading variable of factor five. Representing the percent of not married households, this variable targets reduced support networks. Paired with a trend of reduced average income, this

group is identified for having difficulty physically recovering from a disaster and potentially a reduced social network to provide psychological or emotional recovery from a disaster.

Factor 6: Occupation. The sixth factor identified in the Rotated Factor Matrix is distinguished by *% Employment Agriculture* and *% Self-Employed.* Removed from the dataset for conceptual overlap, these variables correlate greatly with employment in primary industries including agriculture, forestry, and fisheries. The US SoVI identifies persons employed in extractive industries, especially self-employed individuals, as being a vulnerable occupation group after a disaster event. An example of an occupational vulnerability is highlighted by the difficulty faced by self-employed fishermen, who may suffer if production is suddenly lost, or the farmers who lose a crop to flooding or disease.

Factor 7: Residential Quality. The seventh factor is dominated by older houses. Houses built before year 2000 is a proxy of general housing quality for Zeeland. The most frequent natural disaster in the Netherlands is storm events. The most deadly events in recent history are due to heat waves. Older houses tend to be more vulnerable to storm damage, contain less insulation, and are less likely to have climate control to mitigate the effects of heat. In addition, only 6% of all dwellings have an air conditioning system (Marijke & Beurskens, 2009). Also loading high on this factor is a negative relation with population change. Although stability within a district is a capacity rather than vulnerability, the similar loading between stable population and old houses may indicate that residents are not moving away from old housing.

Factor 8: Access to Healthcare. The eight factor contains the dominant variable *(1k € PP) Spending, Public Order & Safety* a variable adapted to represent potential for the region. The municipal level variable is inverted to represent a lack of public investment, thus a vulnerability for the municipality.

Factor 9: Evacuation Potential. The last factor contains one significant variable, *(km PP) Distance Major Roads*. Representing lifelines and an ability to move people away from an area, major roads are necessary to convey traffic quickly. The amount of roads per residents may indicate a level of congestion for evacuation potential.

5.5 Geographic Discussion

Zeeland is an interesting case for measuring Social Vulnerability. The fragmented delta province contains large portions of land resting below mean sea level (Figure 6). Often time, it is assumed that vulnerable coastal populations reside in lower elevations due to conditions including low property values and risk perceptions. Figure 15 identifies districts with foreign and elderly populations above 25%. A high portion of elderly population is found along the beach communities, containing areas of the highest elevation in Zeeland. Foreign populations are clusters in the Southern Lobe of Zeeland. This may be explained by one of two different situations; that foreign populations live near to the industrial Municipality of Terneuzen, or that Belgians have crossed the border to and reside in Zeeland's south.

The inclusion of proximity to public transportation is a concept unique to this social vulnerability analysis. In the case of Zeeland, where vehicle ownership is generally low among young adults, an ability to get to a university largely requires public assistance. Many students are able to use the advantage of rail to commute to school, although students needing to get from Terneuzen to HZ face one example of the problem posed by uneven access to public transportation every day. A daily commute from Terneuzen to Vlissingen via public transportation required multiple bus transfers and a ferry crossing, resulting in over an hour of travel time each way to move a relatively short distance. Students living near a train station are provided quick transportation into Vlissingen, where the train station is only a short walk from HZ University of

Applied Sciences. Fragmentation in the landscape may be a hassle for commuters, but can also bottleneck rapid evacuation efforts.

5.6 Methods Discussion

Baker's (2009) Gulf of Mexico index has proven useful at the US County scale. When applied to the Zeeland level of district analysis, the weight placed on factors becomes skewed and disproportional due to the definition of district boundaries formed by land-use type. Methods proposed for adapting the model provides a smoothing effect for problems encountered involving variable distributions and single-type land use districts. Methodological revisions provide flexibility for more accurate indexing at fine scale or county level. Also, when the validity of concepts within the input dataset are scrutinized to strip low quality variables and redundancy, a greater representation of the data can benefit the index as more concepts of vulnerability are included.

Many analysis methods and design criteria were tested to determine a best methods approach for measuring social vulnerability in Zeeland. Each decision tool was examined in depth to understand consequences for the Zeeland SVI. For example, to examine the effects of Promax versus Varimax rotation on the model output, each was used during experimental Principal Axis Factoring. The outputs were nearly identical regarding specific effects on the model. The only difference between rotation methods was the identification of the top loading value for factor six. While Promax rotation identified *Near Hotel per 1k residents* as the top loading, Varimax selected percent female as the top loading variable. The difference in values in loading values was 0.033 for percent Female and 0.151 for *Near Hotel per 1k residents.* In the situation that these variables were switched for indexing, the measureable difference seen in the index would hardly be noticed because the rescaled variance for factor six is only 5.3%.

On a larger scale of testing, SoVI methods were applied to the Zeeland dataset. The rigidity of the methods presented issues for disagreements of factor contributions. In addition, the significant difference identified between SoVI methods consulting the Scree test versus Kaiser Criterion found the method unsuitable for application in Zeeland. In addition to running simple correlations among indexes, the experimental methods were tested geographically with multiple method in attempt to find patterns of difference among test indexes. One example of these tests is found in Figure 18. This map illustrates the geographic differences in the Kaiser-consulted SoVI and Scree-consulted SoVI. While yellow and blue districts represent relative stability, while green indicates a reduced score when moving from the Kaiser Criterion to Scree Test and orange indicated an increase in relative social vulnerability.

Other methods resting considered data selection criteria's influence on factor loadings. To ensure a high quality analysis for Zeeland, the hundreds of test models were run testing the consequences of each decision made for data collection, processing, and analysis design. The method developed for Zeeland is prized for its stability, use of real data, statistical methods, and ability to return relatively reliable results, with reduced sensitivity to distributions of data and changes in input variables.

The necessity to load multiple variables per factor was apparent when Middelburg-Centrum defined the upper limit of the social vulnerability index continuously with experimental models. A result of the methods found in the Gulf of Mexico index designates the central district of Zeeland as the most vulnerable district in Zeeland. Analyzing the calculations reveals that 71% of the capital district's score is contributed for containing the highest level of commercial density in Zeeland. The magnitude of the positive skew in the distribution of commercial density in Zeeland is a product of land-use planning, where commercial density is greatest in city centers.

The result of multiple variables loading per factor helps to bring distributions towards center while expressing a related trend of vulnerability.

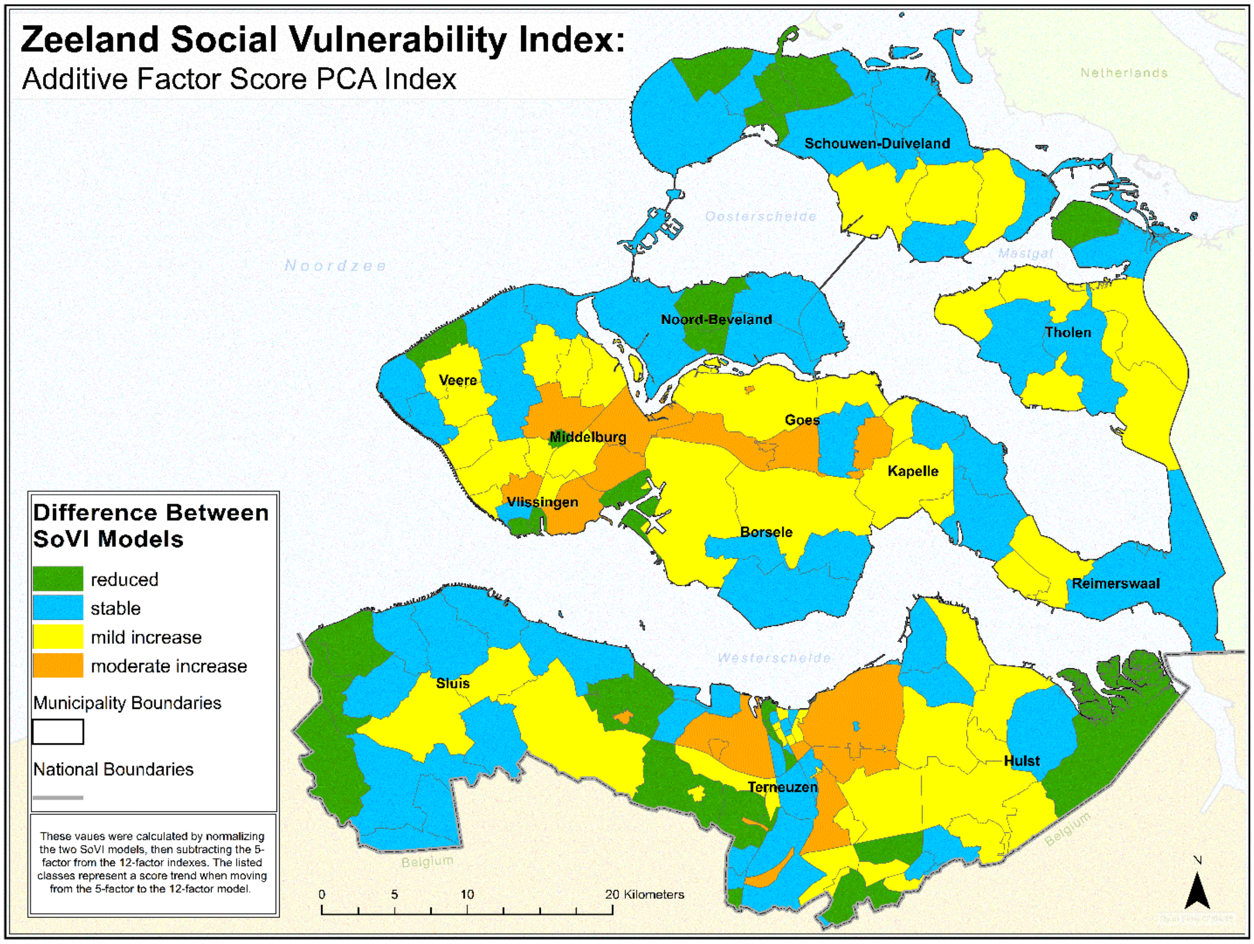


Figure 18: Experimental Methods Testing

Application of the adjusted GOM methods presented within this study offers a performance improvement when the spatial scale is fine. For use with a US county equivalent scale, the average-weighted method is effective because land use and population conditions receive a smoothing effect across a larger canvas. Comparatively, many of the US counties that the index was designed to measure have an area larger than Zeeland per unit. When the target scale of analysis is fine, the inclusion of more variables is necessary if at least for the assurance that skewed

data resulting from data limitation is smoothed. The methods presented within this study include all input variables for indexing to report a more complete representation of social vulnerability.

CHAPTER 6: CONCLUSIONS

The objective of this analysis is to provide a method for measuring social vulnerability in the Dutch province of Zeeland that considers geographic and cultural uniqueness for assessment of Dutch social vulnerability. Extra attention was paid to the selection of indicators for measuring social vulnerability unique to Zeeland. Blended frameworks from multiple related studies resulted in the methods adapted to measure social vulnerability in Zeeland. Influence from Baker's (2009) methods resulted in the use of Exploratory Factor Analysis, the use of real data, and weighting methods. Cutter et al. (2003) influenced the study through the inclusion of all input variables for index construction.

The Factor analysis of 35 indicators of vulnerability resulted in nine factors explaining about 72% of the total variance. The factors of social vulnerability in Zeeland are *Density of the Built Environment and Public Support, Reduced Wealth and Single Households, Infrastructure Accessibility and Career Qualifications, Recovery Capacity and Female Gender, Personal Wealth, Occupation, Residential Quality, Access to Healthcare, and Evacuation Potential.* The weighted index identifies dense commercial, industrial, and residential as containing the highest levels of social vulnerability. In addition, the southern lobe of Zeeland contains the highest social vulnerability scores due to the intersection of multiple factors of social vulnerability. Eight of the ten highest vulnerable districts are located in the Industrial and heavy shipping Municipality of Terneuzen, positioned on with access to the Westerschelde, which is the only unfortified estuary of the Netherlands.

This study contributes to risk awareness by presenting a social vulnerability index aimed for application at a fine level of analysis in the Netherlands. Replication of this study can help to

identify trends of community social vulnerability, and provide a method of monitoring efforts that may mitigate social vulnerability within the study area. More than half of a century without catastrophic disaster has potential to distort risk perceptions and knowledge of appropriate behavior for preparation, reaction, and recovery from a large-scale natural disaster event.

The Zeeland Social Vulnerability index is limited in several aspects that must be addressed. First, the level of analysis proved problematic for data availability and methods developments. The nature of the district often includes only single land use type within district boundaries. Low data quality districts were identified as containing more the 20% missing data for the entire 2012 KWB dataset. All of the 17 low quality data districts identified, contained less than 100 residents due to presence of commercial, industrial, or agricultural dominance of land use. Terneuzen was recognized as a problem municipality for measurement due to containing 16 of the 17 low quality districts. These districts were removed from the analysis to retain a high quality dataset for analysis.

Largely a factor of the level of analysis, the amount of data available for the Zeeland SVI was limited. Consideration of Dutch social vulnerability at the municipal level would provide access to a much larger dataset including data for government and politics, consumer and producer prices, construction, environment, and many other community attributes publicly offered by CBS StatLine. Analysis at the municipal level would also result in more geographic averaging and a loss of spatial variation.

The study is important for identification of vulnerable districts in the Zeeland for application in hazard mitigation planning. Although results of the analysis are limited by an inability to validate the district scores quantitatively, the methods contain room for improvement in the development of indicators of social vulnerability resulting from complex systems

relationships. Moving the level of analysis to examine the municipalities of the Netherlands would provide more depth for determining the correct indicators of vulnerable populations.

Lastly, this study was limited by its scope. The entire mass of Zeeland fits within the boundaries of many US Counties. Small spatial coverage should result in less variation within index scores. If the same methods and data are applied to all of the districts in the Netherlands, the visual representation of intra-district vulnerability in Zeeland may be suppressed by a larger range of index scores. The expansion of the study would be useful for identifying Zeeland's relative social vulnerability as a whole.

The Zeeland ZVI provides a method for measuring social vulnerability with the help of several supporting studies to obtain methods best fit for the uniqueness of the study area. The study can help guide planning and mitigation efforts though the geographic representation of relative social vulnerability in Zeeland. When applied as a layer of flood risk assessment, a social vulnerability index extends the depth of human data concerning flood risk. Future research on vulnerability in Zeeland may help to focus the accuracy of the index to provide a better representation of social vulnerably found within the population living on the environmentally vulnerable Southwest Delta of the Netherlands.

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VITA

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