Quantifying Remoteness for Construction Projects Using Nighttime Satellite Imagery and Machine Learning

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Abstract –

Remoteness, although a subjective concept, has indispensable consequences. It can support decision-makers in quantifying risks and feasibilities of developing newly discovered mineral deposits, resilience planning and evaluation of accessibility challenges of remote communities, or support agency budget allocations for much-needed services. Developing a remoteness index typically involves merging spatial and temporal data from a variety of incompatible sources such as topographical, census, and travel cost and duration. This paper presents a novel method for generating a measure of remoteness for any geographical location based on the nighttime satellite imagery. This continuous measure, herein referred to as Nighttime Remoteness Index (NIRI), is generated using machine learning-based models that link the intensity and statistical features of nighttime lights to remoteness; the predictive model is trained and validated using the nighttime satellite imagery and the Accessibility Remoteness Index for Australia (ARIA). This method does not require local data; hence, it is not limited by political jurisdictions or geographic boundaries. The NIRI is developed by using multivariate adaptive regression splines, and support vector machines regressions, after examining several other machine learning techniques. The NIRI maps of Australia and North America are developed based on the validated models.

Keywords –

Remoteness; Accessibility; Resource Projects; Resilience; Nighttime Satellite Imagery; Machine Learning; GeoTIFF

1 Introduction

Remoteness is a relative term. It is defined as "situated far from the main centers of population; distant" [1]. Remote could be used to refer to the fringes of a megacity that have sparse access to public transit or medical aid or to an uninhabited corner of the earth that has rarely seen human activity. Remoteness can be highly subjective, and its labeling can be controversial as it might have social, economic, technical, or political implications associated with it. These challenges may result in inherent biases that can hamper the objective measurement of remoteness.

The quantification of remoteness can assist decision makers in many domains, including 1) risk quantification for construction and industrial projects; 2) the resiliency assessment for communities and their underlying infrastructure; 3) policy making and research regarding resource allocation, public projects, and accessibility to essential services.

First, quantifying remoteness helps in risk assessments of large construction projects. The choice of location is particularly crucial for industrial projects due to their specific demands for skilled labor, material, and equipment [2]. The prevalence of remote projects is on the rise due to several factors. For natural resources projects, the depletion of conventional and accessible deposits has urged explorations in ever distant areas. Infrastructure projects are proposed to connect inaccessible communities and emerging markets to population hubs and open waters. Renewable energy projects such as hydroelectric dams and wind farms are built to harness clean but distant potentials. Quantifying the remoteness risk is an important step in assessing the overall risk of such projects, and in determining their development feasibility. Remote projects suffer from cost overrun, schedule slippage, and operability problems respectively 30%, 29%, and 70% more [3]. The distance to economic hubs represents access challenges to skilled trades and determines the safety and productivity implications of shift rotations that have employees work for several weeks followed by weeks-long leaves. Remoteness also affects access to raw materials, the most suitable modes of transportation, and access to markets or downstream treatments for the products of such remote projects. In this context, remoteness is a measure of vulnerability in adhering to the schedule and budget that make such developments economically feasible.

Second, with ever-growing implications of climate change and extreme weather effects, understanding remoteness is crucial in creating expert systems for resiliency assessment and planning for remote communities and infrastructures. Physical remoteness is an inherent quality of cities, townships, and communities and plays a major role in assessing their resiliency and vulnerability [4]. A quantification of remoteness can benefit mitigation strategies and response plans for natural disasters. For example, remoteness can function as an input to regional multi-severity casualty estimations [5] or similar vulnerability functions.

Third, accessibility is the inverse of remoteness and while distinct in their perspective, the two are highly correlated [6]. Accessibility reflects the proximity to population centers that have the capacity to provide healthcare, education, and other essential services. Quantifying remoteness and accessibility is essential in policy making and budget allocation for public projects, including public health, education, and infrastructure projects. For example, a measure of remoteness was used to guide the eradication of malaria in Lao People's Democratic Republic. The study's success prompted its extension for achieving similar disease eradication goals and improving overall health in Vanuatu, and the Solomon Islands [7].

Approaches to the development of remoteness and accessibility indices are data intensive, mostly based on census and transportation data that takes a long time to collect and require specific strategies based on the range of their policy implications. Therefore, their applicability and scope are usually limited to certain spatial or temporal contexts due to the restricting nature of their input data and its level of aggregation. For example, an index developed to facilitate policy making on a national level may not be valid at the community level due to the loss of resolution. Remoteness indices are also typically developed for a specific jurisdiction, ranging from local to national, but rarely crossing national borders due to data ownership and compatibility. Even adjoining countries have difficulty comparing accessibility indices since there exists no standard method for their development.

As such, a *universal continuous remoteness index*, developed from a readily available source of data, that is applicable to different geographical, spatial, and temporal contexts can be utilized in a multitude of situations and be of utmost value.

1.1 Objective and Scope

Nighttime satellite imagery is an independent and readily available data source, and it can be used to understand the distribution and the growth of populations over time. The objective of this paper is to examine the potential of nighttime satellite imagery to measure remoteness and to build a continuous remoteness index that can be calculated for any location, and for any time.

Sections 2 and 3 review the related efforts on quantifying remoteness and elaborate on the nighttime satellite data used for the development of the remoteness index introduced in this work. Section 4 discusses the methodology used to develop the proposed nighttime remoteness index (NIRI), while sections 5 and 6 discuss the results, their validity, and finally the conclusions.

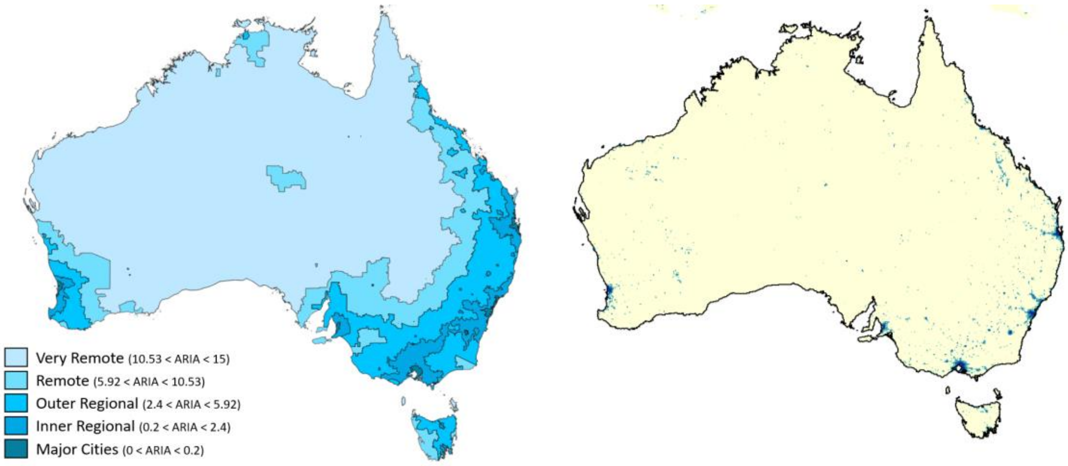
2 Approaches to Quantifying Remoteness

The proximity of human settlements to economic hubs is an important factor for countries with large land masses and only moderate populations as they strive to provide essential services to their residents. Two such countries are Canada and Australia who rank 222nd and 228th respectively out of 233 countries with respect to population density in 2018 [8].

Australia is a global leader in the study of proximity for practical purposes. One of the earliest of such studies was an index to distinguish the remoteness of rural areas created by associating population data with grid sections of the national map [9]. The index was based on the distance of the center of each grid to the center of the nearest populated grid. A contour map was drawn reflecting discrete categories of remoteness and accessibility. The remoteness index was later upgraded and named as the Australian rural, remote & metropolitan areas (RRMA) classification [6]. Both indices were criticized due to the subjectivity and the effect of the grid layouts on the index values assigned to specific regions.

In 1998, the continuous Accessibility Remoteness Index for Australia (ARIA) was created using census data to define population centers [10]. Travel times were incorporated in ARIA by overlaying the ground transportation network of roads and highways. This allowed the index to classify a region's accessibility to general practitioners, pharmacies, cardiovascular services, scientific grants, and urban infrastructure. As the index is linked to government funding policies, there was some concern about the fairness and reliability of some of the classifications. Although ARIA was calculated as a nominal index, the published version summarized it as discrete contour maps comprising five remoteness categories. In this way, the impact of moving a line could appear tremendous for communities on or near those boundaries.

A set of indices for remoteness and accessibility was developed for Canadian townships to measure and compare their accessibility to health, retail, and financial services [6]. It largely followed the ARIA methodology but instead of using the driving distance, the indices were scaled by the most affordable mode of transportation to reach the fundamental services. This accounted for the lack of year-round road networks and the local practices



(a) (b)

Figure 1: a) The target variable: ARIA Map of Australia for 2011 [11,12]. b) The predictor: Average stable nighttime lights from satelite imagary of Australia in 2011 [13]. (both figures are reconstructed).

of using travel modes that better suited the region.

3 Nighttime Satellite Imagery

Satellite images are breathtaking and pique our imagination. They contain immense data and have great potential to provide us with valuable information. At first glance, the images can estimate electrification rates if coupled with population data [14]. More generally, they serve as a proxy for human development. Images can be compared over time to understand growth patterns in locations around the world [14].

Economic growth can be seen as the expansion of lighted centers, reductions in the dark spaces between centers, and as the increased intensity of lights in highly urbanized centers. Where reliable statistical data are unavailable, using nighttime imagery to estimate economic indicators [15] and socio-economic factors has proved accurate and effective [16].

Development can also be viewed as a measure of economic equality. With this perspective, the Night Light Development Index (NLDI) [16] measures the intensity of nighttime lights and their distribution and forms a Gini coefficient versus the distribution of the population. In effect, the resulting Gini coefficient interprets the comparative wealth of the neighborhoods without the use of monetary measures of wealth. Significant correlations were found between the NLDI and other data-intensive development factors such as the Human Development Index (HDI), Human Security Index (HSI), and electrification rates. While NLDI provides a spatial depiction of development in a country, it does not reflect an area’s proximity to developed centers.

Shifts in economic activity have also been identified using nighttime imagery. The discovery of minerals in one area in Madagascar was made evident by the dramatic appearance and growth of nighttime lights in the area over a period of 5 years. The lights resulted from the development of mining facilities, local commerce, and communities to support workers. The mine was also identified to be the cause of the dimming of light intensity and slowed economic activity at a town further away [17].

Although the use of satellite nighttime imagery has many successes, some shortcomings have been discovered. In mapping global economic activities, satellite nighttime imagery methods were unable to account for activity that did not generate light, such as agriculture [19]. Along the same theme, regional cultural or operational practices, such as restricting the use of outdoor lights at night, can affect the results if the analysts are not aware of local practices. Although nighttime satellite lights are a reliable source for comparative analysis within similar regions, methods to validate findings are helpful in identifying such shortcomings.

4 Nighttime Remoteness Index (NIRI)

This work uses machine learning techniques to develop a predictive model linking the intensity and statistical features of the nighttime satellite data to remoteness. A model is trained to map a feature vector extracted from the nighttime satellite data (i.e., the predictor, or the independent variable) to the ARIA remoteness values (i.e., the target, or the dependent variable). The predictions of this model are further used to develop a continuous remoteness index, herein referred to as the nighttime satellite imagery (NIRI) for any given geographical location. NIRI maps the degree of remoteness to a nominal scale between 0 to 100, with

0 being the least remote, and 100 being the most remote point in the spatial context where NIRI is developed. The NIRI is independent of national boundaries and the data collection and integration challenges often related to local jurisdictions. Using the satellite data available for different time periods, NIRI can be automatically adjusted to reflect remoteness for a given temporal context, and it can be utilized to study changes in remoteness over time.

The majority of work was done in R programing language by taking advantage of Raster library. The maps are developed using ArcGIS® software. The following sections respectively elaborate on 1) the nature and the format of the input nighttime data; 2) the feature engineering and the choices regarding the mathematical representation of the input data in formulating the predictor variables; 3) calculating the target variable; 4) the predictive modeling process, mapping the predictors to target variables; and 5) the generation of NIRI based on the prediction results.

4.1 Predictor Variable: Nighttime Satellite Imagery

National Oceanic and Atmospheric Administration's National Geophysical Data Center (NOAA) published nighttime satellite imagery data annually from 1992 to 2013. Two data sets are available. The average lights data are calculated as the average readings during the year. Readings affected by clouds, moonlight, sunlight, aurora, and glare are excluded. The average stable lights data are further adjusted to exclude temporary light effects caused by, for example, wildfires and visual background noise. The data are available in 8-bit quantized georeferenced tagged image file format (GeoTIFF) as 30-arc-second resolution maps from -180 to 180 degrees Longitude and -65 to 75 degrees Latitude. GeoTIFF is an image file embedded with metadata, such as the reference coordinate system and pixel resolution, and spatial or georeferenced data in the form of pixel parameters [20] [20].

4.2 Feature Engineering

For any location on the map, a feature vector is generated for the purpose of training and testing the predictive models; a series of statistical features and summary statistics are extracted from the nighttime satellite data and in the neighborhood of a given location. This neighborhood is defined by a radius, the size of which can have important implications on the final index. The perceived remoteness of a location will vary depending on the region size and the distance in the context of major construction projects. For example, a site located more than 200km from a populated area can be considered remote in North America but perceived as relatively less remote in Africa [3]. A continuous remoteness index shall be sensitive to absolute distance from populated areas.

Therefore, this paper uses multiple neighborhood sizes to calculate the feature vector; individual feature vectors are calculated for four different influence radii of 100km, 300km, 500km, and 1000km, and they are concatenated together. The feature extraction process is further adjusted to reflect the proximity of open waters, ensuring that the model is expressive to the coastlines. This is intended to take into account the effect of open waters on the summary statistics of a given location; for example, while two locations may have similar readings on the nighttime satellite data, their corresponding remoteness indices can differ based on proximity to open waters.

4.3 Target Variable

In the next step, the target variables are calculated. Because Australia has established a robust and long-term record of indexing remoteness and accessibility, ARIA was used for this purpose. ARIA is published as contour maps, dividing Australia into five classes based on the measure of remoteness (see Figure 1) [11]. For any location, the target variable can be considered as either, first, the remoteness class (e.g., "very remote", that can be extracted from the ARIA map), or second, the actual nominal value of remoteness (ranging from 0 to 15 in the case of ARIA). The former formulates a classification problem that links the predictor variable (i.e., readings from the nighttime satellite images, see section 4.2) to their corresponding class of remoteness. This does not allow for introducing a continuous index that accounts for the gradient changes in remoteness. The latter choice results in a regression problem; and hence, allows the development of NIRI as a continuous index. However, nominal ARIA values are only known for the classes' borders from the overall map. The latter was used in this paper.

4.4 Predictive Modeling

The feature vectors and the target variables are passed to a machine learning model; several algorithms from regression-based modeling techniques were used for the purpose of predicting the target variable using the predictors, including the linear regression, the multivariate adaptive regression splines (MARSplines), the support vector machines regression (SVR), and the k-nearest-neighbor regression. Several validity tests were performed on the prediction results including the stratified random resampling and a non-random geographic split test. The residuals were carefully investigated to avoid overfitting and modal behaviors.

Moreover, an iterative model tuning campaign was carried forward to optimize the behavior of the models based on various definitions of cost parameters.

4.5 NIRI Development

The predictive models map the intensity and the statistical features of the nighttime data to the ARIA index. In this step, the model predictions are normalized across the geographical context for which the NIRI maps are being developed (e.g., across the entire map of Australia). The normalization allows for the resulted NIRI to specify the remoteness of any point at a value between 0 and 100, reflecting the relative remoteness of that location within its spatial context. This also allows for comparison of NIRI values between geographical locations, and it makes NIRI applicable to all regions.

When expanding the use of NIRI to other regions, the index shall be normalized based on the context of the region in question. It must be separately developed for countries with major cultural and geographic differences. This is due to the different mechanism of illuminating cities and population settlements across the globe, the geographic and cultural differences, among others [17].

5 Validation and Discussion

To train and test the predictive models, more than 7000 data points were selected on the region borders of the ARIA map (i.e., where the nominal value of remoteness is known). The feature vectors were calculated for all these locations using the process described in section 4.2.

The accuracy of the models is established by performing several validity tests, including the geospatial half split test; the ARIA map is split in two halves; the models are trained on one half, and they are used to predict the remoteness values in the other half. The best performing model is used to predict remoteness and develop the NIRI maps based on the normalization steps described in Section 4.5.

5.1 Results

Among the trained models, the SVR achieved the highest coefficient of determination, R^2=0.94 while, MARSplines produced similar results with R^2=0.93. Both models performed reliably in terms of the residuals. The non-random geographic split test, using Eastern Australia data to train and Western Australia data to test posed the highest challenge to coefficients of determination, however, it resulted in R^2=0.85 and R^2=0.84 for SVR and MARSplines, respectively. The SVR produced slightly less normally distributed residuals for the geographic split test in comparison to MARSplines, and hence, MARSplines is less prone to overfitting and more appropriate for these data. Therefore, MARSplines is chosen as the best performing model and is used hereafter to create the NIRI maps using the procedure described in section 4.5.

Figure 2 and 3 show the NIRI maps of Australia and North America, generated using MARSplines model and the nighttime satellite data of 2011. Figure 4 shows the superimposition of NIRI contours (iso-remote lines), on the average stable lights of North America for 2011. NIRI envelopes the light clusters normal to the direction of remoteness gradient from population centers to remote areas with great accuracy.

5.2 Discussion

The spacing of the corresponding grid to build the index determines the resolution of the ultimate NIRI map and has an immediate effect on its accuracy as well as the computation time. The triangulation error increases as the resolution of the grid increases, subjecting the corresponding maps to both random and systematic errors. More importantly, larger grids mean that each point represents a larger area. This increases the occurrence of index locations that do not represent their areas. To examine the sensitivity of the grid size on the accuracy of the map, analysis was performed to identify the potential systematic and random impacts on the results. Figure 5 plots the average and standard deviation of NIRI for a region in the southeast of Australia encompassing Sydney and Melbourne for four grid sizes ranging from 0.2 to 1.2 degrees. The random error disappears as the average and the standard deviation of the index start to converge in grid sizes below 0.8 degrees. Therefore, depending on the size of the coverage area, the desired resolution, and the computational power available, a grid size of 0.8 degrees or smaller produces reliable results.

Because NIRI is a continuous index, it allows establishing remoteness contours at any interval and for any region. Once the models are built to link the nighttime satellite imagery to remoteness as the target variable based on Australia data, the same models can be used to compute NIRI for other regions of the world. This extends the use of the index to a variety of applications. Once the model is run, the relative remoteness difference between any two points can be measured for risk assessment and other purposes.

NIRI can be used to better understand and quantify the resiliency of communities and their underlying infrastructure. In the case of infrastructure resiliency, NIRI can be used as an additional factor to improve mitigation strategies for natural disasters [21]. Combining an understanding of remoteness and accessibility with casualty estimations can optimize the use of the limited resources in the face of natural disasters such as earthquakes, tsunamis, and hurricanes.

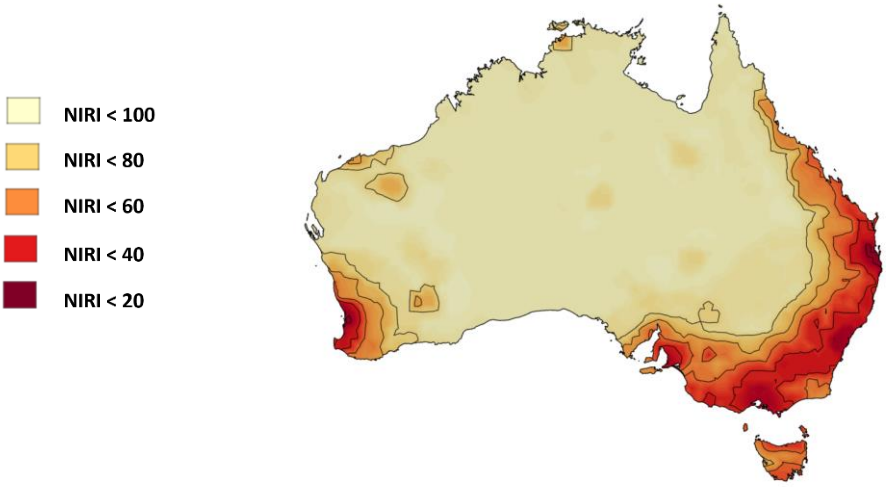


Figure 2: NIRI Map of Australia for 2011

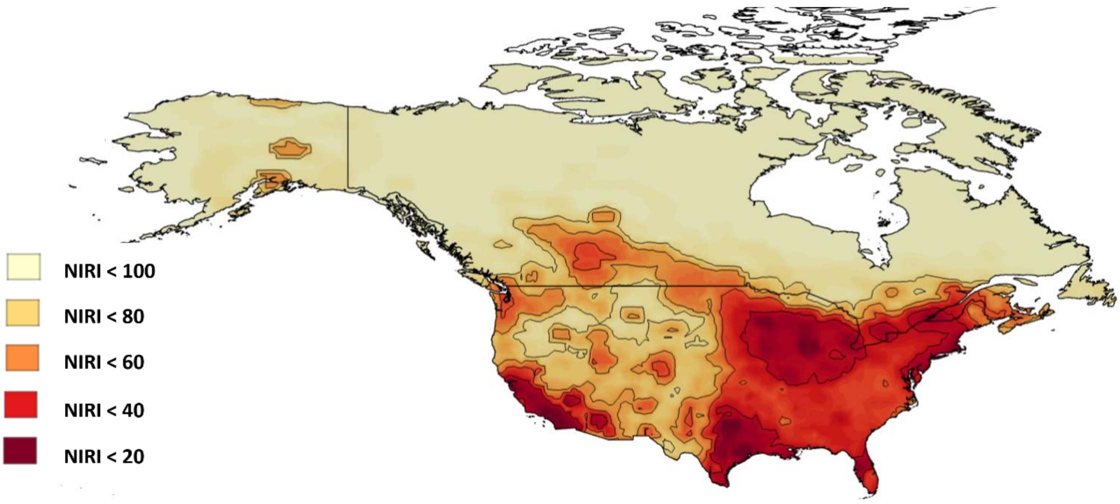


Figure 3: NIRI Map of North America for 2011

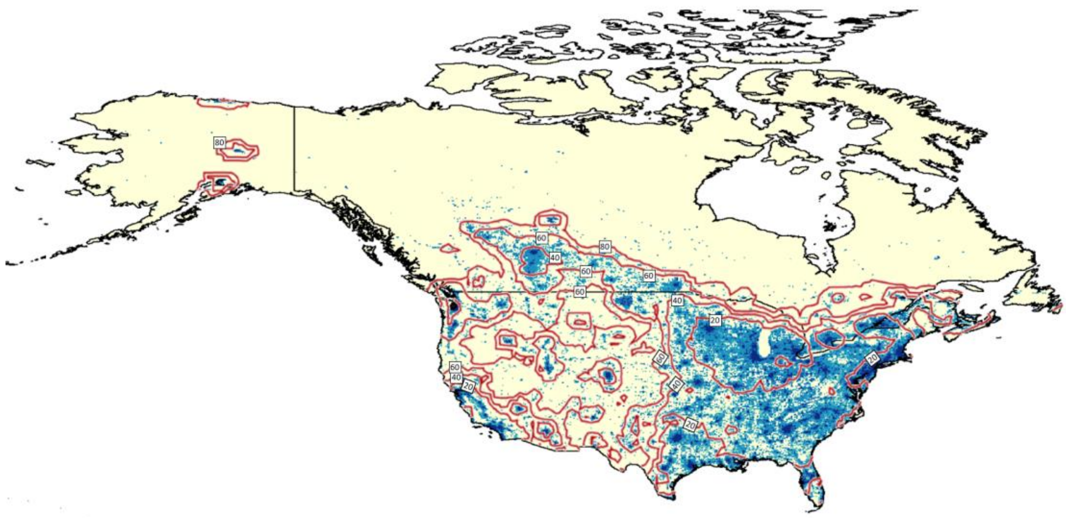


Figure 4: NIRI Contours (Iso-Remoteness Lines) Superimposed on Average Stable Nighttime Lights of North America for 2011

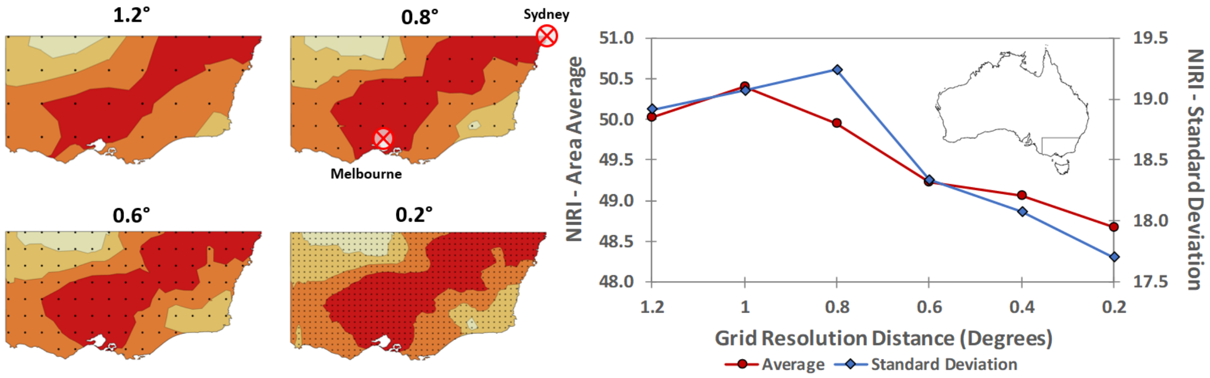


Figure 5: Grid Spacing Sensitivity Analysis Results

Regional remoteness indices were directly utilized in vulnerability analysis of road networks for south east Australia [22], such frameworks and programs can be expanded to any other part of the world by utilizing NIRI. Several models are proposed to forecast damage and severity for seismic events. For instance, NIRI can be a direct input to regional multi-severity casualty estimations [5] and Earthquake vulnerability functions [23] to calibrate those models for physical location characteristics. Previous studies have linked remoteness to both resiliency and vulnerability of communities and proposed adaptation pathways to consequences of climate change and extreme weather events to those communities [4]. NIRI can quantify remoteness for implementation of such strategies.

Moreover, NIRI can help in research applications at a variety of economic and social sciences' fronts. Satellite data in general [24], and nighttime satellite imagery in particular [15~19] have been effectively used in several studies to explore various economic outcomes including poverty. Separate studies have established links between the prevalence of poverty and remoteness characteristics of communities [25]. NIRI can be utilized effectively as an input to such models to better understand similar phenomena.

6 Conclusions

Remoteness is hard to measure, yet it is a crucial factor in determining the success and feasibility of large international projects and assessing the resiliency and vulnerabilities of remote communities. The existing means of quantifying remoteness require extensive data collection and are based on the integration of multiple data sources. A global measure of remoteness is needed that is not limited in terms of its applicability to different geographical contexts and time periods. This paper proposes a novel method that exploits the readily available nighttime satellite data for developing a continuous measure of remoteness that is not limited to local jurisdictions or certain borders. While most research on nighttime satellite imagery has been focused on the characteristics of illuminated clusters and its relationship with human development, this paper links the lack of such light clusters to remoteness.

In this study, the nighttime satellite imagery proved to accurately predict a multidimensional composite index of remoteness. The nighttime data is used as a predictor of remoteness and to create a continuous remoteness index, NIRI, that describes remoteness and its directional gradient with great accuracy for a variety of risk and resiliency assessment tasks.

NIRI can be developed across different regions and as well in time. Although this paper only used 2011 data to establish the predictive model, the index can be developed using nighttime satellite imagery of other points in time. This allows NIRI to measure the changes of remoteness not only across regions but also across time.

Acknowledgments

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