New approach of water quantity vulnerability assessment using satellite images and GIS-based model: An application to a case study in Vietnam

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Abstract

Water deficiency due to climate change and the world's population growth increases the demand for the water industry to carry out vulnerability assessments. Although many studies have been done on climate change vulnerability assessment, a specific framework with sufficient indicators for water vulnerability assessment is still lacking. This highlights the urgent need to devise an effective model framework in order to provide water managers and authorities with the level of water exposure, sensitivity, adaptive capacity and water vulnerability to formulate their responses in implementing water management strategies. The present study proposes a new approach for water quantity vulnerability assessment based on remote sensing satellite data and GIS ModelBuilder. The developed approach has three layers: (1) data acquisition mainly from remote sensing datasets and statistical sources; (2) calculation layer based on the integration of GIS-based model and the Intergovernmental Panel on Climate Change's vulnerability assessment framework; and (3) output layer including the indices of exposure, sensitivity, adaptive capacity and water vulnerability and spatial distribution of remote sensing indicators and these indices in provincial and regional scale. In total 27 indicators were incorporated for the case study in Vietnam based on their availability and reliability. Results show that the most water vulnerable is the South Central Coast of the country, followed by the Northwest area. The novel approach is based on reliable and updated spatial-temporal datasets (soil water stress, aridity index, water use efficiency, rain use efficiency and leaf area index), and the incorporation of the GIS-based model. This framework can then be applied effectively for water vulnerability assessment of other regions and countries.

***Keywords**:* Water vulnerability, MODIS, spatial datasets, correlation analysis, GIS-based model

1. Introduction

Water is a vital resource for people and many industries including agricultural, industrial and domestic applications (Anandhi & Kannan, 2018; Vorosmarty et al., 2010). It helps to sustain ecosystems but it causes disasters like floods or droughts for human communities (Brown et al., 2015). The excessive and inappropriate use of water resources has increased considerably throughout the world. According to the Global International Geosphere-Biosphere Programme (IGB), total water global freshwater withdrawals amounted to 4 trillion m^3 in 2014, representing a six-fold increase over the period 1900-2014 (Alcamo et al., 2003; aus der Beek et al., 2010; Flörke et al., 2013). Water use per capita throughout world varies greatly depending on the latitude, climate and level of countries' or regions' development.

Water stress levels vary greatly in the world's regions and countries. The Middle East and North Africa regions have experienced extremely high rates of water stress when their freshwater withdrawals are greater than 80% (Ritchie and Roser, 2020). Several countries throughout South Asia and East Asia are experiencing medium to high levels of water stress (Ritchie and Roser, 2020). Nearly 80% of people on our planet have suffered high threats regarding water security (Vörösmarty et al., 2010). Water security has been influenced by abiotic factors like climate, and anthropogenic factors such as population and changes in land cover. Their relationships are explored when a water vulnerability assessment is conducted (Plummer et al., 2012). Identifying appropriately the list of indicators with sufficient input data is crucial and these contribute to a proper vulnerability assessment. Figure 1 illustrates a summary of water vulnerability components and sub-components. There are five main components, namely water resources, physical environment, economic, social and institution with several sub-components which are also depicted in this figure. Those sub-components or indicators are then categorized into three vulnerability assessment components (Exposure, Sensitivity and Adaptive Capacity). In general, the assessment of vulnerability is a very complicated process due to the multi-disciplinary nature of the problem, lack of knowledge and understanding of vulnerability theoretical frameworks and input data for required indicators related problems (Anandhi and Kannan, 2018; Gain et al., 2012).

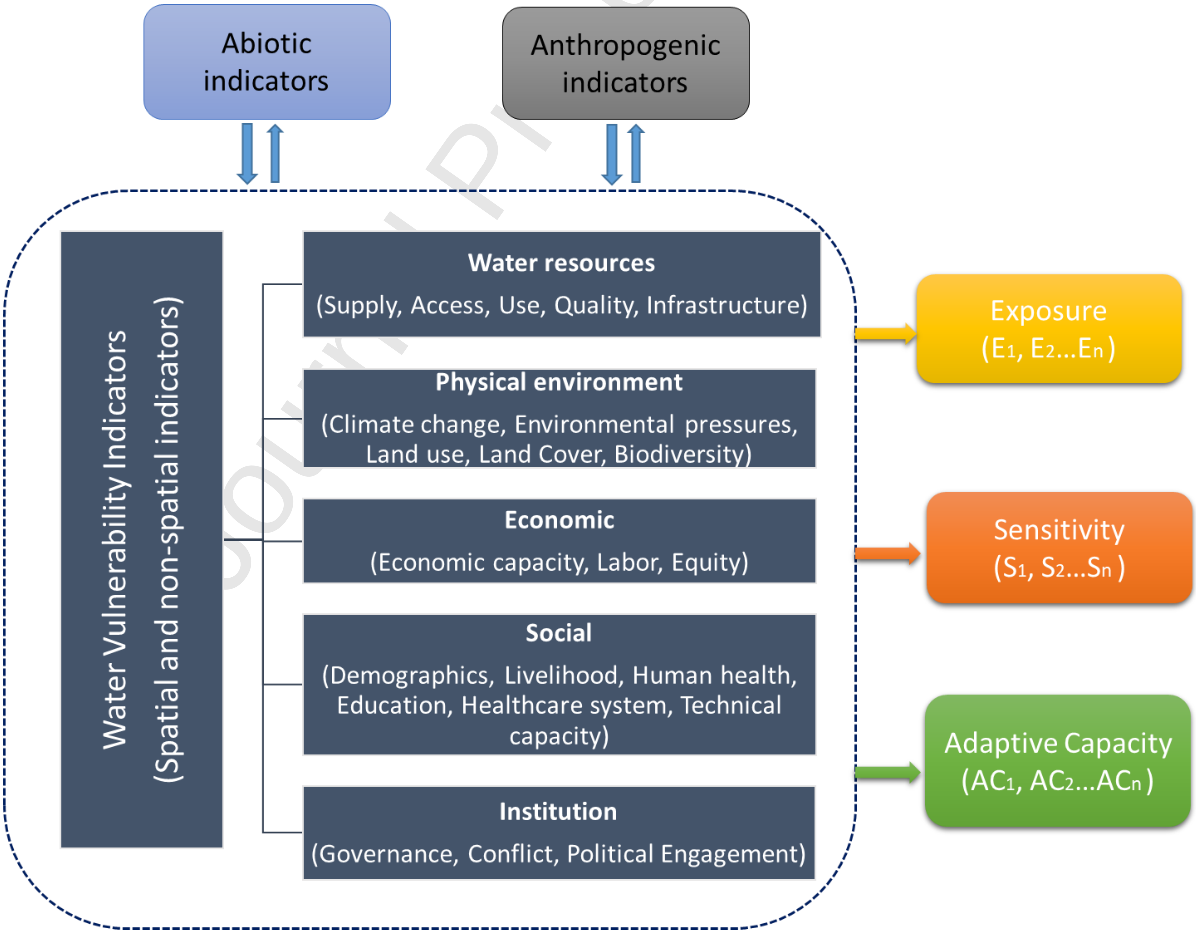


Figure 1. List of potential water vulnerability indicators (modified from (Plummer et al., 2012))

Previous studies have applied econometric methods by collecting information from surveys and questionnaires or index-based methods. These are derived from indicators and quantitative analyses of water vulnerability assessments (Bär et al., 2015). Indicators are identified by systems thinking approaches developed by experts in working in the water sector. The variables of vulnerability assessment can be selected through the Driver – Pressure – State - Impact – Response (DPSIR) framework (Jun et al., 2011). Satellite remote sensing datasets like MODIS, Sentinel or Landsat have been utilized to monitor water resources and to acquire input data for water assessment over the world (Khosravi et al., 2018; Sheffield et al., 2018).

A variety of methods and frameworks for vulnerability assessment have been proposed and applied in many studies. For example, the DRASTIC model and Catastrophe Theory have been used to assess groundwater vulnerability (Khosravi et al., 2018; Sadeghfam et al., 2016). However, there are several challenges associated with these methods: (1) not enough variables for water vulnerability assessment, (2) the unavailability and inaccurately input data for indicators, (3) limitations in applying spatial and temporal data from satellite images, (4) the practical applications of the framework, and (5) tools being limited in supporting water managers with their required water planning and management needs. This study aims to address these issues. Specifically, the research attempts to build a new spatial approach framework for water quantity vulnerability assessment based on mainly time series remote sensing data. Those spatial data were integrated with statistical data for water quantity vulnerability assessment. The novelties of the study are: (1) applying updated spatial-temporal satellite images from reliable datasets as important vulnerability indicators such as elevation from ASTER GDEM version 3, leaf area index and net primary production from MODIS datasets, and soil water stress from Consortium for Spatial Information; (2) utilizing GIS-based model for assessment; (3) incorporating different satellite datasets and statistical datasets in the ArcGIS 10.4 platform to construct spatial distribution of water vulnerability across ecological and provincial contexts. Overall, the evaluation of water quantity vulnerability is of vital importance for water managers in making the best decisions that improve the sustainability of water resource withdrawals.

2. Materials and methods

2.1. Study area

The study area is the country of Vietnam. Vietnam's climate is strongly influenced by a monsoon-influenced tropical system with average temperature, precipitation and humidity ranging from 22-27^{o}C, 1500-3300 mm, and 70% - 85%, respectively. Based on the similarity of geographical and climatic conditions, Vietnam comprises eight ecological zones and these are the Northeast (NE), Northwest (NW), Red River Delta (RRD), South Central Coast (SCC), North Central Coast (NCC), Central Highland (CH), South West (SW) and Mekong Delta (MD) (Figure 2). Water sources in Vietnam mainly originate from its river basin system. There are 2,360 rivers in Vietnam with a length greater than 10km. Red River, Mekong River and Dong Nai

River are the three main river watersheds where about 65% of the country's population living along these rivers (Le Luu, 2019). Water resources management in Vietnam has historically focused on freshwater conservation for agricultural production for hundreds of years. According to the data of FAOSTAT, Vietnam is one of the world's main agricultural water users with around 77.75 billion m^3 per year and, importantly, water stress reached a medium-to-high level in 2007 (Ritchie and Roser, 2020). In recent years there has been no data for water stress in Vietnam yet.

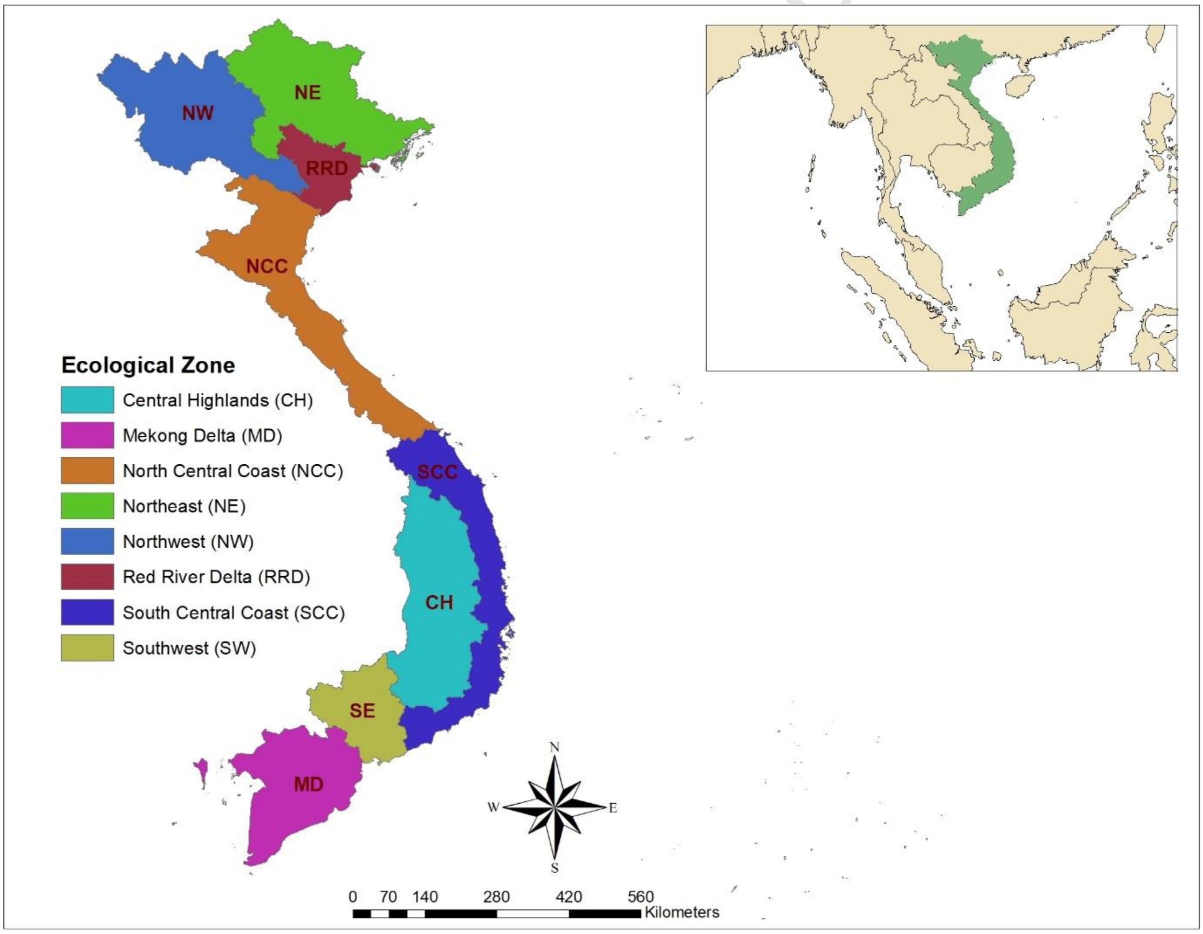


Figure 2. Location map of the study area

Since the late 1980s, Vietnam has experienced many water-related problems like water pollution, flood disasters and water shortages which have compromised the economic transition process and highlighted the dangers posed by climate change (Dang et al., 2019; Ngo et al., 2018; Norrman et al., 2008). A comprehensive understanding of water vulnerability not only minimizes the future vulnerabilities but also reduces the damage caused by water disasters on fragile ecosystems. Specially, it contributes to implementing an effective integrated water management system for Vietnam which not only addresses water problems but also introduces other environmental benefits like recognition of climate change and being prepared for natural disasters.

2.2. Data acquisition

Recent decades have experienced a substantial growth in openly available remote sensing data with a high resolution. Such data is increasingly playing an important role in many studies. These data also provide a vital input for this study. Six global gridded geographic datasets, specifically GADM, ASTER GDEM, CHIRPS, Terra MODIS, Global Aridity datasets and Global Soil Water Balance datasets were used to conduct the water vulnerability assessment (Table 1). The property characteristics of these data differ widely, so it is vital to harmonize data layers so that detailed spatial variables that appropriately constructing the indices of water vulnerability can be properly processed.

Table 1. Spatial variables and datasets used in water quantity vulnerability assessment

Variable	Scene ID	Dataset	Spatial Resolution	Temporal Resolution

Variable	Scene ID	Dataset	Spatial Resolution	Temporal Resolution
Administrative boundaries (all levels of sub-division)	GADM	Gadm36_VNM version 3.6		2018
Elevation	ASTERGDEMV003	ASTER GDEM v3	30m	2000
Precipitation	CHIRPS-v2.0	Climate Hazards Group InfraRed Precipitation	4.8-km grid (1/20 degree)	Yearly, 1981-2018
Net Evapo-transpiration	MOD16A3GF.006	Terra MODIS	500m	Yearly, 2000-2019
Soil Water Stress	SWC_fr	Global Soil-Water Balance datasets	1000m	Montly,1970-2000
Priestley–Taylor alpha coefficient	alpha	Global Soil-Water Balance datasets	1000m	Yearly, 1970-2000
Aridity Index	Ai_et0	Global-Aridity datasets	1000m,	Yearly, 1970-2000
Leaf Area Index	MOD15A2H.006;	Terra MODIS	500m	8 day, 2000-2019
Net Primary Production	MOD17A3HGF.006	Terra MODIS	500m	yearly, 2000-2019

The study also used data from statistical sources and other documents. Administration unit, land use types, education, socioeconomic conditions and water supply systems were collected from Vietnam's national statistical yearbook for 2018. Water damage data, economic loss and flood risk index were recently provided by Luu et al. (2019) and the Central Committee for Flood and Storm Control (CCFSC) of Vietnam. The total human affected by

2.3. Data analysis

2.3.1. Images processing

ESRI ArcMap v10.4 was employed to process spatial data. Administrative boundaries from GADM served to clip or extract elevation, precipitation and other remote sensing data to the GADM country codes. ModelBuilder in ArcGIS 10.4 helped to convert spatial datasets to Excel datasets for further calculations. All spatial and statistical datasets were compiled according to the study site's provincial and ecological areas (Figure 3).

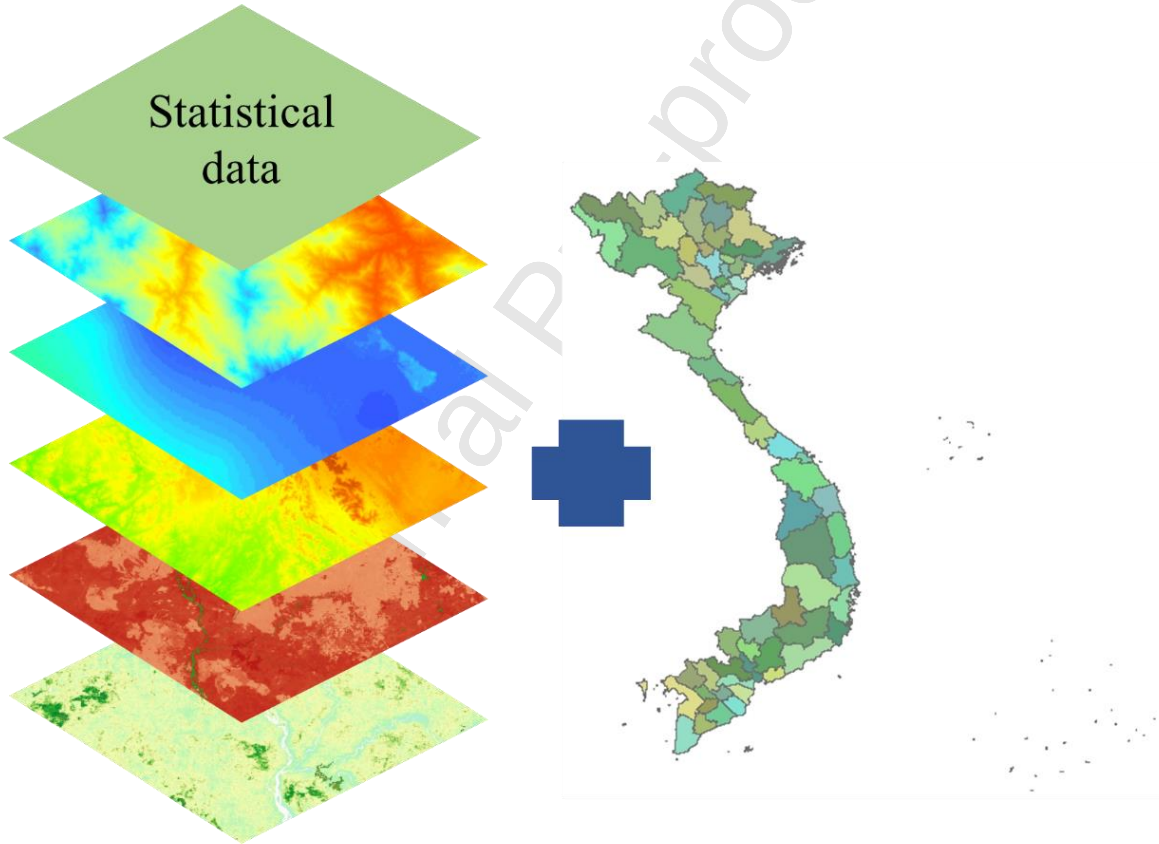


Figure 3. Incorporation of spatial datasets, statistical data set and the study site

2.3.2. Vulnerability assessment

One of the most popular concepts of vulnerability was presented in the 2001 IPCC report (Thornes, 2002). There are six steps in the vulnerability assessment process.

The most important step is to determine appropriate indicators or variables through consultations with experts, conducting a literature review or a field survey. Next is the collection of input data for those indicators by a variety of sources such as field survey, statistical data and remote sensing datasets. The third step is normalization of input datasets via the formula involving the UNDP's Human Development Index (HDI) (Duong et al., 2017; McNicoll, 2007).

$$X_{ij} = \frac{X_{ij} - Min\,X_{ij}}{Max\,X_{ij} - Min\,X_{ij}} \quad (1)$$

Where X_{ij} represents for normalized score of the j indicator for the ith area.

The next one is to calculate the indicators' weight according to the Iyengar and Sudarshan method (Iyengar and Sudarshan, 1982) method as stated here:

$$W_j = \frac{C}{\sqrt{Var\,(X_{ij})}}$$

(2)

$$C = \sum_{j=1}^{K} \frac{1}{\sqrt{Var(X_{ij})}} \quad (3)$$

Where K is the number of indicators, C is a normalizing constant, and W_j is the weight of indicator j (0<1<W_j)

The index for each indicator for in each area was estimated with the calculated weight in the previous step via the following formula:

$$M_{ij} = W_J \times X_{ij} \quad (4)$$

Where M_{ij} is the index of j factor in i^{th} area

After establishing the indices of indicators, the index of exposure, sensitivity, adaptive capacity and water vulnerability are estimated using the equations below:

$$V_h = \frac{\sum_1^n M_{ij}}{n} \tag{5}$$

$$WVI = \left(V_E + V_S + (1 - V_{AC})\right) / 3 \tag{6}$$

Where V_h is the index of E, S and AC component (h=E, S, AC); n is the total number of indicators for each E, S and AC; and WVI represents the water vulnerability index.

All vulnerability indicators are integrated and visualized by ArcGIS 10.4 software. Vulnerability maps are constructed according to ecological and provincial scale. There are five level of vulnerability including: very low, low, medium, high and very high.

3. Results and Discussion

3.1. Water quantity vulnerability assessment framework

The new water vulnerability assessment framework is built based on the general vulnerability assessment of IPCC, while the quantitative vulnerability assessment is devised by applying the index calculation method, normalization method, and weight evaluation method devised by Iyengar and Sudanrshan (Duong et al., 2017). The availability and accurately of input data for identified indicators is an integral part of this framework. The calculated results will help researchers in water resource management strategies to develop models for mitigating or adapting to climate change in the context of population growth and the drivers of economic development.

The water quantity vulnerability assessment framework is divided into three main layers (Figure 4): a data collection layer, a calculation layer and an output layer. The data collection layer will provide input data for the calculation layer. The major sources including satellite data, national or regional statistical data and information from experts, journals and regional documents will be used to collect data for their variables. Collected input data are stored in a database system, while statistical data can be displayed in Microsoft Excel and spatial data is processed by ArcGIS 10.4.

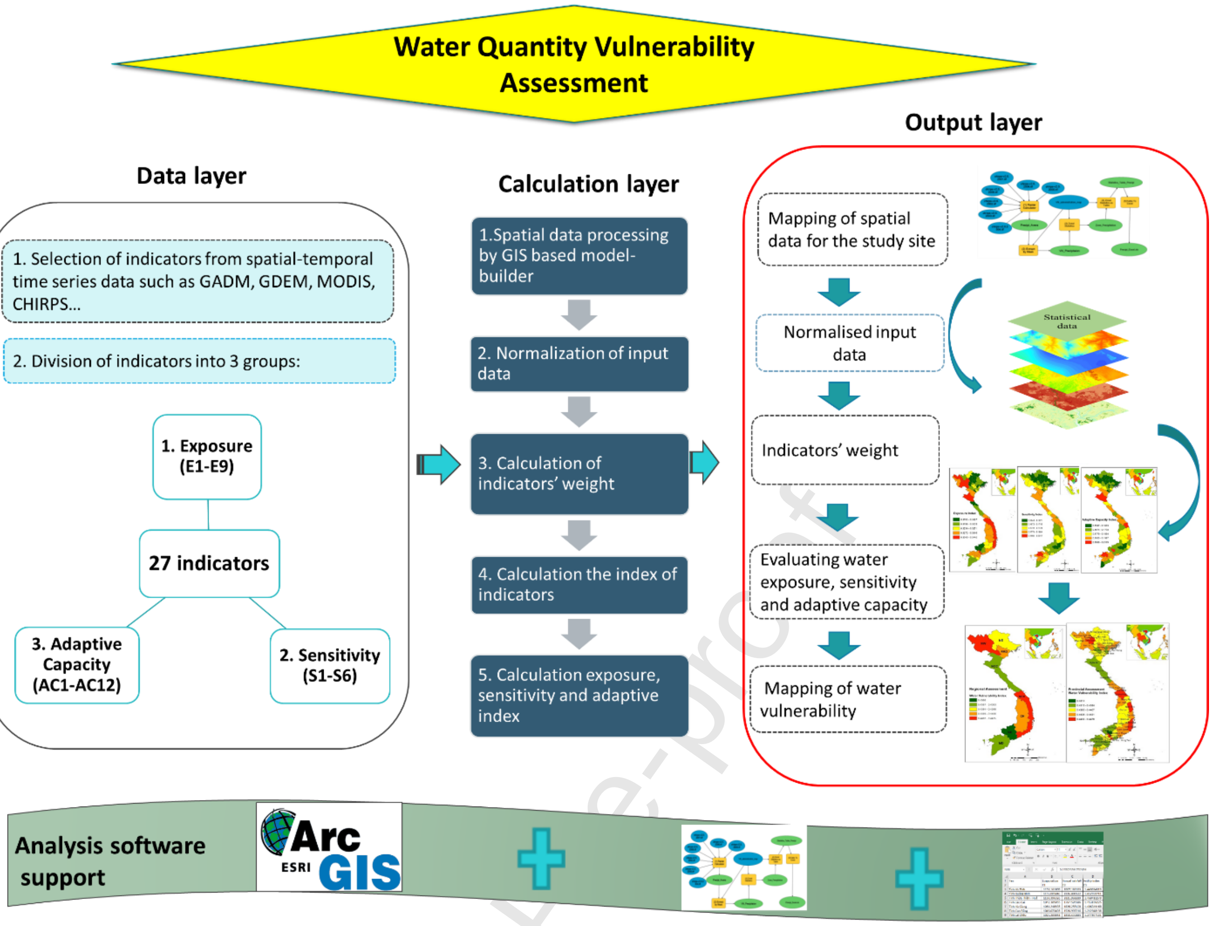


Figure 4. The framework of water vulnerability assessment

The calculation layer comprises five steps. The first step is to process satellite images by a GIS-based ModelBuilder function. The other steps including normalization of input data, calculating the weight of these data and the calculation of components and indications follow the vulnerability assessment method. The output layer will display results of the water vulnerability assessment in the form of tables, maps and graphs; this entails integration with Excel program and ArcGIS 10.4. This module is able to demonstrate the calculated outputs of exposure, sensitivity and adaptive indices for each province or each ecological zone. It also makes it possible to present calculated water quantity vulnerability index (WVI) of the study site for specific time periods.

The results can be illustrated by maps so that policy-makers or local authorities can easily identify the degree of water vulnerability for their regions in order to implement the best strategies for water management.

3.2. Selection of water vulnerability indicators

Indicators collected are divided into three groups, i.e. Exposure (E), Sensitivity (S) and Adaptive Capacity (AC) (Table 2). A greater number of indicators which can be acquired will create more appropriate results for understanding vulnerability assessment. Through a literature review and the limitation of data at the study site, the total number of variables is 27 indicators including 9 for exposure components, 6 for sensitivity components and 12 for adaptive components. These indicators originate from many sources. Spatial data are collected from satellite datasets such as MODIS images, ASTER GDEM and Consortium for Spatial Information. Other data are derived from national and provincial statistical yearbooks and relevant journal papers.

Table 2. The selected indicators for water vulnerability assessment

Component	Indicator	Code	Unit	Period	Data Source
Exposure	Evapotranspiration	E1	mm	1981-2018	Trabucco and J.Zomer, 2018
	Annual rainfall	E2	mm	1981-2018	Climate Hazards Group InfraRed Precipitation (CHIRPS)
	Aridity index	E3		1970-2000	Consortium for Spatial Information
	Flood index	E4		1989-2015	(Luu et al., 2019)

Component	Indicator	Code	Unit	Period	Data Source
	Elevation	E5	m	2016	ASTER GDEM version 3
	Priestley–Taylor alpha coefficient	E6		1970-2000	Consortium for Spatial Information
	Impervious surface ratio	E7	%	2000-2018	Vietnam statistical yearbook
	Population density	E8	person/km^2	2000-2019	Vietnam statistical yearbook
	Population growth rate	E9	%	2000-2020	Vietnam statistical yearbook
Sensitivity	Irrigation -Eroded earth, rock	S1	m^3	1989-2015	(Luu et al., 2019)
	Economic loss	S2	Million VND	1989-2015	(Luu et al., 2019)
	Soil Water Stress	S3		1970-2000	Consortium for Spatial Information
	Agricultural production land	S4	km^2	2000-2018	Vietnam statistical yearbook
	Female	S5	Thousand people	2000-2018	Vietnam statistical yearbook
	Poverty rate	S6	%	2000-2018	Vietnam statistical yearbook
Adaptive Capacity	Water Use Efficiency	AC1	g/Cm^2 mm	2000-2019	Calculated from NPP and evapotranspiration
	Rain Use Efficiency	AC2	g/Cm^2 mm	2000-2019	Calculated from NPP and precipitation
	Leaf area index (LAI)	AC3	m^2/m^2	2000-2019	MODIS data (MOD15A2)

Component	Indicator	Code	Unit	Period	Data Source
	River density	AC4	m/km^2	2010	Hanoi University of Science
	Road density	AC5	m/km^2	2010	Hanoi University of Science
	Pervious surface	AC6	%	2000-2018	Vietnam statistical yearbook
	Percentage of trained employed workers at 15 years of age and above	AC7	%	2000-2018	Vietnam statistical yearbook
	Total foreign direct investment until 2018	AC8	Mil.USD	2000-2018	Vietnam statistical yearbook
	Number of health establishments	AC9	Establish-ments	2000-2018	Vietnam statistical yearbook
	Percentage of urban population provided with clean water by centralized water supply system	AC10	%	2000-2018	Vietnam statistical yearbook
	Percentage of household having hygienic water	AC11	%	2000-2018	Vietnam statistical yearbook
	Annual income	AC12	Thousand VND	2000-2018	Vietnam statistical yearbook

The water vulnerability assessment was determined by combining important spatial indicators that include the evapotranspiration, annual precipitation, aridity index, soil water stress, Priestley–Taylor alpha coefficient, leaf area index, water use efficiency and rain use efficiency. Annual precipitation data was collected from Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) for the years 1981-2018 when floods and droughts were studied (Isundwa and Mourad, 2019). Aridity index (AI) was evaluated from mean annual precipitation and mean annual reference evapo-transpiration (Trabucco and J. Zomer, 2018). It can be acquired from the Consortium for Spatial Information. Higher aridity index indicates less aridity and this data can be applied for research on environmental conservation, sustainable water development and climate change projects.

The annual soil water stress was estimated by the average of monthly soil water stress. Soil stress coefficient (K_{soil}) represents soil water stress (SWS) which was calculated by the ratio of monthly soil water content (SWC_m) and the maximum amount of soil water content for evapotranspiration process (SWC_{max}) according to this formulation (Trabucco, 2010):

$$K_{soil} = SWC_m / SWC_{max}$$

$$SWS = K_{soil} * 100$$

Leaf Area Index (LAI) is defined as the leaf occupied area in a unit of land (Fang and Liang, 2014). The research used the annual LAI values in standard deviation of the leaf area index (LAI) for the 19 years from February 2000 to December 2019, which processed the MODIS images – MOD15A2 version 6 product. This dataset is the acquisition of the Terra sensor in an 8-day composite dataset with a 500m resolution. The version 6 product is of superior quality compared to other versions of 1000m resolution. MODIS land products were validated by the MODIS Land Team and Earth Observing System Validation Program Office (Justice et al., 2002; Morisette et al., 2002).

Water Use Efficiency (WUE) is presented as the amount of biomass produced (gram of carbon mass per m^2) per mm of water used by crops (Hatfield and Dold, 2019). Annual water use efficiency is calculated as the ratio of net primary production (g C/m^2/mm) per amount of water loss which were defined by units of annual evapotranspiration (mm). Rain Use Efficiency (RUE) is identified by the ratio of the net primary production and amount of annual precipitation (Dardel et al., 2014). Net primary production (NPP) is identified as total amount the carbon which ecosystems receive through the photosynthetic reduction of CO_2 discounted for plant autotrophic respiration (Chapin and Eviner, 2007; Running et al., 2000). Photosynthesis is affected by droughts, floods and other types of extreme climate patterns (Zhang et al., 2017). NPP has the negative correlation with water disasters. So, the estimation of NPP plays an important role in predicting climate change and its impact on water issues that increasingly threaten the ecosystem. This paper used NPP as an indicator to assess water vulnerability index. NPP datasets were acquired from Terra MODIS 17A3H with a resolution of 500m for the study site covering the period 2000-2019.

3.3. Mapping of satellite data

Spatial data after collecting were processed in ArcGIS 10.4 using ModelBuilder function. Leaf Area Index, Precipitation or Net Primary Production are displayed as time series spatial raster image. ModelBuilder makes it possible to analyse these data through analytical procedures. The model created from this function can be transferred into the tool and then allowed to share and be applied in other studies that examined different regions. ModelBuilder is a visual programming tool that serves to build workflows with a sequence. Figure 5 presents the explicit modelling process of extracting precipitation from remote sensing datasets. Other spatial data are analysed with a similar process. The blue blocks are primary input data, the yellows ones are geo-processing tools and the green blocks are the results of one geo-processing tool and subjected to the input of another tool in the model. The model in Figure 5 consists of five steps each one using a processing tool: (1) evaluating the world's average precipitation from 1970 to 2018 by raster calculation tool or cell calculation tool; (2) extracting data for study area by extract by mask tool; (3) determining statistic values for each region or area by zonal statistic tool; (4) reporting the results on a table by zonal statistic; and (5) converting these data into an Excel spreadsheet. Extracted data from satellite images are analysed in the following steps using Excel and R programming.

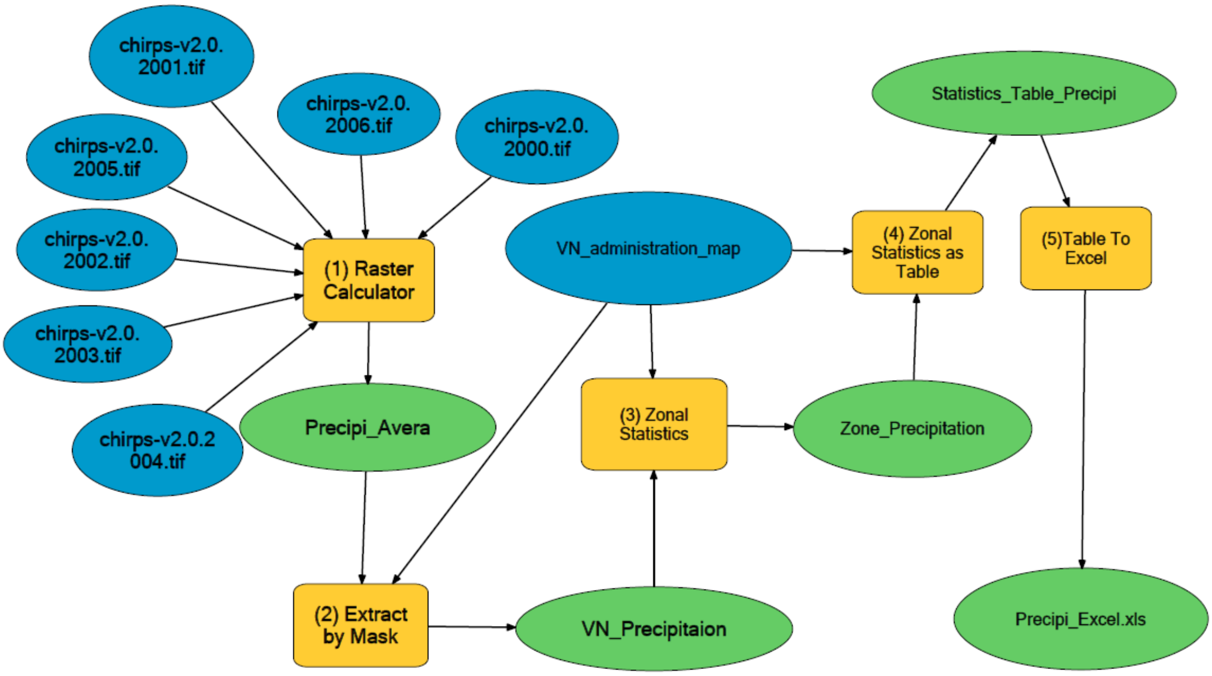


Figure 5. The example of a GIS-based model for precipitation data processing

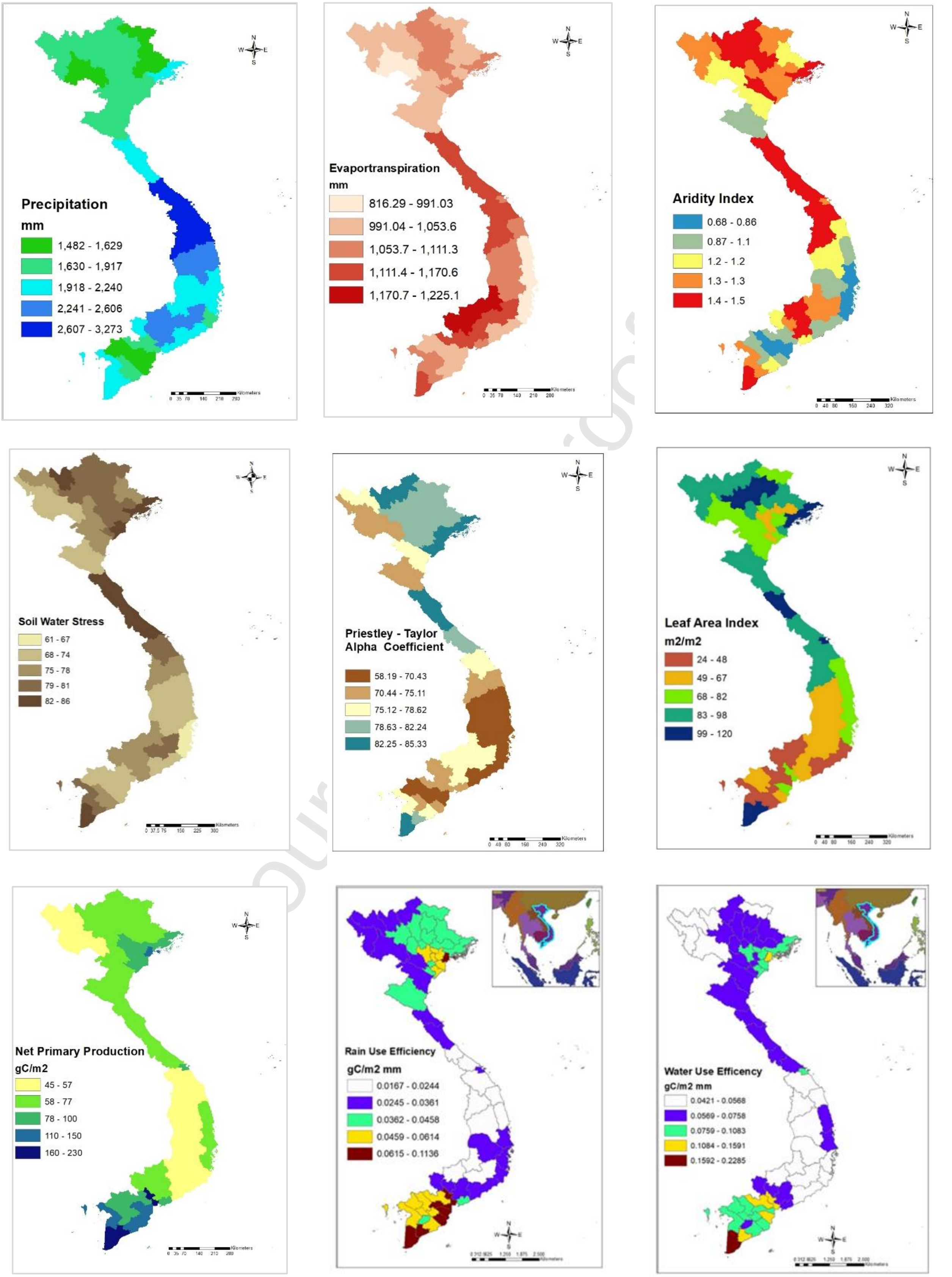
Yearly actual evapotranspiration data was estimated by the average of evapotranspiration from 1950 to 2000 (Trabucco, 2010). The annual precipitation in Vietnam ranges from about 1480 mm to 3270 mm and the mean annual evapotranspiration is about 810 mm to 1220 mm (Figure 6). While annual precipitation is higher in the central region and lower in the north area of Vietnam, the provinces in the country's south west region represent have more annual evapotranspiration. Figure 6 illustrates the Vietnam aridity index which is extracted from the Global Aridity Index dataset with high-resolution (30 arc-seconds) global raster climate data from 1970 to 2000. The aridity index for all provinces in Vietnam is higher than 0.65 which means Vietnam belongs to the humid climate class according to Table 3. The most humid area in Vietnam is the central coast region with an aridity index of nearly 1.5.

Table 3. The Classification of climate types based on aridity index (adapted from (Trabucco and J. Zomer, 2018))

Aridity Index	Climate type
< 0.03	Hyper Arid
0.03-0.2	Arid
0.2-0.5	Semi-Arid
0.5-0.65	Dry sub-humid
> 0.65	Humid

Provinces in Vietnam's south central coast region have the highest value of soil water stress with more than 80% of water available for evapotranspiration, indicating high water content in soil so there is less water vulnerability in this area. In contrast, Khanh Hoa and Ninh Thuan provinces experience less soil water stress and higher water vulnerability with SWS value ranging from 61% to 67%. The Priestley–Taylor alpha coefficient (PAC) was calculated by the fraction of annual actual evapotranspiration and the annual potential evapotranspiration (Trabucco, 2010). The value of PAC ranges from 0-100%. The higher value of PAC illustrates lower water vulnerability so consequently, PAC was selected as one of the indicators for assessing water vulnerability. It can be seen in the figures below that while the north of Vietnam has higher PAC values than other regions, the central highland and south central coast experience lower PAC values.

Low values of LAI can be seen in the southeast area and Mekong Delta, followed by the Central Highlands zone. Hau Giang and Long An provinces had a LAI index below 30 m^2/m^2, while in comparison, Ca Mau and Bac Kan experienced higher LAI values with nearly 115 m^2/m^2 (Figure 6). LAI are influenced by natural factors, for example climate but there are also human factors involved such as farming and deforestation activities. LAI is deemed to be an indicator which impacts on water resources. This is due to the processes of evapotranspiration, water flow and infiltration, and aquifer recharge (Taugourdeau et al., 2014). Higher level of LAI value results in a much reduced water risk (Isundwa and Mourad, 2019).



Precipitation
mm
1,482 - 1,629
1,630 - 1,917
1,918 - 2,240
2,241 - 2,606
2,607 - 3,273
Evaportranspiration
mm
816.29 - 991.03
991.04 - 1,053.6
1,053.7 - 1,111.3
1,111.4 - 1,170.6
1,170.7 - 1,225.1
Aridity Index
0.68 - 0.86
0.87 - 1.1
1.2 - 1.2
1.3 - 1.3
1.4 - 1.5
Soil Water Stress
61 - 67
68 - 74
75 - 78
79 - 81
82 - 86
Priestley - Taylor
Alpha Coefficient
58.19 - 70.43
70.44 - 75.11
75.12 - 78.62
78.63 - 82.24
82.25 - 85.33
Leaf Area Index
m2/m2
24 - 48
49 - 67
68 - 82
83 - 98
99 - 120
Net Primary Production
gC/m2
45 - 57
58 - 77
78 - 100
110 - 150
160 - 230
Rain Use Efficiency
gC/m2 mm
0.0167 - 0.0244
0.0245 - 0.0361
0.0362 - 0.0458
0.0459 - 0.0614
0.0615 - 0.1136
Water Use Efficency
gC/m2 mm
0.0421 - 0.0568
0.0569 - 0.0758
0.0759 - 0.1083
0.1084 - 0.1591
0.1592 - 0.2285

Figure 6. Mapping of spatial distribution for Vietnam's provincial remote sensing indicators

Higher WUE and RUE values can be observed in the Mekong Delta. In contrast, the Central Coast area and Central Highlands have experienced lower levels of WUE and RUE. The country's northwest region also suffered from poor water use efficiency. The provinces Lam Dong, Kon Tum and Dak Nong in the Central Highlands area have the lowest value of NPP; about 50 g C/m^2 resulting in lower WUE and RUE. In contrast, Mekong Delta and Red River Delta experienced higher levels of NPP. Ca Mau province witnessed the highest value of NPP with 230 g C/m^2 and it had the highest level of WUE and RUE, followed by Bac Lieu province.

3.4. The weights of indicators

The weights of selected indicators are identified in Table 4 that represent their contribution to the issue of water quantity vulnerability. There are four main methods to evaluate indicators' weights: (1) identifying the weights by expert consultants and interviews; (2) assumption of the equal weight for all variables; (3) applying multivariate statistical techniques; and (4) using the Iyengar and Sudarshan method. The fourth method is the easiest to apply and the most feasible for this study. The indicators' weights were determined by the Iyengar and Sudarshan method via the Excel function. These weights were calculated independently for each component of exposure, sensitivity and adaptive capacity that are illustrated in Table 4. Impervious surface ratio, female ratio, population density and river density were identified as having higher relative importance compared to other indicators in this vulnerability assessment.

Table 4. Results of the weight calculation

Component	Indicator	Code	Weight
Exposure	Evaporation	E1	0.135
	Annual rainfall	E2	0.0951
	Aridity index	E3	0.0908
	Flood index	E4	0.0877
	Elevation	E5	0.079
	Priestley–Taylor alpha coefficient	E6	0.1013
	Impervious surface ratio	E7	0.1709
	Population density	E8	0.1433
	Population growth rate	E9	0.097
Sensitivity	Irrigation -Eroded earth, rock	S1	0.1666
	Economic loss	S2	0.1482
	Soil Water Stress	S3	0.1851
	Agricultural production land	S4	0.1276
	Female ratio	S5	0.215
	Poverty rate	S6	0.1575
Adaptive Capacity	Water Use Efficiency	AC1	0.0833
	Rain Use Efficiency	AC2	0.0939
	Leaf area index (LAI)	AC3	0.0703
	River density	AC4	0.1325
	Road density	AC5	0.1062
	Pervious surface	AC6	0.0665
	Percentage of trained employed workers at 15 years of age and above	AC7	0.079
	Total foreign direct investment until 2018	AC8	0.0816
	Number of health establishments	AC9	0.0897
	Percentage of urban population provided with clean water by centralized water supply	AC10	0.0729

Component	Indicator	Code	Weight
	system		
	Percentage of household having hygienic water	AC11	0.0468
	Annual income	AC12	0.0773

3.5. Spatial distribution of water vulnerability

The indices of E, S, AC and WVI were then calculated and ranked for ecological zones and provincial areas as well. Of the eight ecological zones, the northeast area experienced both the lowest level of exposure, sensitivity and adaptive capacity which are indicated in Table 5. Very low vulnerability occurs in Southeast area. The Mekong Delta although has the highest level of sensitivity, it exposes low vulnerability due to exhibiting very high level of adaptive capacity compared to the other ecological zones. The South Central Coast area is greatly influenced by flood disasters and extreme climate events (Luu et al., 2019). It is one reason causing the highest level of water vulnerability sensitivity in the South Central Coast (Table 5). The study results suggest that the very high vulnerable area are the South Central Coast and Northeast, followed by Red River Delta and Central Highlands.

Table 5. Results of water quantity vulnerability assessment for the ecological zones

EZ	Exposure	Sensitivity	Adaptive Capacity	WVI	Vulnerability level
Northeast	0.3193	0.1671	0.1671	0.4398	Medium
Northwest	0.3323	0.1698	0.1764	0.4419	Very high
Red River Delta	0.3229	0.1681	0.1701	0.4403	High

North Central Coast	0.3270	0.1795	0.1885	0.4393	Low
South Central Coast	0.3401	0.1763	0.1861	0.4435	Very high
Central Highlands	0.3280	0.1695	0.1757	0.4406	High
Southeast	0.3202	0.1713	0.1816	0.4366	Very low
Mekong Delta	0.3269	0.1801	0.1891	0.4393	Low

The indices for exposure, sensitivity and adaptive capacity at the provincial level were also established (see Figure 7). The most vulnerable provinces are Yen Bai, Binh Dinh, Khanh Hoa, Ho Chi Minh, Ninh Thuan, Da Nang and Quang Nam. In contrast, Binh Duong, Hoa Binh, Tay Ninh, Nghe An, An Giang, Ha Tinh experienced a low level of water vulnerability (Figure 8a). Results concerning provincial water vulnerability indices can help local authorities with their water systems planning and deciding on what is the best strategy to implement.

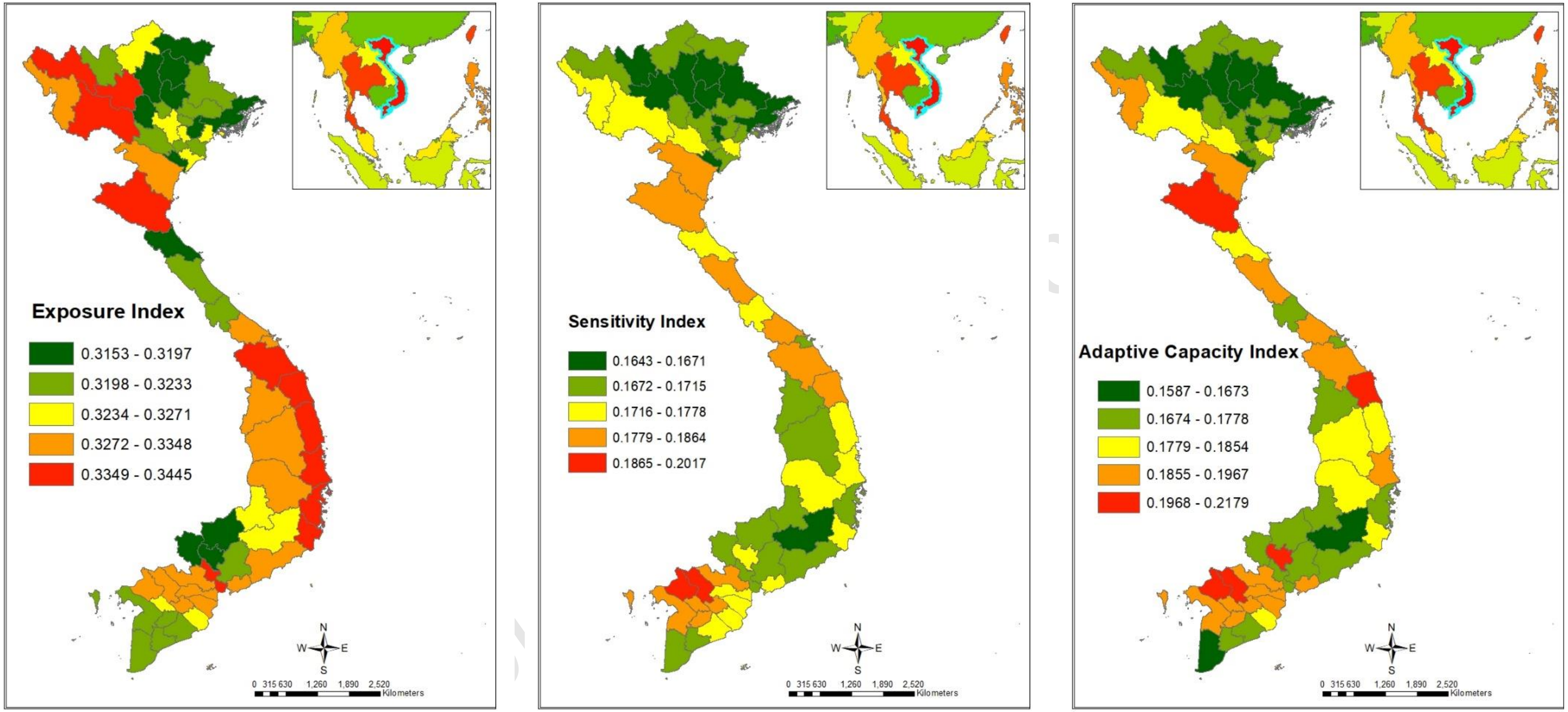


Figure 7. Spatial distribution for provincial exposure index (a), sensitivity index (b) and adaptive capacity index (c)

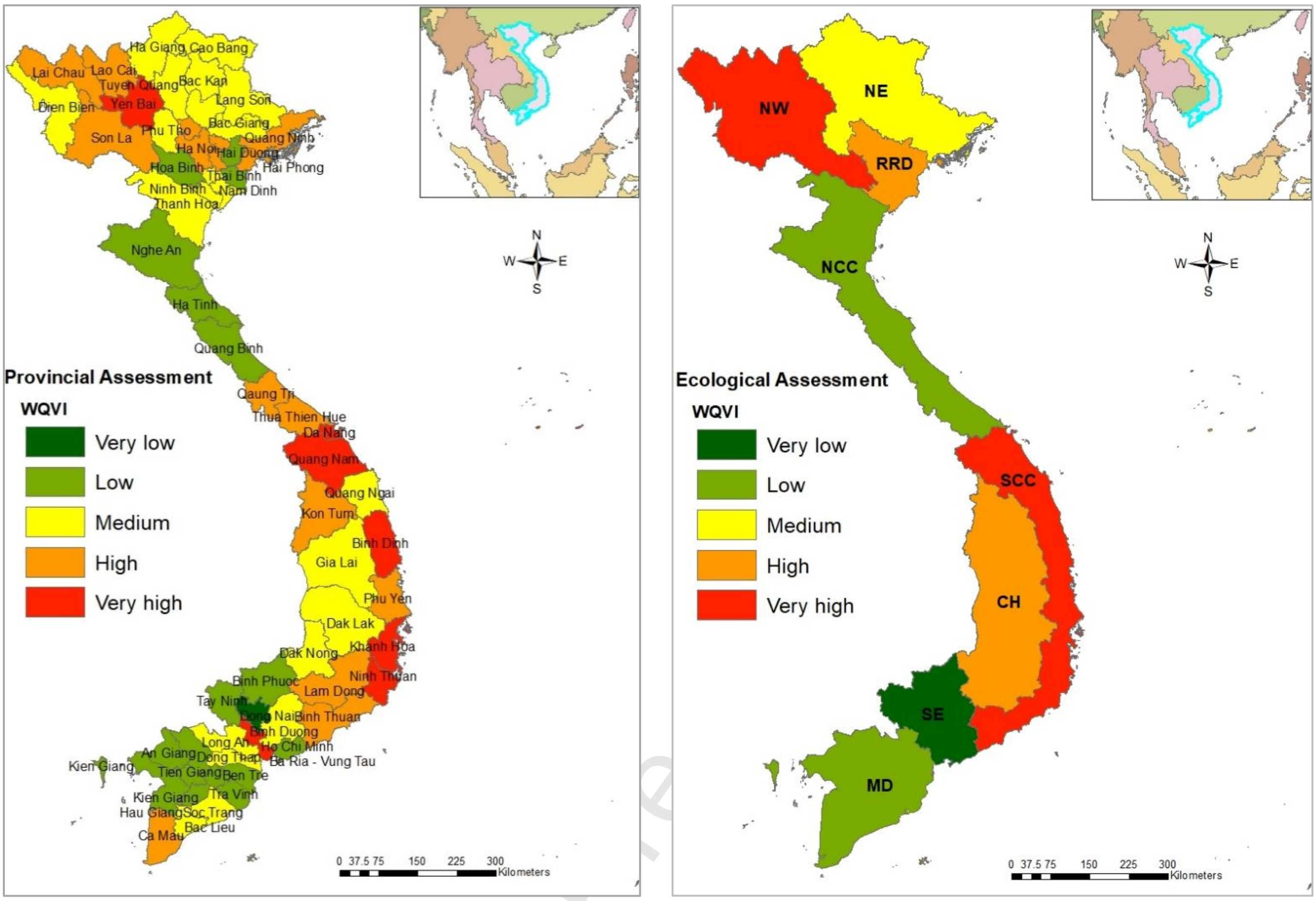


Figure 8. Spatial distribution of provincial water quantity vulnerability index (a), and ecological water quantity vulnerability index (b)

The vulnerability index is influenced by all three components of exposure, sensitivity and adaptive capacity. The spatial distribution of water quantity vulnerability for Vietnam's eight ecological zone is provided in Figure 8b. This picture clearly indicates the most vulnerable ecological zones which are the South Central Coast and the North West. Those areas also experienced poor water use efficiency levels. The South Central Coast area has a higher exposure index with lower adaptive capacity and it suffers the highest vulnerability index. It is also evident that the South East is the least vulnerable due to the lower level of exposure and the fact that the Mekong Delta is highly resilient because adaptive capacity there is very high.

4. Overall discussion

The approach can be applied easily for other studies and regions with freely accessible spatial data sources. Assessing water quantity vulnerability is to identify regions and communities that need to prioritize planning and implementing water strategies in terms of water stress across the world. The finding indicates the South Central Coast has very high level of water quantity vulnerability. The South Central Coast area also was identified as the highest vulnerable area to typhoons and floods (Nguyen et al., 2019; Luu et al., 2019). The Northwest region was illustrated as very high vulnerable area in the study due to the lower level of community's resilience which was presented in the other studies of vulnerability assessment for Vietnam (Few & Tran, 2010; Thanh Thi Pham et al., 2020). The framework employed 27 important spatial-temporal indicators, however; it did not explore other influential factors such as freshwater availability, water stress, water withdrawal for different reasons or other institutional indicators due to the unavailability of data in the study area. In addition, water related hazards like water pollution and contamination should be undertaken in the research. These aspects should be incorporated in further water vulnerability assessment studies.

Uncertainties in the study should be addressed through verification processes by survey, questionaries and a communication between experts from different fields such as social, technical and political fields. For example, indicator's selection and indicator's weight should be cross-checked through consultations with scientists and local officials so that it will help the current framework become more refined. In the scope of this study, the verification of the results were carried out on the total number of human affected (deaths, injured, missing) by flood, flash-flood, rain, storm and typhoon and water quality vulnerability index using a multiple linear regression analysis in R. Human affected data were collected from Sendai Framework for Disaster Risk Reduction the Central Committee for Flood and Storm Control (CCFSC) of Vietnam from 1989 to 2015. The coefficient of determination (R^2) is one of statistical measures, which is applied to assess the model performance (Anandhi and Kannan, 2018). If the R-squared is greater than 60%, it is considered acceptable for hydrological simulation and prediction (Anandhi and Kannan, 2018; Moriasi et al., 2007; Santhi et al., 2001). There was a linear relationship between the water quantity vulnerability and the observations of human affected by water related hazards with the multiple coefficient of determination (R-squared) of 0.6463 and residual standard error of 0.6406. Figure 9 indicates that the results of new approach are reasonable as residuals are close to straight dashed lines.

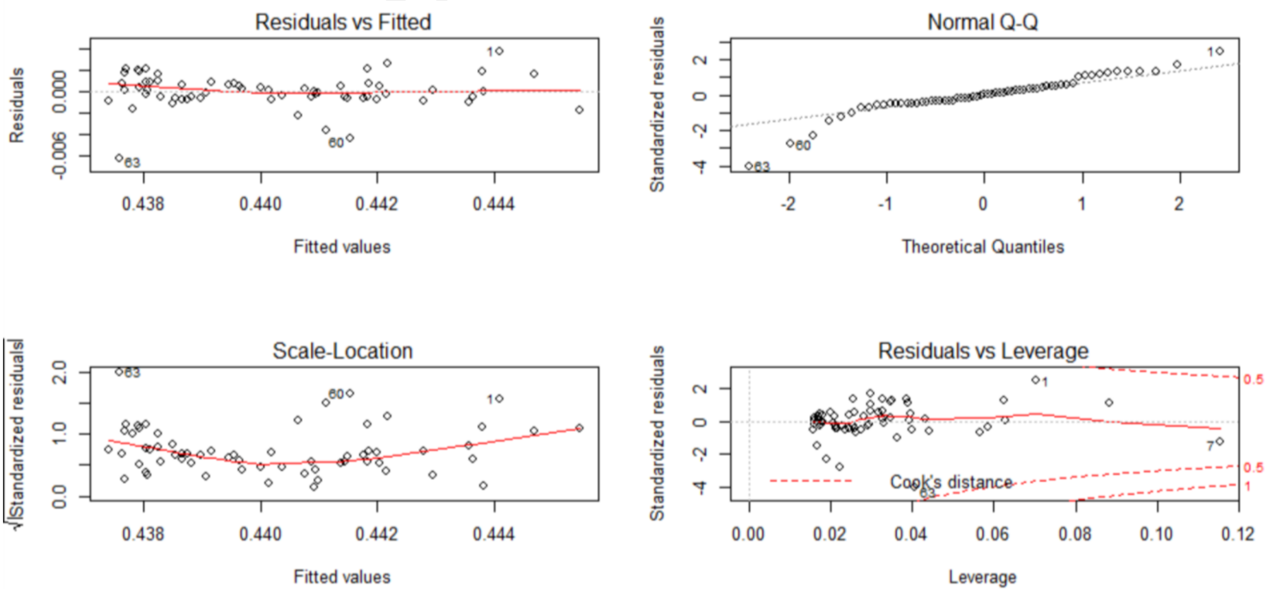


Figure 9. Linear regression plots

Furthermore, the further water vulnerability assessment should consider the concept of sustainability in the DPSIR (Driver-Pressure-State-Impact-Response) framework for the selection of vulnerability's indicators. Moreover, it should be applied machine learning methods like Analytical Hierarchy Process (AHP), the Fuzzy Logic, Weights of Evidence (WOE) and Logistic Model Tree (LMT) to improve the results of the framework (Khosravi et al., 2018). Finally, the accepted framework should integrate climate change and population growth scenarios so that a future water vulnerability index can be predicted.

The results of the study are still beneficial although its limitations and uncertainties. Firstly, it can be used for water quantity vulnerability adaptation and mitigation research by providing standardized input data for site selection of alternative water practices. Secondly, it helps practitioners and administrators identify influencing factors to water quantity vulnerability in order to support them more understanding the water system. In addition, it allows policy makers appreciate baseline data and wide range of information for water implementation practices. Finally, the water quantity vulnerability framework of the study employing updated spatial datasets is an indispensable approach for countries where lack of efficient data for conducting vulnerability and impact analyses.

5. Conclusions

Appropriate evaluation of water vulnerability is vital if we are to understand the impact of climate change and human activities on water resources. Water managers must have the most effective water management strategies in the future where climate change will influence much of what human societies do. Several methods and frameworks of vulnerability assessment are available, but their performance can be compromised by several obstacles due to the unfeasibility and unavailability of input data. This study developed a new assessment framework that considered the contribution of satellite datasets like Terra MODIS and the utilization of GIS-based model. The integration is very useful and flexible for the complexity of vulnerability assessment. Moreover, this study calculated the indices of water quantity vulnerability components and constructed spatial distribution maps of water exposure, sensitivity and adaptive capacity in different scales for a case study. This part of the study was based on 27 chosen time series indicators. The findings indicated that the South Central Coast experiences extremely vulnerable, while the South East region is the least vulnerable region. Yen Bai, Binh Dinh, Khanh Hoa, Ho Chi Minh, Ninh Thuan, Da Nang and Quang Nam provinces are classified as very high vulnerability. Through the calculation of indicators' weight, it can be concluded that more responsible variables for high level of water vulnerability are impervious surface ratio, population density, healthcare establishment, water use efficiency and river density. Vietnam's growing population is accompanied by an increase in the impervious surface infrastructures like high-rise building and deforestation. These activities are triggering a high rate of water quantity vulnerability. A future work should be considered scenarios namely population, water availability, climate change to enhance water vulnerability evaluation and increase the resolution of the framework in identifying vulnerable hotspots. In addition, the machine learning methods and field observations should be integrated to increase the accuracy of such framework.

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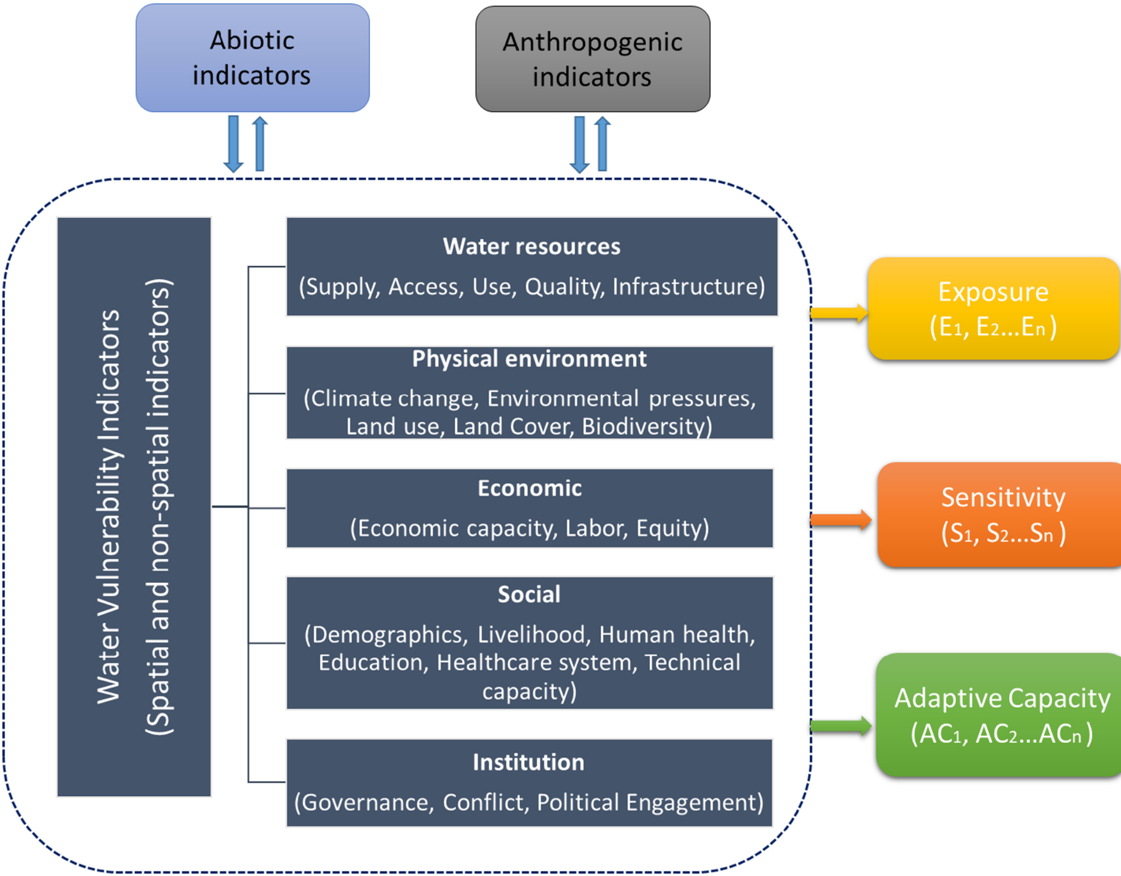
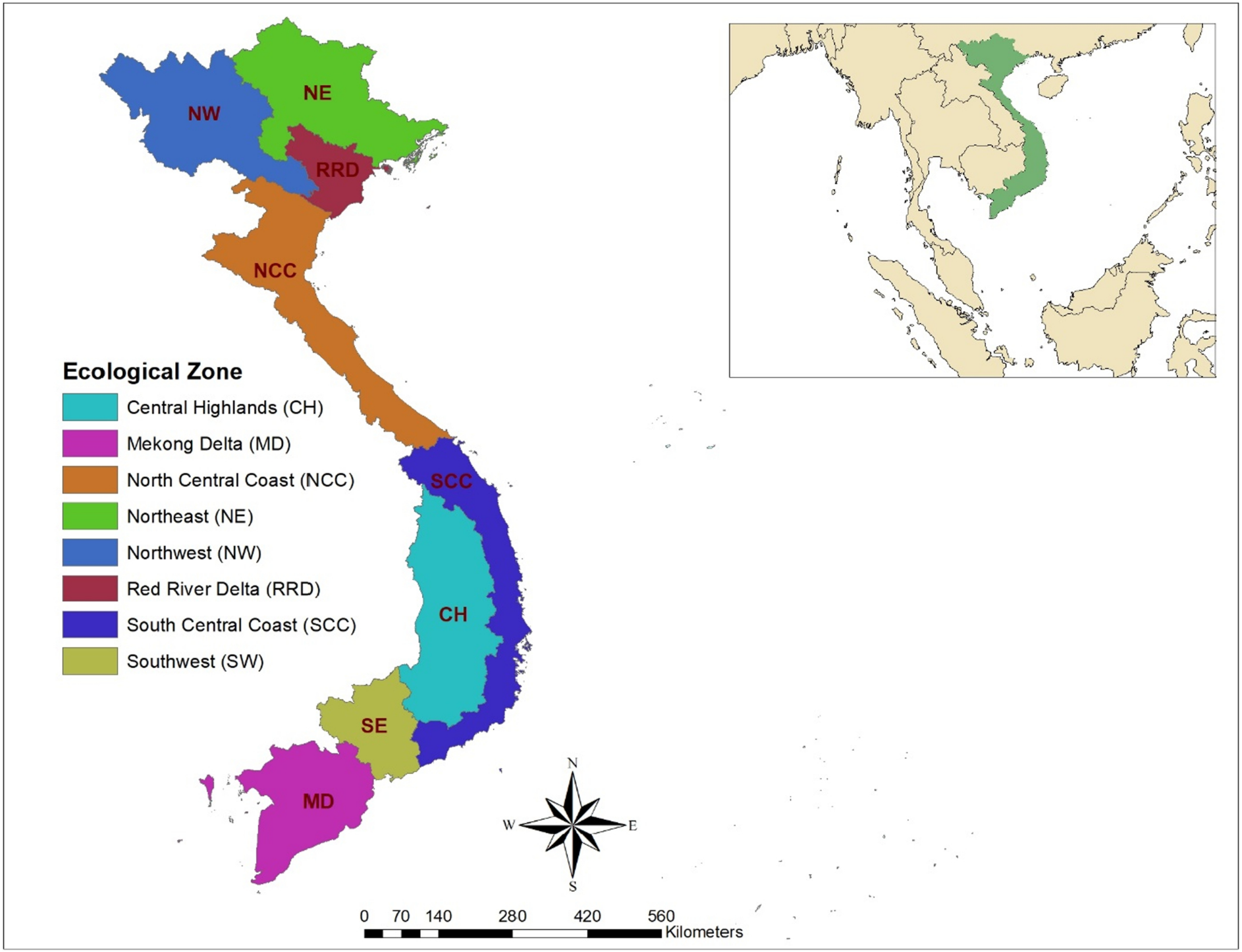

Abiotic indicators
Anthropogenic indicators
Water Vulnerability Indicators
(Spatial and non-spatial indicators)
Water resources
(Supply, Access, Use, Quality, Infrastructure)
Physical environment
(Climate change, Environmental pressures, Land use, Land Cover, Biodiversity)
Economic
(Economic capacity, Labor, Equity)
Social
(Demographics, Livelihood, Human health, Education, Healthcare system, Technical capacity)
Institution
(Governance, Conflict, Political Engagement)
Exposure
(E_1, E_2...E_n)
Sensitivity
(S_1, S_2...S_n)
Adaptive Capacity
(AC_1, AC_2...AC_n)

Figure 1


NE
NW
RRD
NCC
SCC
CH
SE
MD
Ecological Zone
Central Highlands (CH)
Mekong Delta (MD)
North Central Coast (NCC)
Northeast (NE)
Northwest (NW)
Red River Delta (RRD)
South Central Coast (SCC)
Southwest (SW)
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W
E
S
0 70 140 280 420 560
Kilometers

Figure 2

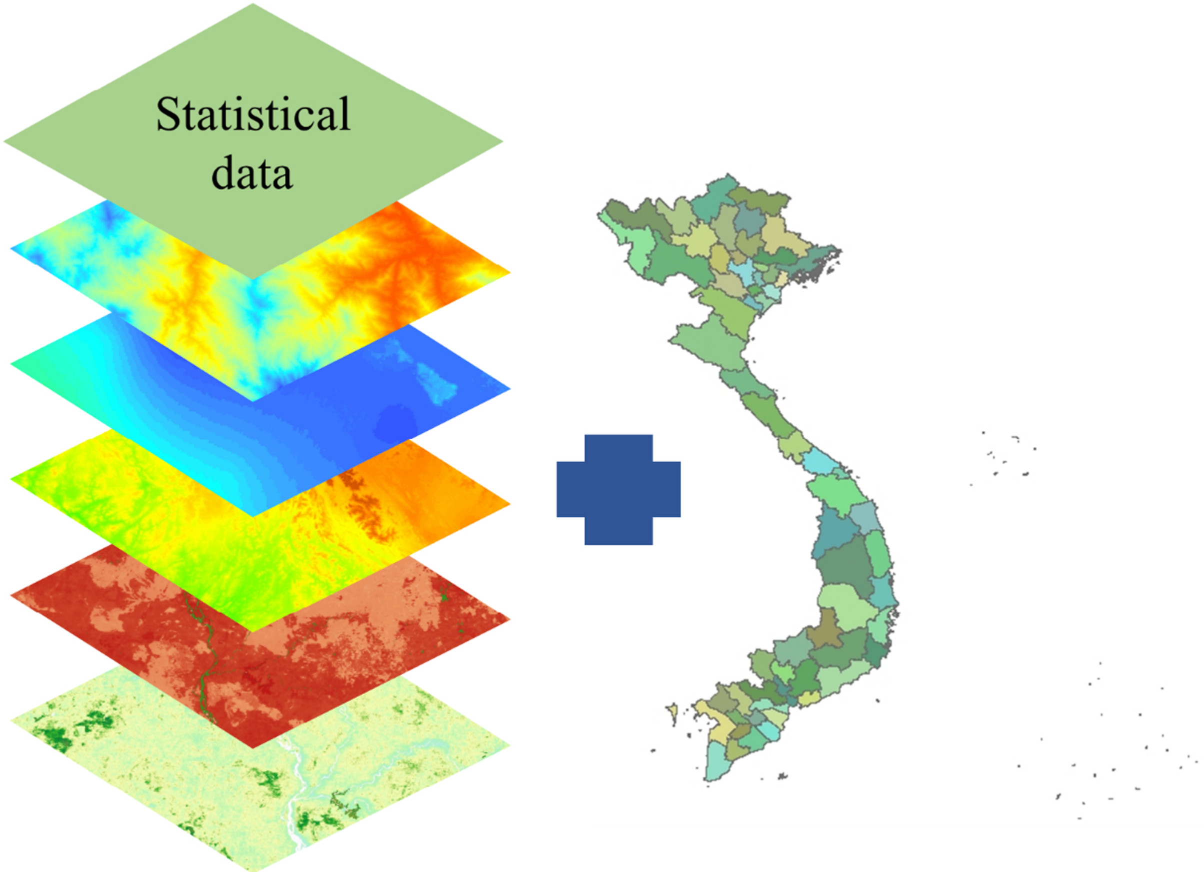
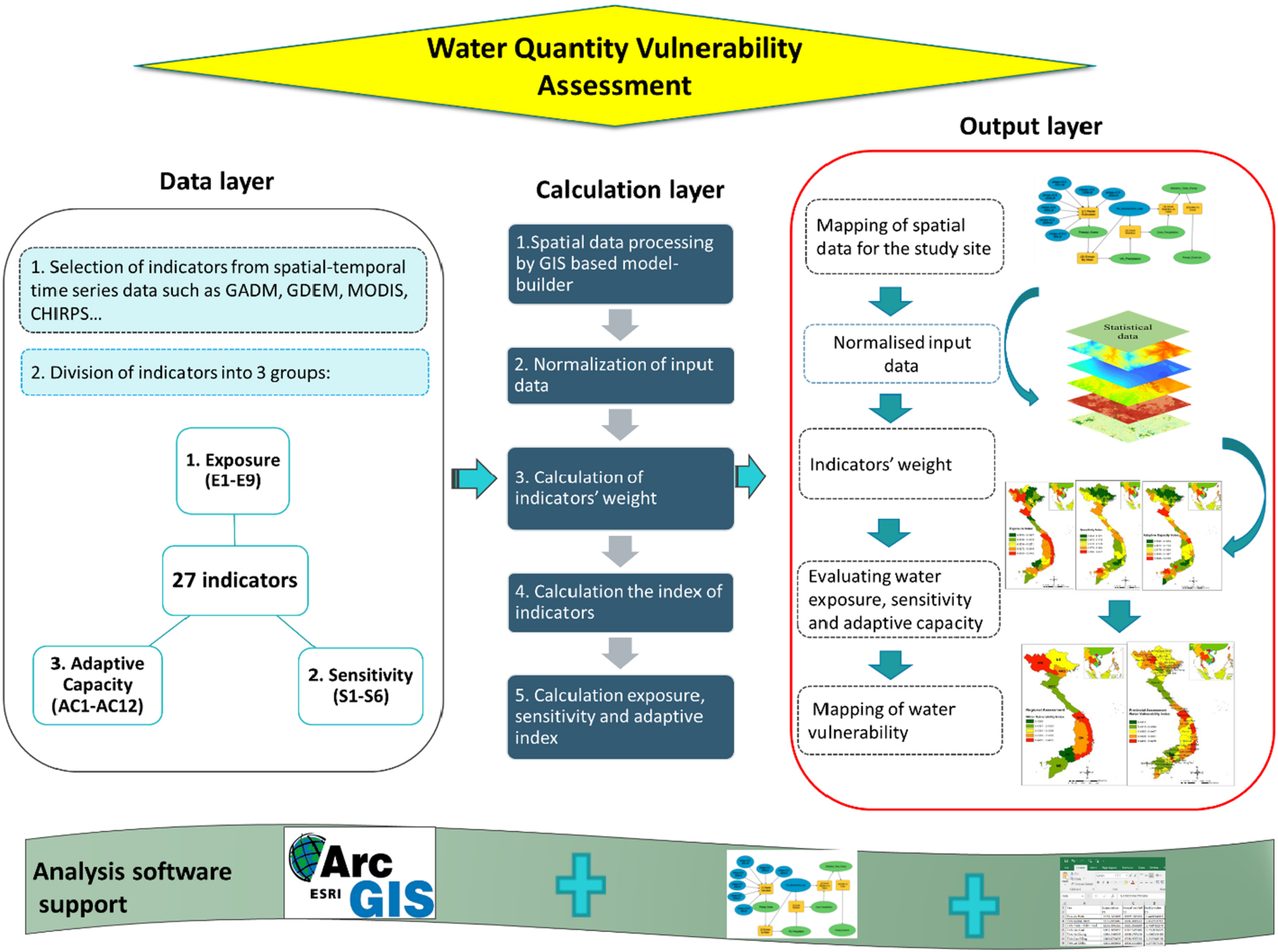
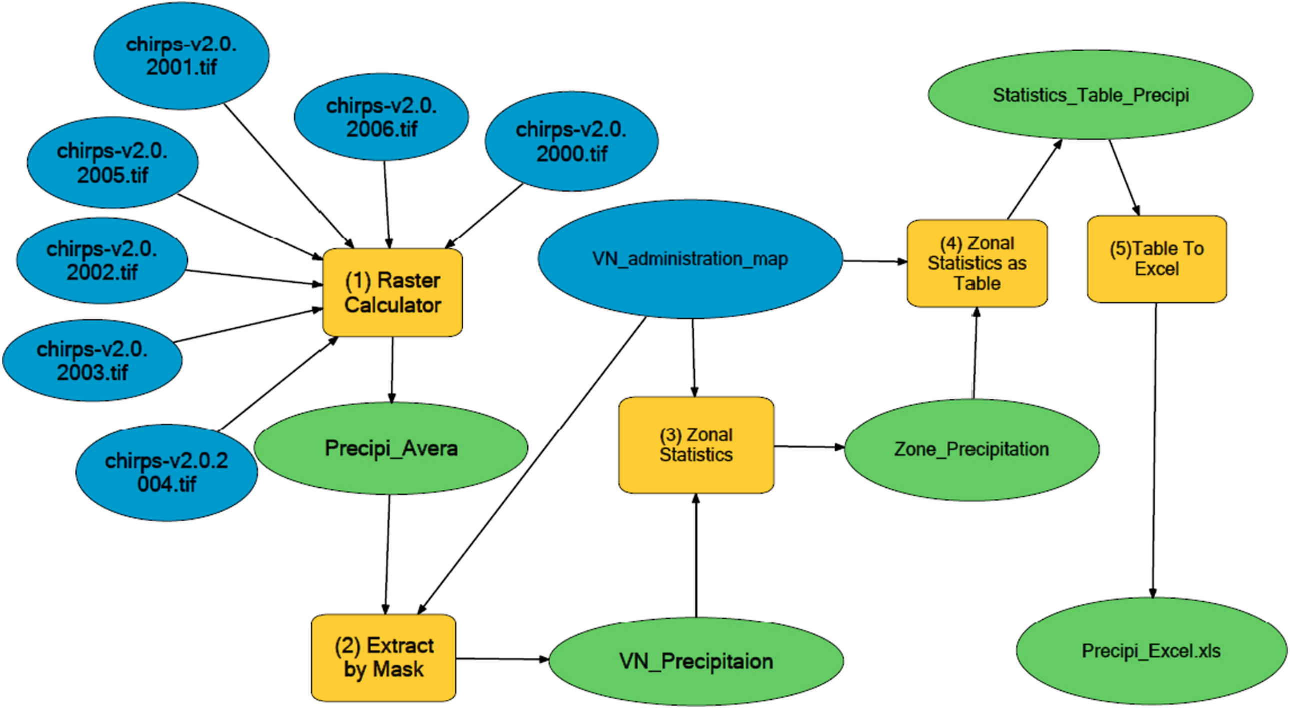


Figure 3



Water Quantity Vulnerability Assessment
Data layer
1. Selection of indicators from spatial-temporal time series data such as GADM, GDEM, MODIS, CHIRPS...
2. Division of indicators into 3 groups:
1. Exposure (E1-E9)
27 indicators
3. Adaptive Capacity (AC1-AC12)
2. Sensitivity (S1-S6)
Calculation layer
1.Spatial data processing by GIS based model-builder
2. Normalization of input data
3. Calculation of indicators' weight
4. Calculation the index of indicators
5. Calculation exposure, sensitivity and adaptive index
Output layer
Mapping of spatial data for the study site
Normalised input data
Statistical data
Indicators' weight
Evaluating water exposure, sensitivity and adaptive capacity
Mapping of water vulnerability
Analysis software support
ESRI ArcGIS

Figure 4



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2003.tif
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(1) Raster
Calculator
Precipi_Avera
(2) Extract
by Mask
VN_Precipitaion
VN_administration_map
(3) Zonal
Statistics
Zone_Precipitation
(4) Zonal
Statistics as
Table
Statistics_Table_Precipi
(5)Table To
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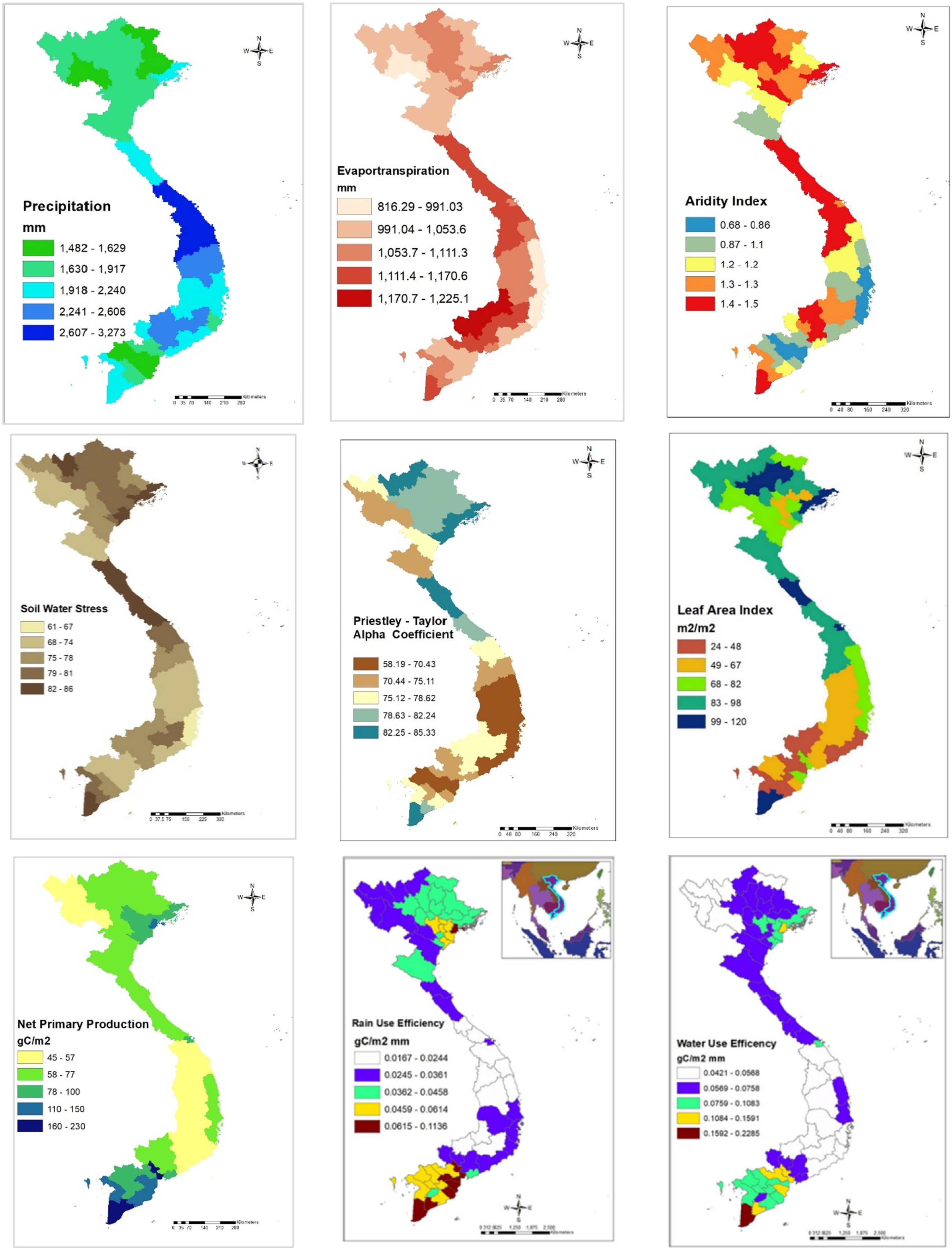
Figure 5



Precipitation
mm
1,482 - 1,629
1,630 - 1,917
1,918 - 2,240
2,241 - 2,606
2,607 - 3,273
Evaportranspiration
mm
816.29 - 991.03
991.04 - 1,053.6
1,053.7 - 1,111.3
1,111.4 - 1,170.6
1,170.7 - 1,225.1
Aridity Index
0.68 - 0.86
0.87 - 1.1
1.2 - 1.2
1.3 - 1.3
1.4 - 1.5
Soil Water Stress
61 - 67
68 - 74
75 - 78
79 - 81
82 - 86
Priestley - Taylor
Alpha Coefficient
58.19 - 70.43
70.44 - 75.11
75.12 - 78.62
78.63 - 82.24
82.25 - 85.33
Leaf Area Index
m2/m2
24 - 48
49 - 67
68 - 82
83 - 98
99 - 120
Net Primary Production
gC/m2
45 - 57
58 - 77
78 - 100
110 - 150
160 - 230
Rain Use Efficiency
gC/m2 mm
0.0167 - 0.0244
0.0245 - 0.0361
0.0362 - 0.0458
0.0459 - 0.0614
0.0615 - 0.1136
Water Use Efficency
gC/m2 mm
0.0421 - 0.0568
0.0569 - 0.0758
0.0759 - 0.1083
0.1084 - 0.1591
0.1592 - 0.2285

Figure 6

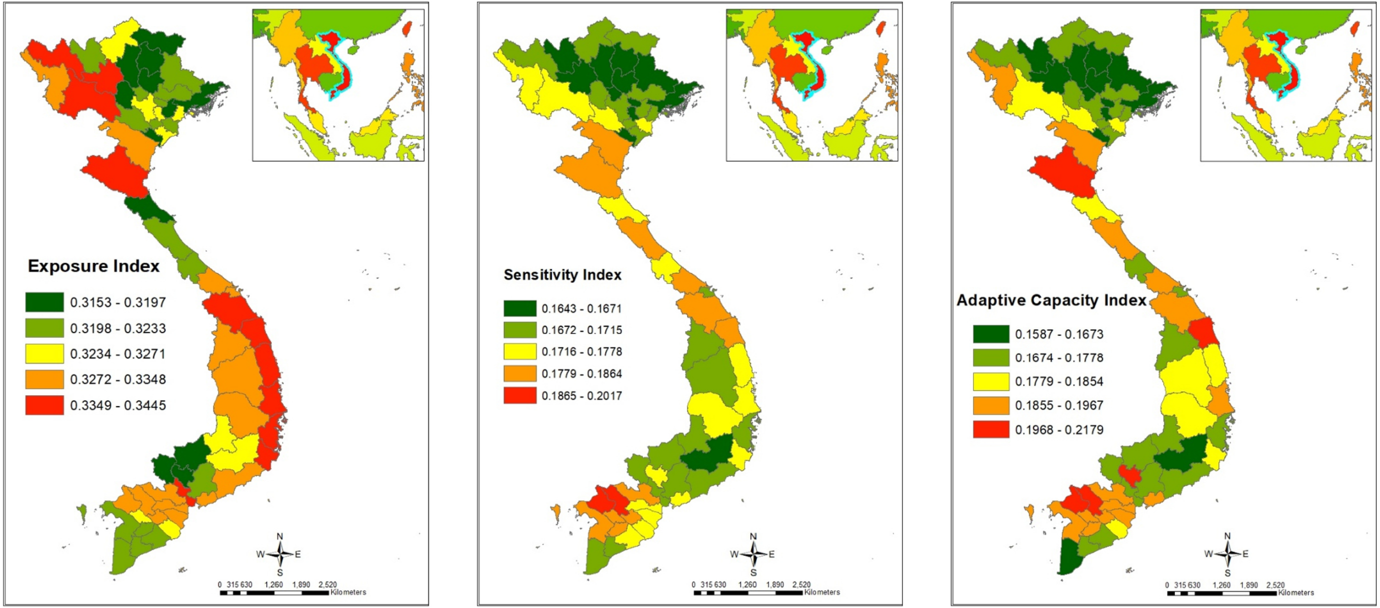

Exposure Index
0.3153 - 0.3197
0.3198 - 0.3233
0.3234 - 0.3271
0.3272 - 0.3348
0.3349 - 0.3445
Sensitivity Index
0.1643 - 0.1671
0.1672 - 0.1715
0.1716 - 0.1778
0.1779 - 0.1864
0.1865 - 0.2017
Adaptive Capacity Index
0.1587 - 0.1673
0.1674 - 0.1778
0.1779 - 0.1854
0.1855 - 0.1967
0.1968 - 0.2179
N
W
E
S
0 315 630 1,260 1,890 2,520
Kilometers

Figure 7

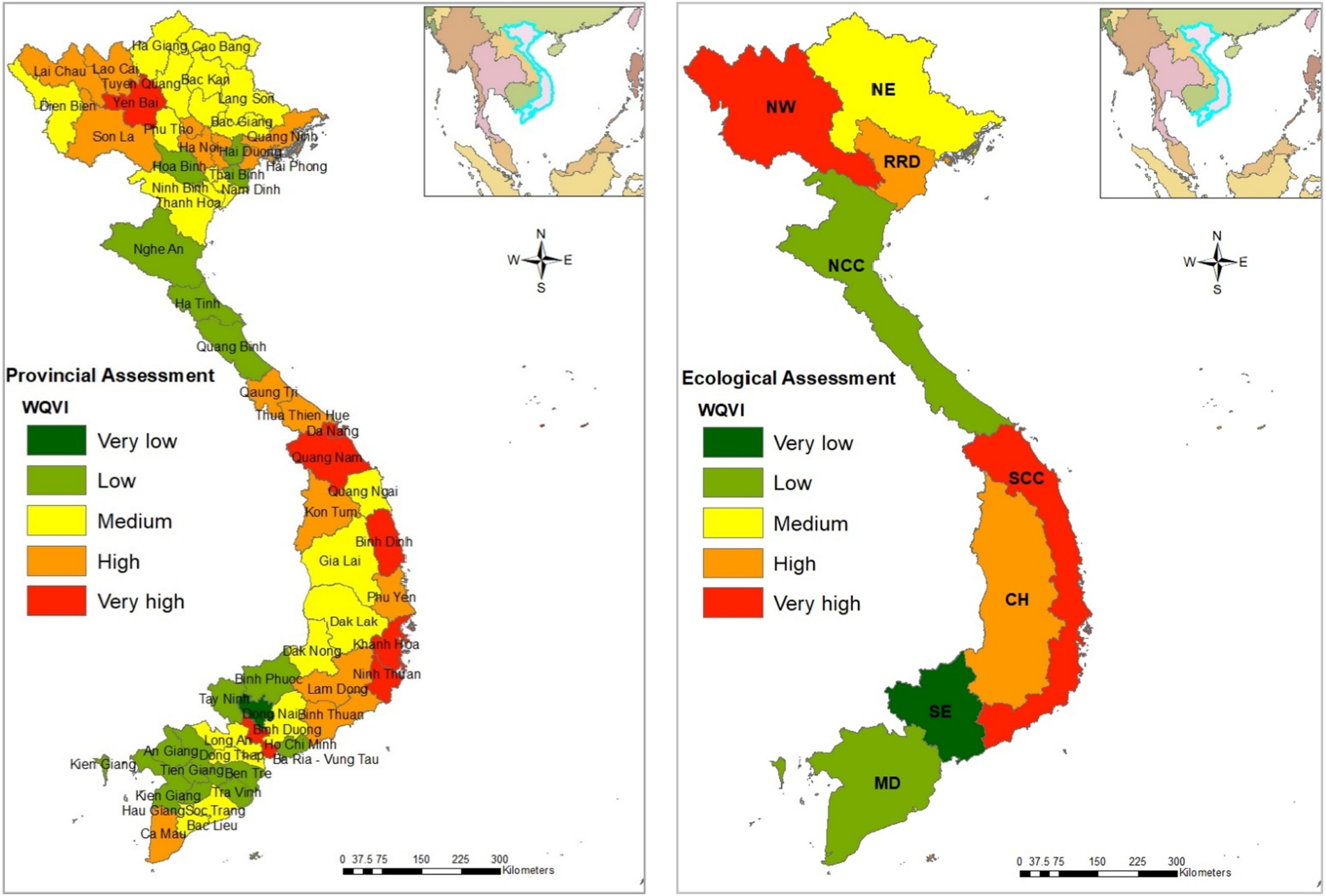
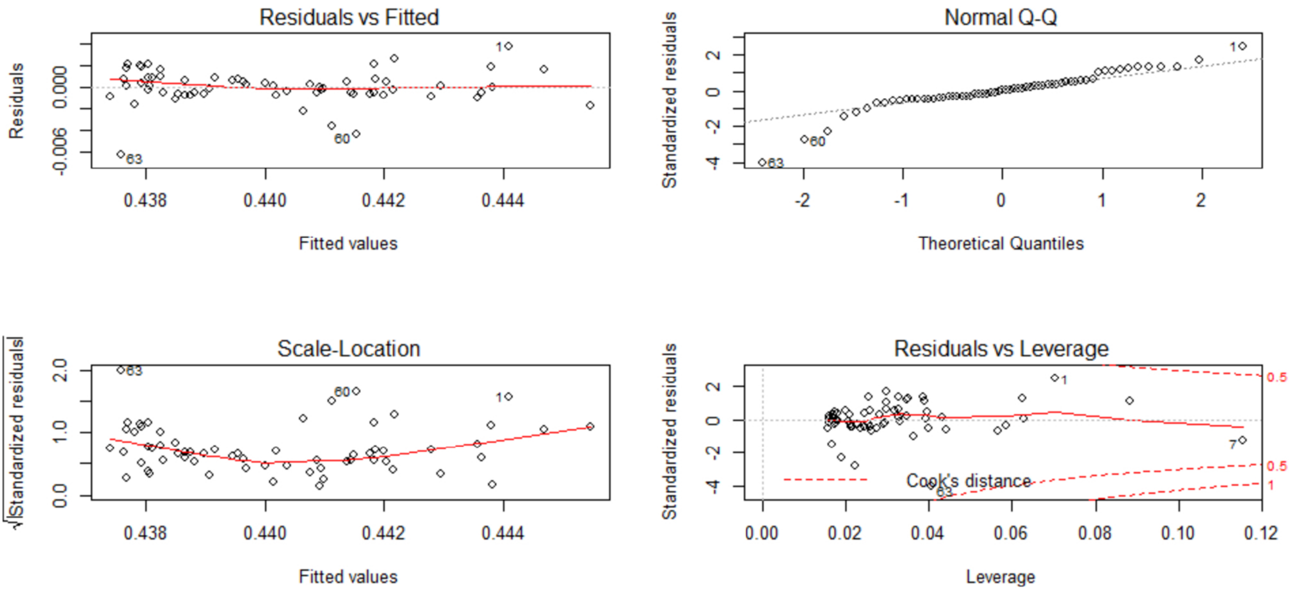

Provincial Assessment
WQVI
Very low
Low
Medium
High
Very high
Ha Giang
Cao Bang
Lai Chau
Lao Cai
Tuyen Quang
Bac Kan
Dien Bien
Yen Bai
Lang Son
Bac Giang
Son La
Phu Tho
Quang Ninh
Ha Noi
Hai Duong
Hoa Binh
Thai Binh
Hai Phong
Ninh Binh
Nam Dinh
Thanh Hoa
Nghe An
Ha Tinh
Quang Binh
Qaung Tri
Thua Thien Hue
Da Nang
Quang Nam
Quang Ngai
Kon Tum
Binh Dinh
Gia Lai
Phu Yen
Dak Lak
Dak Nong
Khanh Hoa
Binh Phuoc
Ninh Thuan
Lam Dong
Tay Ninh
Dong Nai
Binh Thuan
Binh Duong
Long An
Ho Chi Minh
An Giang
Dong Thap
Ba Ria - Vung Tau
Kien Giang
Tien Giang
Ben Tre
Kien Giang
Tra Vinh
Hau Giang
Soc Trang
Ca Mau
Bac Lieu
0 37.5 75 150 225 300 Kilometers
N
W
E
S
Ecological Assessment
WQVI
Very low
Low
Medium
High
Very high
NW
NE
RRD
NCC
SCC
CH
SE
MD
0 37.5 75 150 225 300 Kilometers

Figure 8



Residuals vs Fitted
Residuals
Fitted values
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Scale-Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Cook's distance
Leverage

Figure 9