Integration of Geospatial Technologies in Monitoring Drought Events in a Coastal Area of Vietnam (Case study: Binh Thuan Province)

Hoa Thi Tran

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

In

Geospatial and Environmental Analysis (Primary)

Interdisciplinary Graduate Educational Program in Remote Sensing (Secondary)

James B. Campbell, Co-Chair

Randolph H. Wynne, Co-Chair

Stephen C. Hodges

Yang Shao

Winston Chow

May 13, 2019

Blacksburg, Virginia

Keywords: Aridity, Drought, Land Management, Human Impacts,

Optical Imagery, Coastal Area, Binh Thuan, Viet Nam

Integration of Geospatial Technologies in Monitoring Drought Events in a Coastal Area of Vietnam (Case study: Binh Thuan Province)

Hoa Thi Tran

SCIENTIFIC ABSTRACT

Drought is a climatic event regarding prolonged "drier than normal" conditions. Precipitation deficits, crop-moisture stress, soil-water unbalance, sudden stream flow cut offs, and low carrying capacity of ecosystems are responses to drought. Drought can occur in humid to arid climates, however, drought is more severe in arid and semi-arid areas due to the fact that in those distinctive areas, water resources are extremely limited and restricted. Additionally, local ecologies and ecosystems in arid regions are very fragile. Once a water competition occurs, critical services of ecosystems such as pure water, recreation, and land productivity will be threatened.

This research focuses on prolonged drought events which have been occurring more frequently in a coastal province of South Central Vietnam – named Binh Thuan. The study area is distinctive because its climate is characterized as one of the driest provinces in Vietnam. Annual rainfall in the North and near the coast of the province is less than 800 mm per year. During 6 months of dry season, there is almost no rain, or less than 50 mm. Due to precipitation deficits and high surface temperatures in recent years, meteorological droughts have occurred more frequently, and lasted longer, thereby stressing water resources for vegetation, wildlife, households, and industry. Occurrence of prolonged droughts has constrained economic activities in the coastal areas, especially agriculture and aquaculture. Furthermore, a long duration of dry conditions coupled with unsustainable land management (such as overgrazing), "drought-sensitive" soils in areas with sand and barren lands may introduce and accelerate risks of desertification processes (land productivity deterioration and unable to recover).

This research uses geospatial technologies to monitor drought severity and drought impacts on land use and land cover. Chapter 1 is a brief introduction and literature review of the drought context in Binh Thuan Province to place the research questions and objectives in content. Chapter 2 discusses the occurrence of meteorological droughts in Binh Thuan Province, then proposes climatic indices able to monitor this type of drought. Chapter 3 focuses on explaining and assessing uneven dry conditions that stressed vegetation health in the study area. This chapter investigates spatiotemporal distributions and frequencies of prolonged agricultural droughts using remotely sensed data and anomalies of precipitation distribution. Results indicate that coastal areas in the North of Binh Thuan are subject to severe droughts. Chapter 4 assesses human impacts on land management and practices in the study area during drought periods. Results show that in recent

years (2010 to present), local governments and residents have implemented strategies to prevent sand dominance and to adapt to water shortages during dry seasons, such as vegetative cover, crop rotation with drought-tolerant plants and wind breaks. Accuracy was assessed using field data collected in the summer of 2016, in conjunction with Google Earth imagery.

In summary, this dissertation enhances understanding of drought events and impacts in Binh Thuan Province by considering different types of drought - meteorological and agricultural drought, and interactions of drought and human impacts upon land management and land practices during dry periods. Furthermore, findings and results of this research have demonstrated the effectiveness of remotely sensed datasets, and other geospatial technologies, such as geographic information systems, in modelling drought severity and in examining efforts and drought-adaptive practices of local residents. This work is a valuable foundation on which further studies can build to support policy development to protect and reserve soil-land productivity in Binh Thuan and other coastal regions of Vietnam affected by prolonged droughts.

Integration of Geospatial Technologies in Monitoring Drought Events in a Coastal Area of Vietnam (Case study: Binh Thuan Province)

Hoa Thi Tran

GENERAL AUDIENCE ABSTRACT

Drought is a temporal climatic event with "drier than normal" conditions. While drought can occur in any climates, it can be more extreme in arid and semi-arid areas where annual rainfall and water resources are limited. Depending on types of drought, its presences and impacts may differ: (1) meteorological drought relates to a decrease of average rainfall/snowfall may resulting in moisture stress, (2) hydrological drought leads to reduction of stream flow and ground water, and (3) agricultural drought influences soil-water-crop balance or vegetation health. Prolonged drought – an abnormally long duration of dry conditions, coupled with unsustainable management in water and land practice may cause losses of land productivity, promote soil erosion, and result in sand dominance in coastal areas. These land degradation processes can lead to "a desert like condition" in impacted areas. This research concerns drought and its impacts in a coastal province in Southern central Vietnam, Binh Thuan. The study area is distinctive because its climate is characterized as one of the driest provinces in Vietnam. Annual rainfall in the North and near the coast is less than 800 mm per year, and during the 6 months of dry season, there is almost no rain, or less than 50 mm. Due to precipitation deficits and high surface temperatures in recent years, meteorological droughts have occurred more frequently and lasted longer, stressing water resources for vegetation, wildlife, households, and industry. Additionally, unsustainable land management, such as overgrazing, coupled with movements of sand and barren lands from the coast inland, have accelerated the risks of land degradation. This research applies an integration of geospatial technologies for monitoring drought severity and impacts on land management, and illustrates how local people have adapted to droughts.

DEDICATED TO

My parents

My husband and my son

My two sisters

My undergraduate mentors

ACKNOWLEDGMENTS

I express special thanks for my major advisor, Dr. James B. Campbell for his guidance, encouragement, patience, and support during my five academic years at Virginia Tech which helped me to overcome challenges in my research and my daily life.

"Jim, thank you so much for being patient while correcting each of my writing errors; for reminding me the deadlines; for sharing your stories; for listening to my stories and giving me advices; for being kind to my family and Khoa!"

I would like to thank my co-supervisor Dr. Randolph H. Wynne for giving me an opportunity to come to Virginia Tech and to enroll in the IGEP program; for giving me funding opportunities to conduct my field research in 2016 and to develop my professional skills in teaching and researching.

I am grateful to my committee members Dr. Steven C. Hodges, Dr. Yang Shao, and Dr. Winston Chow for their services and valuable advice from the beginning of forming my research ideas to my graduation.

I sincerely appreciate Vietnamese Government for generously granting me a scholarship for pursuing a Doctoral degree in the United States in the first two years.

I would like to thank Virginia Tech Graduate School, IGEP program, University Library, Poole Endowment Fund, Digital Globe Foundation, Meteoblue team, Department of Geography, and Department of Forest Resources and Environmental Conservation for their generosity in granting me funding opportunities, and datasets to conduct my research and publications.

I am grateful to faculty members and staff in the Department of Geography, and Department of Forest Resources and Environmental Conservation for their assistance in resolving difficulties that I was dealing with my research, my classes, and my daily life.

I am thankful to my colleges at Hanoi University of Mining and Geology, my field research assistants, my IGEP friends, my lab mates: Tammy, Jie, Sanam, Iris, David, Jill, Cameron, Sam, Sherin, Augustine, Snehal, and Wyatt for sharing enjoyable moments and encouraging me to overcome difficulties.

Finally, I want to thank my parents, my parents in law, my sisters, my husband, my dear two-year old son, Khoa. Without their support, encouragement, and sympathy, my research could not be done. I acknowledge my Vietnamese friends and families here in Blacksburg for their caring and sharing when I am thousands of miles from my home country.

Thank you all!!!

Table of Contents

Chapter 1- Introduction, Study Area, Literature Review, Problem Statement, and Research Purposes

1.1. Understanding aridity, droughts, and different types of droughts

Aridity and drought are two climatic terminologies referring to dry conditions due to limitation of moisture content. In this research, the topic of drought will be discussed under context of its occurrence and severity in a semi-arid region, so it is necessary to clearly distinguish between aridity and drought.

1.1.1 Aridity: definition, key indicators, and impacts

Aridity is a permanent factor of a climate system which can be used to quantify and qualify the dryness of an area. Following the "Glossary of Meteorology, American Meteorological Survey", aridity is defined as "the degree to which a climate lacks effective, life-promoting moisture". The Food and Agriculture Organization of the United Nations, FAO, identifies aridity as a climatic element expressing the relationship between rainfall and temperature which is usually applied to categorize climate zones, such as: humid, sub-humid, semi-arid, arid, and hyper-arid. Aridity as determined by the FAO can be represented by a ratio between precipitation and potential evapotranspiration accounting for atmospheric moisture, solar radiation, and wind (Spinoni, Vogt et al. 2015).

Aridity is a climatological concept to indicate local climatic characteristics with respect to degree of dryness. The formation of dryness in a certain area depends on many factors, such as geographical location, wind systems, rainfall distribution, and air temperature (Joseph and Ganor 1986, Botzan, Marino et al. 1998, Paltineanu, Mihailescu et al. 2007). Geographical location determines distribution of oceanic moisture into land including impacts of topography. For instance, increased distance to ocean can reduce precipitation (Diaz-Padilla, Sanchez-Cohen et al. 2011, Nyamtseren, Feng et al. 2018); the Gobi Desert of Central Asia is an example. Wind systems play an important role in circulating air masses which may bring more precipitation to one region but less in others. In arid areas, there are typically few of storms and cyclones. Rainfall and temperature are two crucial factors relating directly to the evapotranspiration process, soil properties, topography, and vegetation cover (Bussay, Toth et al. 2012, Nastos, Politi et al. 2013, Chavez, Moreira-Munoz et al. 2019). In arid areas where rainfall is extremely limited, much of the precipitation can be quickly evaporate due to hot air and surface temperatures, sometimes resulting in no measureable precipitation.

Aridity can be computed using individual or combined climatic indices. Simply, as defined by the FAO, it can be the ratio between precipitation and evapotranspiration (row 1, table 1), or ratios between precipitation and mean temperature (row 2-6, table 1). Each of these indices requires different input datasets, some are more complicated, such as the UNEP index which requests hours of solar radiation, and adjusted hours between day-night for refining temperature factor (UNEP 1993).

Table 1. Some examples of arid indices.

Index	Equation	Classification	Number
UNEP (UNEP 1993)	$IU=\frac{P}{PET}$ Where, $PET= 16 \text{ x } Nm \text{ x } (\frac{10xPm}{I})^a$ $I=\sum_{i=1}^{12}(\frac{Tm}{5})^{1.514}$	IU<0.05: Hyper-arid 0.05≤ IU <0.2: Arid 0.2≤ IU <0.5: Semi-arid 0.5≤ IU <0.65: Dry sub humid 0.65≤ IU ≤1: Sub-humid IU> 1: Humid	1
De Martonne's arid index (de Martonne 1926)	$I_{DM}=\frac{P}{T+10}$	I_{DM}<10: Arid 10≤ I_{DM} ≤20: Semi-arid 21≤ I_{DM} ≤24: Semi-humid I_{DM}> 24: Humid	2
Thornthwaite index (Thornthwaite 1948)	$PE=\sum_{n=1}^{12} 115(\frac{P}{T-10})^{10/9}$ Units: inches (precipitation), and ^{0}F (temperature)	PE<16: Arid 16≤ PE ≤31: Semi-arid 32≤ PE≤ 63: Semi-humid PE>63: Humid	4
Minar's moisture certainty(Sobisek 1993)	$I_M=\frac{P-30(T-7)}{T}$	I_M<0: Highly arid 1≤ I_M ≤7: Arid 8≤ I_M ≤14: Semi-arid 15≤ I_M ≤21: Stable 22≤ I_M ≤28: Semi-humid I_M> 28: Humid	5
Pinna combinative index(Baltas 2007)	$I_P=\frac{1}{2}(\frac{P_y}{T_y+10}+\frac{12P_d}{T_d+10})$	I_P<10: Arid 10≤ I_P ≤20: Semi-arid I_P> 20: Humid	6
Lang's rainfall factor (Neira, Verbist et al. 2010)	$I_L=\frac{P}{T}$	I_L<40: Arid 40≤ I_L ≤60: Semi-arid 60≤ I_L ≤100: Semi-humid I_L> 100: Humid	7
P: Monthly/yearly precipitation in total (mm) T: Monthly/yearly mean temperature (^{0}C) P_y: Yearly precipitation (mm) T_y: Yearly average temperature (^{0}C)		P_d: Precipitation of the driest month in a year (mm) T_d: Temperature of the driest (^{0}C) PET: Potential evapotranspiration Nm: Adjustment factor related to hours of daylight I: Heat annual index	

1.1.2. Droughts: definition and classification

Drought is defined as moisture imbalance between months, or anomalies in "*water supply which is less than water demand*" creating "*drier than normal*" condition (Botzan, Marino et al. 1998). Similar to aridity, drought is related to dryness of climate, but it is a temporal climatic feature representing a period of water deficits that may be rainfall shortage, or soil-water stress, or lack of stream flows (Alley 1984, Botzan, Marino et al. 1998). Additionally, while aridity permanently dominates an area, drought can occur at any locations from humid to arid regions, however it arises more frequently and severely in arid areas where water resources are constrained. As an uneven climatic event, occurrence and duration of drought not only depends on physical and social characteristics of local areas but also is driven by the general trends of global climate, such as incidence of warmer global climate or oceanic oscillation (the ENSO - The El

Niño Southern Oscillation) (Bannayan, Sanjani et al. 2010, Zhang, Qian et al. 2017, Nyamtseren, Feng et al. 2018). Areas near the coast can be more sensitive to these changes of climate.

Drought occurrence varies location to location, and time to time, thus, definitions of drought are currently much broader compared to the past. In the past, drought was identified upon deviation from average precipitation which is close to the definition of aridity (Huo, Dai et al. 2013, Tabari and Aghajanloo 2013, Wu, Xu et al. 2018). However, recently, precipitation shortfall refers to only one of the four main types of drought- meteorological drought. The other three are agricultural, hydrological, and economic drought. Figure 1 shows the flowchart of chronological occurrences of these types and their impacts provided by the National Drought Mitigation Center (NDMC).

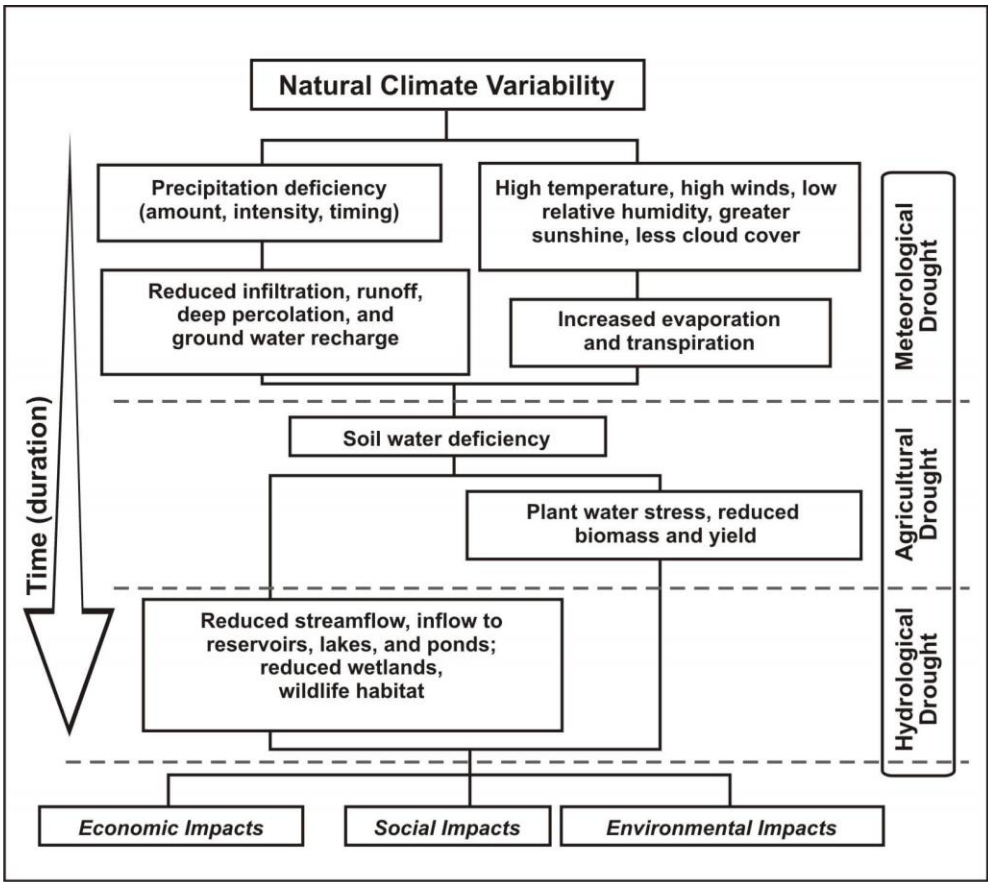


Figure 1. Chronological occurrence of four main types of drought (NDMC)

1.1.3. Impacts of drought and how to monitor drought

Drought can affect ecosystems, environments, and communities differently. The NDMC uses the term "drought dominoes" to depict impacts of drought. Either directly or indirectly, drought may result in the "fall of all" environmental -economic-social properties even though drought only hits "the first domino of the line". With respect to the environmental impacts, first and foremost, occurrence of drought leads to sudden cut-offs in water supply (Salinas, Gironas et al. 2016). If this event lasts longer, plants' and animals' survival will be threatened as consequences of food scarcity, drinking water shortage, migration, losses of soil productivity, lower stream flow levels, soil erosion, and etc. (Maes and Steppe 2012, Jia, Pan et al. 2016, Andujar, Krakauer et al. 2017, Le Page and Zribi 2019). Drought also increases the risks of wildfires, such as the 2017 wildfires damaging mountainous areas in California. In arid areas, drought has dramatically impacts on land degradation processes. If drought occurs more frequently and there are no appropriate solutions to mitigate its impacts, the risk of desertification may increase (Mortimore 1988, Merino, Martin et al. 1990, UNEP 1993). Desertification is the process of becoming desert threatening 40% of the Earth's landscape (UNEP 1993).

For economic impacts, droughts have significant influences on agriculture and aquaculture. Due to the lack of water, and moisture stress, vegetation health will be affected resulting in damages to both quality and quantity of crops (Liu, Li et al. 2004, Maes and Steppe 2012, Nichol and Abbas 2015). Additionally, due to the reduction of water levels in reservoirs, growth and health of aquatic species will be restricted. Lower water levels also lead to difficulties for business and shipping on water transportation, for hydrological power supply, and irrigation (NDMC). Otherwise, requests for pure water during drought periods might increase dramatically, leading to pay-out of pocket expenses for water.

Reduced incomes, health issues, crop losses, public safety, and migration are obvious examples of social impacts due to droughts. Therefore, drought monitoring and forecasting require both management and policy relevance.

As stated above, drought has four different types represented by different factors or indicators known as drought indices (information of common drought indices are summarized in the "handbook of drought indicators and indices" published by the World Meteorological Organization). Therefore, it is possible to monitor individual, two, or all types depending how sufficient datasets are. In-situ data and records are robust but not continuous and they are less effective for drought mapping. Furthermore, there are measurement standards and monitoring requirements that must be met to enable comparisons across space and time. There are some common drought indices which uses in-situ data such as the PDSI – Palmer Drought Severity Index (Palmer 1965, Alley 1984, Botzan, Marino et al. 1998), the SPI – Standardized Precipitation Index (McKee, N. J. Doesken et al. 1993, McKee, N. J. Doesken et al. 1995), the CMI – Crop Moisture Index, etc. Those station-based indices are similar in computation to indices of aridity using records of rainfall, temperature, evapotranspiration process, and soil-water balance.

Vegetation health and surface temperature monitoring are commonly applied to determine trends in distribution of agricultural drought using geospatial technologies (remote sensing and geographic information system – GIS). Some ordinary indices are: VHI – Vegetation Health Index (Kogan 1990, Kogan 1997, Kogan 2001), VEgDRI- Vegetation Drought Response Index, NDVI – Normalized Difference Vegetation Index, ESI- Evaporative Stress Index, etc. (Bhuiyan, Singh et al. 2006, Asner and Alencar 2010, Nichol and Abbas 2015, Jia, Pan et al. 2016, Bhuiyan, Saha et al. 2017, Dong, Li et al. 2017, Roundy and Santanello 2017, Tran, Campbell et al. 2017).

Hydrological drought and socioeconomic drought are much more complicated to monitor in comparison to other drought types because of the necessity of using both in-situ and remotely sensed data for computing. The SWSI- Surface Water Supply Index, the PDI- Palmer Hydrological Drought Index, and the SRSI- Standardized Reservoir Supply Index are examples of hydrological drought indices (Botzan, Marino et al. 1998, Bannayan, Sanjani et al. 2010, Nichol and Abbas 2015, Salinas, Gironas et al. 2016, Speich 2019). Currently, there is no available socioeconomic drought index since socioeconomic drought occurs when demand for a good or service exceeds supply due to the water shortfall, there is a need for approaches specific to regional economies.

1.2. Study area – Binh Thuan province, Vietnam

1.2.1. Brief introduction of study area [1]

Binh Thuan is the southernmost province of the South Central Vietnam, bordering Lam Dong and Ninh Thuan province in the north, Dong Nai province in the west, Bia Ria-Vung Tau province in the southwest, and the East Sea in the South and South east within 192 km coastlines. There are several islands located in its shelf, such as Lao island, Cau island, Ba island, and Phu Quy island. Phu Quy island is the biggest, which is 56 nautical miles away from Phan Thiet city, the administrative district of Binh Thuan.

Binh Thuan is located in the intersection between the high mountainous region in the West and Southwest (the Central Highlands), and the narrow coastal plain in the East and Southeast. Thus, the terrain is very complicated (Figure 2). Plateaus and mountains around 1000 m in height are highly weathered and split by narrow valleys. The plains are divided into two parts: (1) inland plains, which are about 100-200 m high surrounded by hills and mountains, and (2) coastal plains accreted by rivers and the ocean. Generally, more than 70% Binh Thuan is hills and mountains from 200 – 1300 m height, plains are covering about 9.5%, and about 20% is sands and sand dunes near coastlines expanding from Tuy Phong to Ham Tan district. The sand has been accreted and eroded by the nearshore hydrodynamic regimes and ocean currents.

The climate of Binh Thuan is characterized by integration between the tropical monsoon zone with no winter, and tropical savanna climate (classified by the Köppen climate classification) (Peel, Finlayson et al. 2007, Thai, Cazelles et al. 2010). Due to impacts of complex terrain and elevation, the climate of Binh Thuan differs locally: drier in the North and wetter in the South. However, Binh Thuan is considered as the driest province in Vietnam (see figure 3– yearly rainfall distribution in Vietnam). The climate is divided

[1] *Information for this section was provided by local authorities and Binh Thuan Government (the People's Committee, the Office of Statistics, and Department of Natural Resources and Environment).*

into two seasons: dry and rainy (wet) seasons which last approximately 6 months each year; driven by global climate and ocean circulation, the duration of these seasons is a subject to change. For example, in the years of El Niño’s occurrence, dry seasons may be longer, causing meteorological drought, and a significant decrease of rainfall. The total rainfall in Binh Thuan is about more than 1000 mm per year mainly distributing in wet seasons from May to October. Dry seasons start from November till the following April; during dry seasons, in some areas in Binh Thuan, there is almost no rainfall or less than 50 mm (Tuy Phong, Bac Binh), but approximately 200 mm on average. Thus, during dry seasons, agriculture, grazing, and aquaculture have to face to fresh water shortage issues. Otherwise, Binh Thuan has received a large amounts of solar radiation, totally 2650 ÷ 2750 solar hours per year, temperature, depending on elevation, is above 27^0C on average, and average wind speed is ranging from 2 ÷ 3 m/s depending on locations (wind speed is stronger near the coastline).

Figure 2. Location of the study area, Binh Thuan Province, Vietnam

Because of characteristics of local terrain, hydrologic systems in Binh Thuan are small, and seasonal: large and full flows in rainy seasons, while partial flows during dry seasons. The total river basin is about 9880 sq. km in coverage, a total length of 663 km, and a yearly water capacity of 5.4 billion m^3 distributed mainly in seven major reservoirs: La Nga River, Luy River, Long Song River, Cai River, Ca Ty River, Dinh River, and Phan River. Otherwise, there are 43 smaller streams with 1970 km in length distributed equally in each part of Binh Thuan. In general, hydrological systems in Binh Thuan are sparse and are not well-connected, leading to a limitation of collecting and gathering rainfall to surface water flows. Because the rivers are seasonal, during dry seasons, water shortages occur very frequently, even though there are many dams and lakes constructed for storing fresh water resources, which contribute directly to water availability within irrigation systems and household uses.

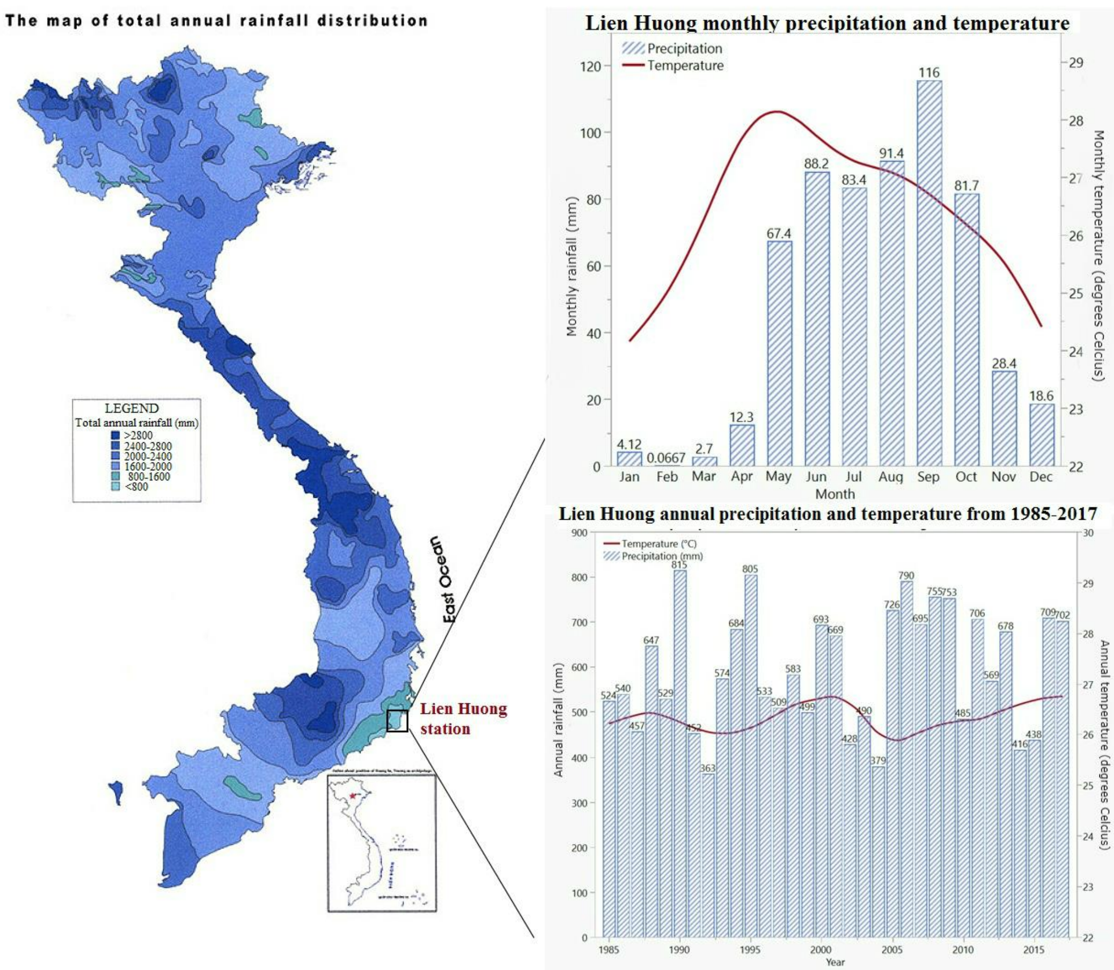


Figure 3. Total rainfall distribution in Binh Thuan in comparison to other parts of Vietnam

The population in Binh Thuan reached about 1,167,023 in 2009, and 1,266,228 in 2015, increasing about 8.5% over 6 years (1.4% per year) which is a moderate rate in comparison with other provinces in Viet Nam. However, nearly 49% of the population lives in the urban areas (towns or cities, such as Phan Thiet, Phan Ri Cua, or LaGi), and approximately 51% are distributed in suburban areas resulting in inequality of population distribution between urban and suburban areas. This difficulty puts pressure on the local labor market, social services, and security management, especially when the rate of urbanization is larger than that industrialization, and migration from suburban to urban are occurring. Consequently, there is a labor shortage in suburban regions for agriculture and forestry, while on the opposite side, in cities, there is a labor surplus. This issue has been challenging local authorities and governmental programs in planning and determining socioeconomic policies.

Utilizing a long coastline, and main reservoirs flowing directly to the ocean, fishing and aquaculture have brought many benefits to Binh Thuan's economy. Binh Thuan has one of the largest fishing grounds in Vietnam. Fresh water and seafood is very high quality for export. Agriculture and forestry in Binh Thuan have had many advantages from the diversity of terrain that forms local climate characteristics. There is a trend to establish specialized areas for grazing, rice production, woodlands, grasslands, rubber plantations, and orchards. Dragon fruits are grown mainly in the Southern areas of Binh Thuan, which have brought a lot of economic benefits, and utilized inexpensive local labor. The value of dragon fruit is much higher than rice and other agricultural products. Dragon fruit plants are a type of cactus which can thrive in dry-conditions. Agriculture and aquaculture in Binh Thuan, however, have faced to many difficulties such as frequent occurrences of extreme weather events, such as drought, flooding, sand movements, land degradation due to deforestation and forest fires.

In summary, the province of Binh Thuan has many advantages and challenges occurring from its physical, climatic, social, and economic characteristics. Learning about those properties will enhance our understanding of the opportunities and difficulties in using and managing natural and social resources in this province.

1.2.2. Overview of the context and impacts of droughts in Binh Thuan

In the North of Binh Thuan (Tuy Phong and Bac Binh district), the dry season lasts approximately 6 months, and there is less than 50 mm of rainfall during those 6 months. Frequently there are 3-4 months without any rain. A longer duration of precipitation deficit will lead to increases in arid conditions due to the higher surface temperature and quickly drying up of water resources and storage. Losses of vegetation cover, barren soil, salinization, and wind erosion are enhanced by frequent prolonged droughts. During the dry season, half of Binh Thuan's coastal area is in drought-affected zones (Pham, Nguyen et al. 2012). Drought has occurred more frequently and severely in Binh Thuan in recent years (Hai, Gobin et al. 2016).

Drought has produced environmental, economic, and social impact, such as water shortages for agricultural lands and households, and it is one of main sources of rapid changes in land use and land cover (LULC) in this coastal province. In the 2015-2016 dry season (winter-spring crop), provincial authorities stated that impacts of severe drought on local agriculture contributed to a dramatic decline of irrigated lands by nearly 50%. The main reservoirs in the Northern districts reduced water levels nearly 80% resulting in thirst for both plants and animals and restricted grazing and cropping. Figure 4 shows changes in water level of Da Bac lake, a man-made irrigation construction in Tuy Phong district. Water level reduced dramatically from April until November – equal to 7 months of water limitations. Additionally, wildfires are other risks threatening forested areas in the Northwest and Southwest of Binh Thuan during drought periods (Tuy Phong, Duc Linh, Ham Tan, and Tanh Linh). As reported by the Department of Agriculture and Rural Development, forest fires might affect 50 % of total forested areas in Binh Thuan due to prolonged durations of dry conditions.

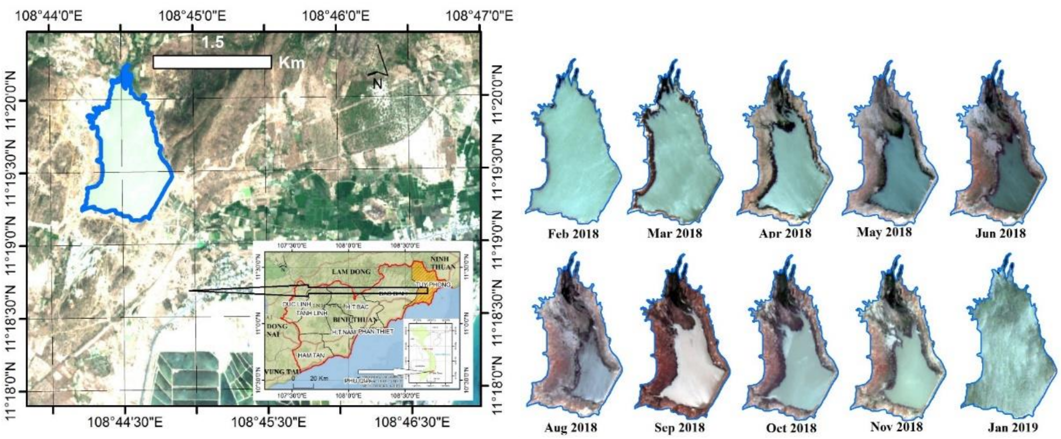


Figure 4. Da Bac Lake in Tuy Phong district and monthly water distribution observed by Sentinel 2 in 2018

Other impacts of drought are land abuse, barren lands, and immigration. With respect to land management practices, impacts of drought may not be significant if irrigation and policies in land management are appropriate and sufficient. However, in recent years, the urbanization and industrialization processes have been speedy, leading to a high demand for labor in big cities and more opportunities for higher incomes. Phan Thiet is the biggest city in Binh Thuan; its population is approximately half of the total in the province. The immigration from rural areas to big cities (such as Phan Thiet) has caused labor shortage in agriculture and aquaculture. As consequences, active agricultural lands have been abandoned, and become barren. Furthermore, sand encroachment, salinization, and and degradation processes are increasing (Thai 1970, Hai, Gobin et al. 2013, Hai, Gobin et al. 2014).

Although drought has had long influences in Binh Thuan due to its distinctive climatic characteristics and geographical location, there has been a dearth of research discussing drought in this province. Recent research mainly focuses on rainfall distribution and using climatic indices (aridity indices) to reveal arid areas (Pham, Nguyen et al. 2012). However, anomalies of rainfall distribution in recent decades have not been carefully discussed. Additionally, some research examined and arid index (UNEP) for zoning drought prone areas. Although this index is not sufficient to indicate occurrence of drought, it created a link between aridity and drought – two terms of dryness degree, and prospective opportunity for utilizing arid indices in meteorological drought monitoring with sufficient long-term datasets.

1.3. Research questions and statement of purpose

1.3.1. Research questions

1. How did precipitation distribute in recent years in Binh Thuan province? Are there any anomalies in that distribution resulting from meteorological drought? How can precipitation indices be applied in capturing meteorological drought occurrence?

Hypothesis 1: There are sudden cut-offs of precipitation which resulted in meteorological droughts in some areas in Binh Thuan where water resources were limited during dry seasons.

Hypothesis 2: Climatic indices relating precipitation such as arid indices – moisture stress, and the SPI – Standardized Precipitation Index can be applied in analyzing historical records to reveal meteorological drought.

2. How are extreme weather events, such as drought, spatially distributed throughout the study area? How severe are those drought-affected areas?

Hypothesis 3: Areas along the coastline are most affected by drought resulting in prolonged period of dry conditions, and a lack of rainfall; resulting in sand mobilization.

Hypothesis 4: Poorly managed agricultural areas (no irrigation, overgrazing) are more subjected to land over use during prolonged droughts, leading to agriculturally abandoned barren lands.

3. How have local residents and authorities recognized and made efforts to prevent and minimize the impacts of drought?

Hypothesis 5: Both households and government agencies have been adapting land management and policies to increase resilience in the face of drought.

1.3.2. Statement of purpose

a. Understand arid conditions within the study area and how to assess anomalies in precipitation in monitoring meteorological drought;

b. Find occurrences and impacts of agricultural droughts via vegetation health monitoring;

c. Map LULC, and LULC changes within the study area based on remotely sensed data, and within coastal areas with high resolution images during drought occurrences to assess human impacts on land management practices;

d. Examine how effective free remotely sensed data (LANDSAT or MODIS) can be in monitoring uneven climatic events such as drought and how effective historical weather datasets are for aridity-drought assessment.

1.4. Research methodology and data resources

1.4.1. Research methodology

In general, this research assesses drought in Binh Thuan by examining integrated models to monitor and evaluate the occurrence, duration, and severity of drought by focusing on revealing climatic conditions, vegetation responses, and spatiotemporal land cover and land use changes. Remote sensing and geographic information systems (GIS) form powerful geospatial tools to acquire up-to-date data and to examine long-term dynamic factors (land use, migration, and climate) to evaluate drought and vegetation - land management processes. Furthermore, this analysis supports evaluation of the effectiveness of governmental policies during prolonged droughts. Because drought has different types which may occur in relation to each other, evaluating or monitoring directly this event requires a synthetic methods including in-situ data, remotely sensed data, and appropriate models for particular areas. Thus, in my research, I have investigated: (1) contributions of climate characteristics and weather extremes in exacerbating" drier-than-normal" conditions in this study area in recent years; (2) vegetation responses due to occurrence of prolonged drought, and (3) changes of land surfaces (especially sand movement and bare surfaces) that have resulted in.

1.4.2. Data resources

Table 2. Datasets used for conducting the study

DATA	DATE (RANGE)	SOURCE
Optical Imagery		
GeoEye 1	Jun 2016	Digital Globe Foundation
Landsat archives	1976-2018	USGS/earthexplorer.usgs.gov
Modis products	2002-1028	NASA/Earth Data
Sentinel 2	2014-2018	ESA/scihub.copernicus.eu
Spot 5	2010	
Worldview 2	May 2011	
Geospatial data		
Terrain and elevation	2007	Department of Natural Resources and Environment, Binh Thuan
Geology	2007	
Geomorphology	2007	
Soil type	2007	
Climate distribution	2007	
Water ground and surface	2007	
Vegetation cover	2007	
Land use	1979, 2007, 2014	

Administrative districts and communes		
Statistical and field data		
Weather records	1986-2018	National weather station, and Meteroblue.com
Population	2009-2015	Department of Planning and Investment
Economy	2009-2015	
Surface temperature	Summer 2016	Field research
Soil component analysis	2005 (Bac Binh) 2012 (soil samples) Summer 2016 (soil samples)	Department of Natural Resources and Environment, Binh Thuan Field research
Others	Data collected from previous projects for reference and validation	

1.5. Structure of the dissertation

I present my study of drought monitoring as five chapters:

- Chapter 1: An introduction and literature review of drought monitoring and drought severity assessment in general and in the study area; Finalizing research questions, datasets, and methodologies to execute the study.
- Chapter 2: Discuss effectiveness of historical precipitation and temperature data recorded at weather station to assess arid conditions and meteorological droughts. This chapter is represented as a manuscript.
- Chapter 3: Revealing spatial and temporal distributions and frequencies of prolonged agricultural droughts – uneven dry conditions in the study area and specifically in coastal regions. This chapter is presented as a publication assessing spatial and temporal distribution drought severity based sequential and time series remotely sensed data over 27 years.
- Chapter 4: An investigation of how local people have managed lands during drought periods, particularly in a coastal area was conducted using a bi-temporal analysis of remotely sensed data at high resolution. The chapter content is represented as a publication.
- Chapter 5: Discussion of outcomes and limitations of the research; proposing future work; and finally research summary and conclusions.

References

Alley, W. M. (1984). "The Palmer Drought Severity Index: limitation and assumptions." Journal of Climate and Applied Meteorology(23): 1100-11009.

Andujar, E., N. Y. Krakauer, C. X. Yi and F. Kogan (2017). "Ecosystem Drought Response Timescales from Thermal Emission versus Shortwave Remote Sensing." Advances in Meteorology.

Asner, G. P. and A. Alencar (2010). "Drought impacts on the Amazon forest: the remote sensing perspective." New Phytol **187**(3): 569-578.

Baltas, E. (2007). "Spatial distribution of climatic indices in northern Greece." Met. App **14**: 69-78.

Bannayan, M., S. Sanjani, A. Alizadeh, S. S. Lotfabadi and A. Mohamadian (2010). "Association between climate indices, aridity index, and rainfed crop yield in northeast of Iran." Field Crops Research **118**(2): 105-114.

Bhuiyan, C., A. K. Saha, N. Bandyopadhyay and F. N. Kogan (2017). "ADVANCES IN REMOTE SENSING AND GIS-BASED DROUGHT MONITORING Analyzing the impact of thermal stress on vegetation health and agricultural drought - a case study from Gujarat, India." Giscience & Remote Sensing **54**(5): 678-699.

Bhuiyan, C., R. P. Singh and F. N. Kogan (2006). "Monitoring drought dynamics in the Aravalli region (India) using different indices based on ground and remote sensing data." International Journal of Applied Earth Observation and Geoinformation **8**(4): 289-302.

Botzan, T. M., M. A. Marino and A. I. Necula (1998). "Modified de Martonne aridity index: Application to the Napa Basin, California." Physical Geography **19**(1): 55-70.

Bussay, A., T. Toth, V. Juskevicius and L. Seguini (2012). "Evaluation of Aridity Indices Using SPOT Normalized Difference Vegetation Index Values Calculated Over Different Time Frames on Iberian Rain-Fed Arable Land." Arid Land Research and Management **26**(4): 271-284.

Chavez, R. O., A. Moreira-Munoz, M. Galleguillos, M. Olea, J. Aguayo, A. Latin, I. Aguilera-Betti, A. A. Munoz and H. Manriquez (2019). "GIMMS NDVI time series reveal the extent, duration, and intensity of "blooming desert" events in the hyper-arid Atacama Desert, Northern Chile." International Journal of Applied Earth Observation and Geoinformation **76**: 193-203.

de Martonne, E. (1926). "Areism and aridity index." Comptes Rendus Hebdomadaires Des Seances De L Academie Des Sciences **182**: 1395-1398.

Diaz-Padilla, G., I. Sanchez-Cohen, R. A. Guajardo-Panes, A. L. Del Angel-Perez, A. Ruiz-Corral, G. Medina-Garcia and D. Ibarra-Castillo (2011). "Mapping of the Aridity Index and Its Population Distribution in Mexico." Revista Chapingo Serie Ciencias Forestales Y Del Ambiente **17**: 267-275.

Dong, H., J. Li, Y. Yuan, L. You and C. Chen (2017). "A component-based system for agricultural drought monitoring by remote sensing." PLoS One **12**(12): e0188687.

Hai, L. T., A. Gobin and L. Hens (2013). "Risk Assessment of Desertification for Binh Thuan Province, Vietnam." Human and Ecological Risk Assessment **19**(6): 1544-1556.

Hai, L. T., A. Gobin and L. Hens (2014). "Uncovering causes and effects of desertification using a Leopold matrix in Binh Thuan Province, Vietnam." Chinese Journal of Population Resources and Environment **12**(1): 57-67.

Hai, L. T., A. Gobin and L. Hens (2016). "Select indicators and prioritize solutions for desertification and drought in Binh Thuan, Vietnam." Chinese Journal of Population Resources and Environment **14**(2): 123-132.

Huo, Z. L., X. Q. Dai, S. Y. Feng, S. Z. Kang and G. H. Huang (2013). "Effect of climate change on reference evapotranspiration and aridity index in arid region of China." Journal of Hydrology **492**: 24-34.

Jia, H. C., D. H. Pan, J. Li, W. C. Zhang and G. Rasul (2016). "Risk assessment of maize drought disaster in southwest China using the Environmental Policy Integrated Climate model." Journal of Mountain Science **13**(3): 465-475.

Joseph, J. H. and E. Ganor (1986). "Variability of Climatic Boundaries in Israel - Use of Modified Budyko-Lettau Aridity Index." Journal of Climatology **6**(1): 69-82.

Kogan, F. N. (1990). "Remote sensing of weather impacts on vegetation in non-homogeneous areas." International Journal of Remote Sensing **11**: 1405-1419.

Kogan, F. N. (1997). "Global drought watch from space." Bulletin of the American Meteorological Society, **78**: 621-636.

Kogan, F. N. (2001). "Operational space technology for global vegetation assessments." Bulletin of the American Meteorological Society **8**(9): 1949-1964.

Le Page, M. and M. Zribi (2019). "Analysis and Predictability of Drought In Northwest Africa Using Optical and Microwave Satellite Remote Sensing Products." Sci Rep **9**(1): 1466.

Liu, A., X. Li, Y. He and F. Deng (2004). "[Simplification of crop shortage water index and its application in drought remote sensing monitoring]." Ying Yong Sheng Tai Xue Bao **15**(2): 210-214.

Maes, W. H. and K. Steppe (2012). "Estimating evapotranspiration and drought stress with ground-based thermal remote sensing in agriculture: a review." J Exp Bot **63**(13): 4671-4712.

Merino, J., A. Martin, M. Granados and O. Merino (1990). "Desertification of Coastal Sands of South-West Spain." Agriculture Ecosystems & Environment **33**(2): 171-180.

Mortimore, M. J. (1988). "Desertification and Resilience in Semi-Arid West-Africa." Geography **73**(318): 61-64.

McKee, T. B., N. J. Doesken and and J. Kleist (1995). "Drought monitoring with multiple time scales. Ninth Conference on Applied Climatology." American Meteorological Society: 233-236.

McKee, T. B., N. J. Doesken and a. J. Kleist (1993). "The relationship of drought frequency and duration of time scales. Eighth Conference on Applied Climatology." American Meteorological Society: 179-186.

Nastos, P. T., N. Politi and J. Kapsomenakis (2013). "Spatial and temporal variability of the Aridity Index in Greece." Atmospheric Research **119**: 140-152.

NDMC, N. D. M. C. "Types of Drought." from https://drought.unl.edu/Education/DroughtIn-depth/TypesofDrought.aspx.

Neira, F., K. Verbist, D. Gabriels, D. Lobo, I. Toro and Y. Carvajal (2010). "Assessment of climate idnices in dry lands of Columbia." Proceedings of the Int. Conf. Arif and Semi-arid devel. through Water(90).

Nichol, J. E. and S. Abbas (2015). "Integration of remote sensing datasets for local scale assessment and prediction of drought." Sci Total Environ **505**: 503-507.

Nyamtseren, M., Q. Feng and R. Deo (2018). "A Comparative Study of Temperature and Precipitation-Based Aridity Indices and Their Trends in Mongolia." International Journal of Environmental Research **12**(6): 887-899.

Palmer, W. (1965). Meteorological drought Research paper. Washington DC, US Weather Bureau. **45**.

Paltineanu, C., I. F. Mihailescu, I. Seceleanu, C. Dragota and F. Vasenciuc (2007). "Using aridity indices to describe some climate and soil features in Eastern Europe: a Romanian case study." Theoretical and Applied Climatology **90**(3-4): 263-274.

Peel, M. C., B. L. Finlayson and T. A. McMahon (2007). "Updated World Map of the Koppen-Geiger climate classification." Hydrology and Earth System Sciences **11**: 1633-1644.

Pham, Q. V., T. B. Nguyen and T. T. H. Bui (2012). Drought Zoning for Binh Thuan Province, in Viet Nam base on ETo Calculator and GIS. GEoinformatics for Spatial-Infrastructure Development in Earth and Allied Sciences. Osaka, Japan, GISWS.

Roundy, J. K. and J. A. Santanello (2017). "Utility of Satellite Remote Sensing for Land-Atmosphere Coupling and Drought Metrics." J Hydrometeorol **18**(3): 863-877.

Salinas, C. X., J. Gironas and M. Pinto (2016). "Water security as a challenge for the sustainability of La Serena-Coquimbo conurbation in northern Chile: global perspectives and adaptation." Mitigation and Adaptation Strategies for Global Change **21**(8): 1235-1246.

Sobisek, B. (1993). Meterological Lexicon, Prague: Acamedia.

Speich, M. J. R. (2019). "Quantifying and modeling water availability in temperate forests: a review of drought and aridity indices." Iforest-Biogeosciences and Forestry **12**: 1-16.

Spinoni, J., J. Vogt, G. Naumann, H. Carrao and P. Barbosa (2015). "Towards identifying areas at climatological risk of desertification using the Koppen-Geiger classification and FAO aridity index." International Journal of Climatology **35**(9): 2210-2222.

Tabari, H. and M. B. Aghajanloo (2013). "Temporal pattern of aridity index in Iran with considering precipitation and evapotranspiration trends." International Journal of Climatology **33**(2): 396-409.

Thai, K. T., B. Cazelles, N. V. Nguyen, L. T. Vo, M. F. Boni, J. Farrar, C. P. Simmons, H. R. van Doorn and P. J. de Vries (2010). "Dengue dynamics in Binh Thuan province, southern Vietnam: periodicity, synchronicity and climate variability." PLoS Negl Trop Dis **4**(7): e747.

Thai, T. V. (1970). "Vietnamese Forest."

Thornthwaite, C. W. (1948). "An approach toward a rational classificatio of climate." Geo. Ev(38).

Tran, H. T., J. B. Campbell, T. D. Tran and H. T. Tran (2017). "Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (Case Study: Tuy Phong, Binh Thuan, Vietnam)." GIScience & Remote Sensing **54**(2): 167-184.

UNEP (1993). World Atlas of Desertification. Lodon, UNEP.

World Organization of Meteorology. Handbook of drought indices.

Wu, Z., H. Xu, Y. Li, L. Wen, J. Li, G. Lu and X. Li (2018). "Climate and drought risk regionalisation in China based on probabilistic aridity and drought index." Sci Total Environ **612**: 513-521.

Zhang, K. X., X. Q. Qian, P. X. Liu, Y. H. Xu, L. G. Cao, Y. P. Hao and S. P. Dai (2017). "Variation characteristics and influences of climate factors on aridity index and its association with AO and ENSO in northern China from 1961 to 2012." Theoretical and Applied Climatology **130**(1-2): 523-533.

Chapter 2: Meteorological Drought Assessment via Precipitation Indices in Binh Thuan Province

2.1. Introduction

This chapter assesses meteorological drought base precipitation indices. Meteorological drought is one type of drought which occurs due to lack of precipitation resulting in a condition of "*drier than normal*" in a certain time at the study area. Using historical precipitation and temperature records at weather stations over 32 years, meteorological drought can be indicated and predicted. The SPI - Standardized Precipitation Index computed by comparing deviations to total rainfall at certain times using more than 30 years of records, is supportive to approach precipitation deficit and meteorological drought. However, this index only involves single datasets of precipitation within ignorance impacts of air temperature. Thus, this study proposes to apply other alternative climatic indices to monitor variations of arid conditions to determine "*drier than normal*" conditions. These indices are computed by ratios between rainfall and air temperature.

2.2. Manuscript

The manuscript has been drafted and is represented in the Appendix 1.

Manuscript title: "Assessment of Arid Intensity, and Meteorological Drought based Precipitation Indices in a Vietnamese Coastal Province (Binh Thuan Province)".

Chapter 3: Monitoring Agricultural Drought Severity in a Coastal region of Northern Binh Thuan

3.1. Introduction

This chapter discusses severity of agricultural drought based on the idea of monitoring vegetation health index (VHI) via satellite images from1989 to 2016. Time series Landsat and Modis images are two main datasets for this study. Results showed that areas near the coast of Binh Thuan (Tuy Phong district) are more severe to agricultural droughts, and this type of drought has been occurring more frequently causing water stress of vegetation.

3.2. Monitoring drought severity in a coastal area of Binh Thuan, Tuy Phong district case study (Publication)

Contents of this chapter is represented as a manuscript which was published in *GIScience & Remote Sensing* journal in February 2017. This paper is shown in Appendix 2.

Hoa Thi Tran, James B. Campbell, Tri Dinh Tran & Ha Thanh Tran (2017). Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (Case Study: Tuy Phong, Binh Thuan, Vietnam). *GIScience & Remote Sensing*, 54:2, 167-184, DOI: 10.1080/15481603.2017.1287838

Chapter 4: Assessing Human Impacts on Land Use and Land Cover Change during Drought Periods

4.1. Introduction

This chapter discusses the context of land use and land cover (LULC), and changes of LULC in Tuy Phong, a Northern district of Binh Thuan, approaching bi-temporal analysis and indices from remotely sensed data to assess and evaluate impacts of Tuy Phong's inhabitants on those changes under dry conditions and water shortage. Data involved in the analysis are high resolution images – the 2011 WorldView 2 and the 2016 GeoEye .

4.2. Impact of drought and local residents on change of land use and land cover in coastal communes of Tuy Phong district (Publication)

Contents of this section is represented as a manuscript which was published in *Remote Sensing* journal in February 2019. This paper is shown in Appendix 3.

Tran, Hoa T.; Campbell, James B.; Wynne, Randolph H.; Shao, Yang; Phan, Son V. 2019. Drought and Human Impacts on Land Use and Land Cover Change in a Vietnamese Coastal Area. *Remote Sens.* 11, no. 3: 333.DOI: 10.3390/RS11030333

Chapter 5: Discussion and conclusion

5.1. Outcomes and limitations of this research

This research was conducted to enhance understandings about the context of dry conditions in Binh Thuan province, Vietnam by assessing meteorological and agricultural droughts and their impacts of humans on land management focusing on coastal areas. The study has shown:

- Firstly, formation of semi-arid condition in the Northern and coastal areas of Binh Thuan was resulted by its geographical location. In those areas, meteorological droughts occurred more frequently and severely. Arid indices with in more than 30 years of observation are supportive to capture those types of drought.
- Secondly, coastal areas are subjects of severe agricultural drought which was represented by reduction on vegetation cover and vegetation heath, including high surface temperatures. Water resources were extremely limited during dry seasons.
- Thirdly, there are several evidences of local human's efforts in protecting and sustainably managing lands to combat droughts and land degradation processes, such as: vegetating for wind break, crop rotation, irrigation system improvements, industrial zone planning (bare land), and economic transition to reduce pressure on agriculture.
- Finally, freely remotely sensed data are very useful in learning spatiotemporal distribution and severity of drought; impacts and interaction of drought and local people on land management. Results of this research are valuable references for further studies in other regions and in modeling drought – human interaction scenarios in coastal areas of Binh Thuan.

However, several limitations restrict this research, such as:

- Soil properties and types of crops have not been discussed deeply to estimating the stress of moisture, and condition of soil-water balancing during drought period (for generating the PDSI, for example). These types of data require field research and sufficient datasets in term of spatial and temporal resolution.
- Quantity and quality of ground and surface water or roles of hydrological systems and reservoirs have been approached but at minimum for understanding hydrological droughts.
- There is lack of authorized information and official reports of governmental efforts to manage land cover and land use to adapt drought. Additionally, socioeconomic constrains of drought are not discussed in this research due to insufficient datasets.

Future works will be investigated in:

- Deriving multi-temporal analyses in land use and land cover in specific regions for fully understanding of the human role in managing and preserving active lands, and for eliminating the misconceptions of variation in changes of the landscape in the study area;

- Quantifying and qualifying water resources in coastal areas to access hydrological droughts, and further analyze impacts droughts on coastal ecosystems, environment, and economies;
- Finding an appropriate model to assess socioeconomic drought including risk assessment of drought generally in the entire province;
- Improving understanding of land degradation processes in the study area in drought contexts to figure out any links or risks of the desertification processes, especially in coastal regions;
- Engaging local residents in proposing and examining prospective solutions for land-water-vegetation management in the study are in stabling mobile sand dunes and in combating desertification;
- Finally, projecting the research ideas in other coastal areas to observe any variations of the models regarding spatial and temporal scale.

5.3. Conclusion

Drought is a natural hazard relating to an occurrence of "*drier than normal*" condition. Occurrence, duration, and severity of drought can be captured using both historical in-situ and remotely sensed data. Worldwide statistics indicate that drought is now increasing in extent and more intensive due to climate change. Additionally, despite of occurring temporally, this hazard tends to stay longer and directly threatens productivity of lands and water supplies. Therefore, more research and projects have been conducted to enhance spatial and temporal understanding of this event as well as to propose effective efforts and solutions in sustainable land management to monitor all four types of drought.

Binh Thuan, the driest province in Southern areas of Vietnam, has being affected dramatically by drought, especially the coastal regions. Prolonged droughts have occurred more frequently affecting vegetation cover, land and soil fertility, and depleting and polluting ground and surface water. This research emphasizes the distribution and severity of two main types of drought: meteorological and agricultural drought, and their roles in introducing drier climatic conditions in coastal areas of Binh Thuan province constraining land management and economic activities. Additionally, this dissertation fills in gaps of understanding about impacts of prolonged drought and inhabitants on land use land cover change. Finally, this dissertation provides strong evidence of the effectiveness of geospatial technologies and remotely sensed data enhancing knowledge and backgrounds of indices applied in monitoring natural hazards, such as droughts and assessing human impacts on changing landscapes. Those typical techniques and datasets area very useful and powerful to support policies- decision making, and ecosystem – environmental management. This research is expected to engage public, governmental, and scholar's attentions in acknowledging risks and impacts drought and land degradation processes in coastal regions.

APPENDICES

Appendix 1

Drafted manuscript: Assessment of Arid Intensity, and Meteorological Drought based Precipitation Indices in a Vietnamese Coastal Province (Binh Thuan Province)

Assessment of Arid Intensity, and Meteorological Drought-based Precipitation Indices in a Vietnamese Coastal Province (Binh Thuan Province)

ABSTRACT

Aridity and drought are two distinctive climatic phenomena relating to limited availability of water resources. Aridity refers to a degree of a permanently dry condition with "lack of life promoting moisture" (American Meteorological Society) while drought temporally occurs as an abnormal dry condition in a period (several weeks or months). Identifying and monitoring drought is more complicated comparing to aridity because its pattern and intensity varies location to location depending on climatic conditions of total rainfall, air temperature, evapotranspiration, soil-water balances, types of vegetation, ground and surface water capacity, as well as local infrastructure and economic background. Although aridity represents a persistent phenomenon of local climatic characteristics (rainfall distribution versus air temperature), abnormalities in monthly, seasonal, or annual arid intensity may refer to potentially occurrence of meteorological drought which relates to precipitation deficits. This paper concerns how effective aridity indices based on precipitation assessment can be investigated in identifying occurrence and intensity of meteorological drought. The study area is one of the driest province located in the South central coast of Vietnam, named Binh Thuan province assessed during an interval of 32 years from 1985 to 2017. Results show that there were variations of drought occurrences and frequencies across different locations in the study area, however, in several periods, drought occurred more frequently and lasted longer durations. A validation of the results with a typical drought index, the Standardized Precipitation Index (SPI) showed similarities in drought pattern occurred in the study area over the observed period.

KEYWORDS: Aridity; Meteorological Drought; Moisture Stress; SPI; Coastal, Vietnam, Binh Thuan

INTRODUCTION

Aridity and *drought* are two terms used to describe climate characteristics of low precipitation and humidity (Yao, Li et al. 2018). However, these two features are distinctive. *Aridity* refers to spatial distributions of degrees of dryness which permanently dominates regions of imbalance in water availability within low average rainfall (Zarch, Sivakumar et al. 2015) resulting in low moisture content and limitations of caring capacity of local ecosystems. Drought, on the other hand, can occur disregarding any precipitation and temperature regime. Aridity can be used to define different climate zones based distribution of precipitation coupling impacts of temperature and evaporation process (Sahin 2012). There are many indices applied in categorizing arid conditions. The simplest and commonest indices involve two factors of average temperature, and total precipitation, such as the De Martonne aridity index (de Martonne 1926), Emberger index (Emberger 1932), Thornthwaite index (Thornthwaite 1948), Minar's moisture certainty (Sobisek 1993), Lang's rainfall factor (Neira, Verbist et al. 2010), or the Pinna combination index (Baltas

2007). Other complicated indices require more input data such as potential evapotranspiration index – UNEP arid index, plus soil moisture and crop index.

Drought, on the other hand, is one of temporal weather extremes relating the abnormal shortage of available water sources. Water sources may refer to rainfall, soil moisture, surface and ground water, or supply and demand for water. Deficiency of water resources in terms of availability and quality will consequently result in drought. Although drought occurs in all climatic zones due to aberrations and variability of rainfall, it occurs more frequently in arid and semi-arid regions where water resources and moisture contents are restricted (Greve and Seneviratne 2015, Spinoni, Vogt et al. 2015). There are four types of drought: *meteorological*, *hydrological*, *agricultural*, and *socioeconomic*. The first three types are associated with the physical phenomenon of presented water contents ((NDMC).

During the drought exposing timescale, meteorological droughts are formed firstly upon variations of climatic exposure such as high temperature, rainfall deficit, and increases of evapotranspiration. Then, shortages of water supply, and loss of moisture will cause "soil-water deficiency which will consequently affect vegetation health resulting in occurrence of agricultural droughts (Gamo, Shinoda et al. 2013). As consequences of a longer duration of water supply deficit, and increase of evapotranspiration process, surface water quantity will decline significant, and subsequently hydrological droughts will occur. Those three types of drought connect each other regarding a duration of the dry and hot conditions then finally lead to environmental, social economic issues. There are series of drought indices can be applied to identify and monitor drought frequency and intensity categorized depending types of input data.

The SPI – Standardized Precipitation Index is one of typical drought indices which can quickly assess meteorological drought via precipitation records from in-situ weather stations or from satellites. The SPI is very common in monitoring variations of temporal resolution of precipitation conditions, which is very useful in learning impacts of rainfall deficit in agriculture and hydrology (McKee, N. J. Doesken et al. 1993, McKee, N. J. Doesken et al. 1995). Categories of SPI values relating dry conditions are represented in table 2. The SPI can be generated within different intervals such as 1 month (SPI 1), 3 months (SPI 3), 6 months (SPI 6), 12 months (SPI 12), and up to 48 months (SPI 48).

Another common index is *PDSI* – the Palmer Drought Severity Index (Palmer 1965), however this index is more complicated, comparing to the SPI because input data require systematic datasets of local water balance regarding evapotranspiration process, and soil-water capability. Although the PDSI is complex, it is very effective in observing long-term drought distinguishing to seasonal aridity (Alley 1984). Nevertheless, any temporal irregularities of arid conditions are possibly representing drought occurrences.

In this study, monthly, seasonal, and annual arid indices (shown in table 2) will be investigated and respectively compared to the monthly, seasonal, and annual SPI index (SPI 1, SPI 3, SPI 6, and SPI 12) for assessing their effectiveness in determining meteorological drought. The study area, Binh Thuan province is located in the Southern coast of Vietnam (figure 1) where the local weather is very distinctive: dry in the Northern and the Eastern coastal areas of the province, and humid in the Southern and the Western areas. Previous research has approached drought assessment based on aridity indices, such as drought zoning using the annual UNEP index (Pham 2012). However, there are some gaps in those studies: (1) the timescale of 10 years was not sufficient; (2) effectiveness of aridity indices in drought indication was not validated; and (3) no types of drought were determined. Thus, in this research, abnormalities of different time-scale arid indices (more than 30 years) are assessed to reveal meteorological drought incidents, the time series SPI will be used as validations for those analyses.

Figure 1. Location of the study area, Binh Thuan province

STUDY AREA

Binh Thuan is located in the southernmost province of the South Central Region, Vietnam; bordering the East Sea in the South and South east within 192km coastline (see figure 1). Binh Thuan is located at the intersection between high mountainous regions in the West and Southwest (the Central Highlands) and narrow coastal plains in the East and Southeast. Thus, the terrain is very complicated. The climate in Binh Thuan is divided into two seasons: dry and rainy (wet) seasons which each lasts approximately 6 months each year; driven by global climate and ocean circulation, the duration of these seasons is subject to change. For example, in the years of El Niño's occurrence, dry seasons may be longer, causing meteorological drought, and a significant decrease of rainfall. The total rainfall in Binh Thuan is about more than 1000 mm per year mainly distributing in wet seasons from May to October. Dry seasons start from November till the following April; during dry seasons, in some areas in Binh Thuan, there is almost no rainfall or less than 50 mm (Tuy Phong, Bac Binh), but approximately 200 mm on average. Thus, during dry seasons, agriculture, grazing, and aquaculture have to face to fresh water shortage issues. Otherwise, Binh Thuan has received a large amounts of solar radiation –totally 2650 ÷ 2750 solar hours per year, temperature, depending on elevation, is above 27^{0}C on average, and average wind speed is ranging from 2 ÷ 3 m/s depending on locations (wind speed is stronger near the coastline). Figures 2 and table 1 represent climatic divisions of Binh Thuan based on governmental reports.

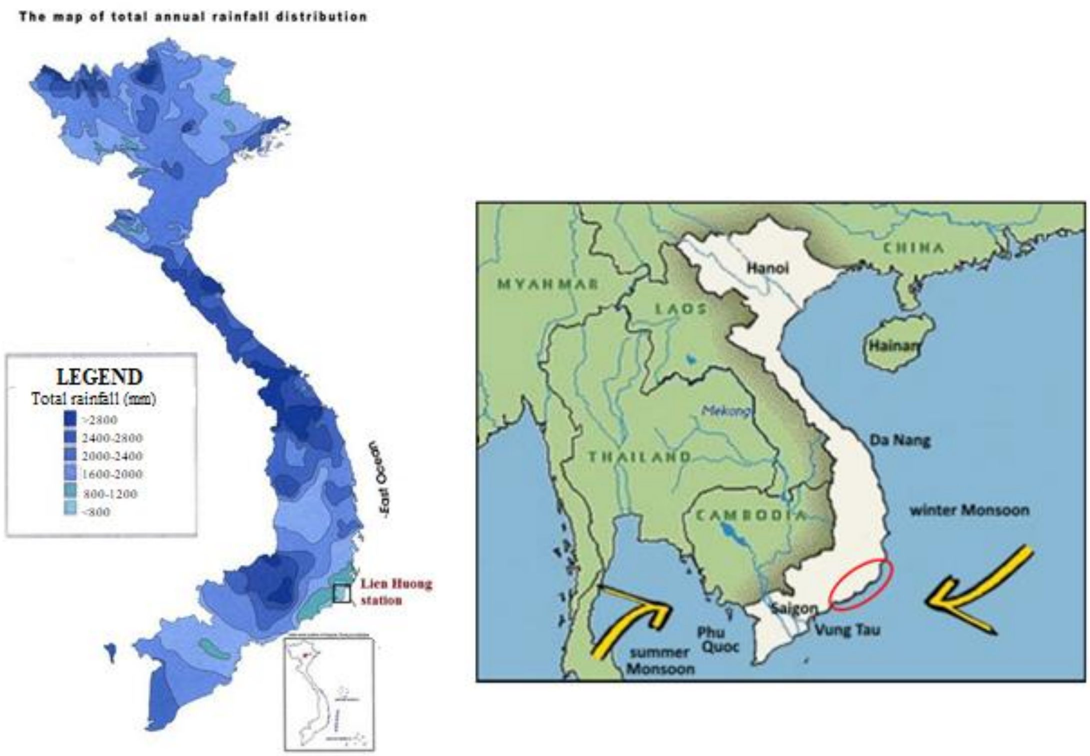


Figure 2. Left image -The Köppen climate classification applied in Vietnam, Binh Thuan (red outlined polygon) is located in the Aw region -tropical savana climate; Right image – direction airflows during monsoon seasons in the Southern Vietnam (Britannica); Left image: annual rainfall distribution in entirely Vietnam shows extremely low level of precipication in Binh Thuan (tortoise color)

Formation of dry conditions in the North and coastal areas of Binh Thuan is explicated upon the typical geogaphic location of the study area, sand dunes distributing near the coastline, distintve vegetation cover, and impacts of upwelling currents in the East during dry season.

Having a long eastern coastal line, bordering with the Central Highlands in the West, the climate of Binh Thuan is regionally divided into distintive mirco-climatic zones, such as *hot* and *dry* in the North and Northeast, or *warm* and *wet* in the South and Southwest. In general, Binh Thuan is located in a tropical savana climate – **Aw** (Thai, Cazelles et al. 2010) chraterized by hot and dry summers, and wet winters. During monsoon seasons, Binh Thuan receives a high moisture content of oceanic airflows, however due to the Highlands (Bi Dup, Lam Vien, and Di Linh) from the Northwest to Southwest, and other mountains such as Hon Ba (1356 m), Se Sai (1128 m), and Chua mountain (1040m) in the Northeast (Binh Vuong Ho, Hien Van Le et al. 1996, Vinh, Hien et al. 2013), which block the Southwestern and Northeastern airflows resulting a majority of rainfall distributtion in the Western slopes. At the Eastern slopes, there are hot, dry winds leading to dramatic decreases of precipitation distribution in Northern and Northeastern areas, sometimes total rainfall is less than 50 mm per approximately 6 months. In contrast, without being blocked, Southern areas receive higher rainfall, orginating from exbulent moisture from the oceans. The lower rainfall, and higher temperatures may lead to drought occurrence in the North and Northeast of Binh Thuan especially during dry seasons.

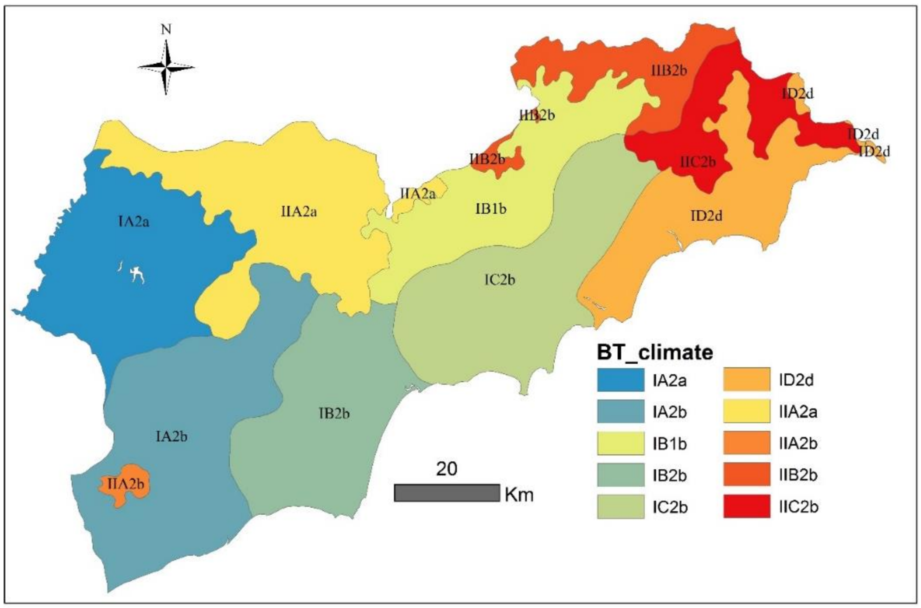


Figure 3. Climate divisions in Binh Thuan

Table 1. Explanation of climate characteristics in Binh Thuan

Symbol	Annual Temp (^{0}C)	Max-Min Temp (^{0}C)	Precipitation (mm)	Dry season (months)
IA2a	>25	7÷9	1500÷2500	4÷5
IA2b	>25	7÷9	1500÷2500	6÷8
IB1b	>25	≥9	1000÷1500	6÷8
IB2b	>25	7÷9	1000÷1500	6÷8
IC2b	>25	7÷9	800÷1000	4÷5
ID2d	>25	7÷9	<800	4÷5
IIA2b	20÷25	7÷9	1500÷2500	6÷8

IIB2b	20÷25	7÷9	1000÷1500	6÷8
IIC2b	20÷25	7÷9	800÷1000	4÷5

The occurrence of upwelling currents in the Southeast shelf also contributes aridity to Northern areas bordering Ninh Thuan province (Chen, Lai et al. 2012). Impacts of these currents are more significant in the Southwest monsoons, which lower the temperature of oceanic airflows resulting rainfall before they reach the coastlines. Consequently, those airflows bring dry and hot air instead of moisture to the coastal areas. Figure 2 describes the distribution of monsoon airflows during summers and winters (right image). Figure 3 shows a map of climatic divisions in Binh Thuan with an explaination about labels on the map is presented in table 1. Northearn areas which are highlighted by orangeish to redish colors are much drier comparing to other regions in Binh Thuan province as annual rainfall is less than 1000 mm.

Additionally, the distribution and occurrence of mobile sand dunes (white and yellow) along the coastline, which are about 10-50 m high on average blocking the moisture from the sea and indirectly enhancing the evapotranspitation process via increasing surface temperature. Based on our field research in 2016, the sand surface temperature increased rapidly and could reach approximately 50^{o}C at noon while air tempearture was around 35 to 40^{o}C, and it still resisted and retained heat till midnight. The higher surface temperture during day time coupling with the high amounts of solar radiation consequently put a pressure of water stress on local vegetation cover which is very fragile and unable to compensate the loss of air moisture. Our recent research in 2017 examining relationships between moisture and temperature conditions regarding occurrence of agricultural droughts have shown these issues (Tran, Campbell et al. 2017).

MATERIALS AND METHODOLOGIES

In order to execute research of hourly and daily rainfall data provided by the Meteoblue team, data were collected at three stations located along the coastal area: Lien Huong, Phan Thiet, and La Gi (see figure 4). These data were modelled and simulated by data input collection from meteorological satellites and local weather stations using NEMS30 model (NEMS: NOAA Environmental Modeling System at 30 km of resolution) from 1985 to 2017. Detailed information is provided at this link: https://content.meteoblue.com.

Based on these data, several arid indices, and a SPI- (Standardized Precipitation Index) was investigated and examined; table 2 represents formulas and categories of those indices. There are five arid indices applied in this case study, which were basically proposed upon relationships between precipitation and air temperature. De Martonne’s index is one of the oldest indices that is commonly applied to divide different arid zones. Lang’s rainfall factor and Minar’s moisture certain are mostly applied to reveal moisture conditions at certain locations. In this research, we are experiencing both monthly and annual De

Martonne's index (I_{DM}), Lang's rainfall factor (I_L), and Minar's index (I_M) for examining differences of those indices to identify arid conditions, and drought duration (months). The other two indices, Thornthwaite's (PE) and Pinna's (I_P) are ordinarily used for assessing precipitation efficiency per year, so in this research, we only calculated yearly values of those two indices for testing meteorological drought occurrence comparing to the SPI 12.

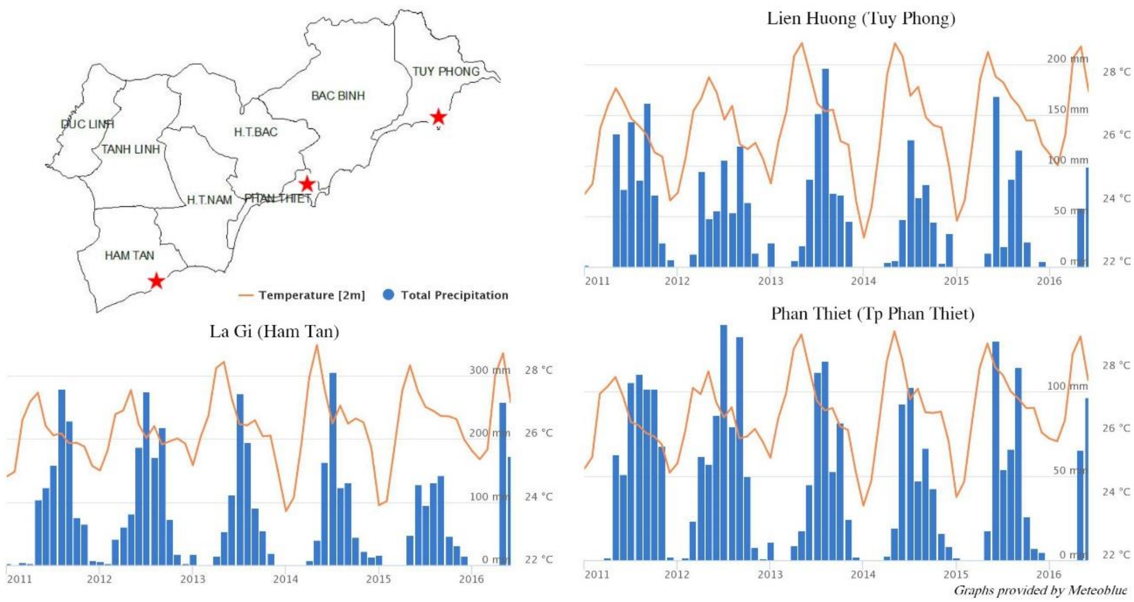


Figure 4. Locations of three stations Lien Huong (Tuy Phong), Phan Thiet (Phan Thiet), La Gi (Ham Tan), and their annual precipitation and temperature from 1985-2017.

Table 2. Summaries of arid indices: name, equation, and classification

Index	Equation	Classification	Note
De Martonne's arid index	$I_{DM}=\frac{P}{T+10}$	$I_{DM}<10$: Arid $10\leq I_{DM}\leq 20$: Semi-arid $21\leq I_{DM}\leq 24$: Semi-humid $I_{DM}>24$: Humid	Monthly Annual
Thornthwaite's index	$PE=\sum_{n=1}^{12}115(\frac{P}{T-10})^{10/9}$ Units: inches (precipitation), and ^{0}F (temperature)	PE<16: Arid 16≤ PE ≤31: Semi-arid 32≤ PE≤ 63: Semi-humid PE>63: Humid	Annual
Minar's moisture certainty	$I_M=\frac{P-30(T-7)}{T}$	$I_M<0$: Highly arid $1\leq I_M\leq 7$: Arid $8\leq I_M\leq 14$: Semi-arid $15\leq I_M\leq 21$: Stable $22\leq I_M\leq 28$: Semi-humid $I_M>28$: Humid	Monthly Annual
Pinna combinative index	$I_P=\frac{1}{2}(\frac{P_y}{T_y+10}+\frac{12P_d}{T_d+10})$	$I_P<10$: Arid $10\leq I_P\leq 20$: Semi-arid $I_P>20$: Humid	Annual
Lang's rainfall factor	$I_L=\frac{P}{T}$	$I_L<40$: Arid	Monthly

		$40 \leq I_L \leq 60$: Semi-arid $60 \leq I_L \leq 100$: Semi-humid $I_L > 100$: Humid	Annual
P: Monthly/yearly precipitation in total (mm) T: Monthly/yearly mean temperature (^{0}C) P_y: Yearly precipitation (mm) T_y: Yearly average temperature (^{0}C)		P_d: Precipitation of the driest month in a year (mm) T_d: Temperature of the driest (^{0}C)	

The Standardized Precipitation Index (SPI) is computed based on a long-time records of rainfall distribution (normally up to 30 years or more) reveal "probability of precipitation" in different time scales (From 1 to 48 months, and can be longer). SPI is similar to other climatic indices using time-series rainfall records, disregarding a required time period for input data. By standardizing distribution of precipitation over a specific time, then assigning new values (SPI values), wet and dry conditions are determined as if SPI is negative, meteorological drought can possibly occur. The smaller the negative SPI is, the more severe that drought is. Nevertheless, if the SPI is positive regarding more rainfall amount at the observing time, the climate is likely wet. Categories of SPI values are shown on table 3.

Table 3. SPI categories (McKee, N. J. Doesken et al. 1993)

SPI values	Interpretation	Drought classes
SPI <-2.0	Extremely dry	Extreme drought
-2.0< SPI <-1.5	Severely dry	Severe drought
-1.5< SPI <-1.0	Moderately dry	Moderate drought
-1.0< SPI <-0.5	Dry	Mild drought
-0.5< SPI<+ 1.0	Nearly Normal	No drought
+1.0 < SPI <+1.5	Moderately wet	
+1.5< SPI <+2.0	Very wet	
SPI <+2.0	Extremely wet	

The SPI can be interpreted at different time scales. For this research, we conducted SPI time scales of: 1 month, 3 months, 6 months, and 12 months for examining short- to medium-terms of insufficient moisture conditions based on abnormal rainfall. Some research has tested effectiveness of SPI time-scales and shown that: SPI 1 and 3 months are effective to reveal short-term moisture stress while SPI 6 and 12 months are more appropriate to evaluate stress of water storage and supply from hydrological systems. However, because the SPI only uses historical precipitation records as input for drought models disregarding effects of temperature, overall water balance and usage are excluded. Furthermore, the SPI model requires systematic data, thus any missing data may result inappropriate output, especially for short duration. In this study, starting with the basic idea of utilizing records of precipitation and temperature over

32 years, we investigated both arid indices and SPI to examine how arid indices can be effectively applied to assess meteorological drought as alternative indices to SPI because at least, those arid indices require two datasets – rainfall and air temperature.

RESULTS AND DISCUSSION

1. Drought indicated by monthly arid indices

Figures 5, 6, and 7 represent four precipitation indices: De Martonne's. Lang's, Minar's, and SPI 1. Based on categories of those indices, computed values at all three stations- LaGi, Lien Huong, and Phan That determine arid conditions at coastal regions of Binh Thuan accounting a wide range of precipitation variation between months; the lower those values are, the more arid the local climate is. All three aridity indices, the de Martonne's, the Lang's, and the Minar's index, indicate extremely arid climate in the study area. There are monthly variations in the values of those indices which were very low during dry seasons: less than 2 for the de Martonnes's and the Lang's, and -20 for the Minar's. However, because all values of those indices were under the arid condition, the monthly alternation between wet and dry conditions to reveal drought occurrence was not expressed. Thus, monthly aridity indices are not sufficient to capture meteorological drought.

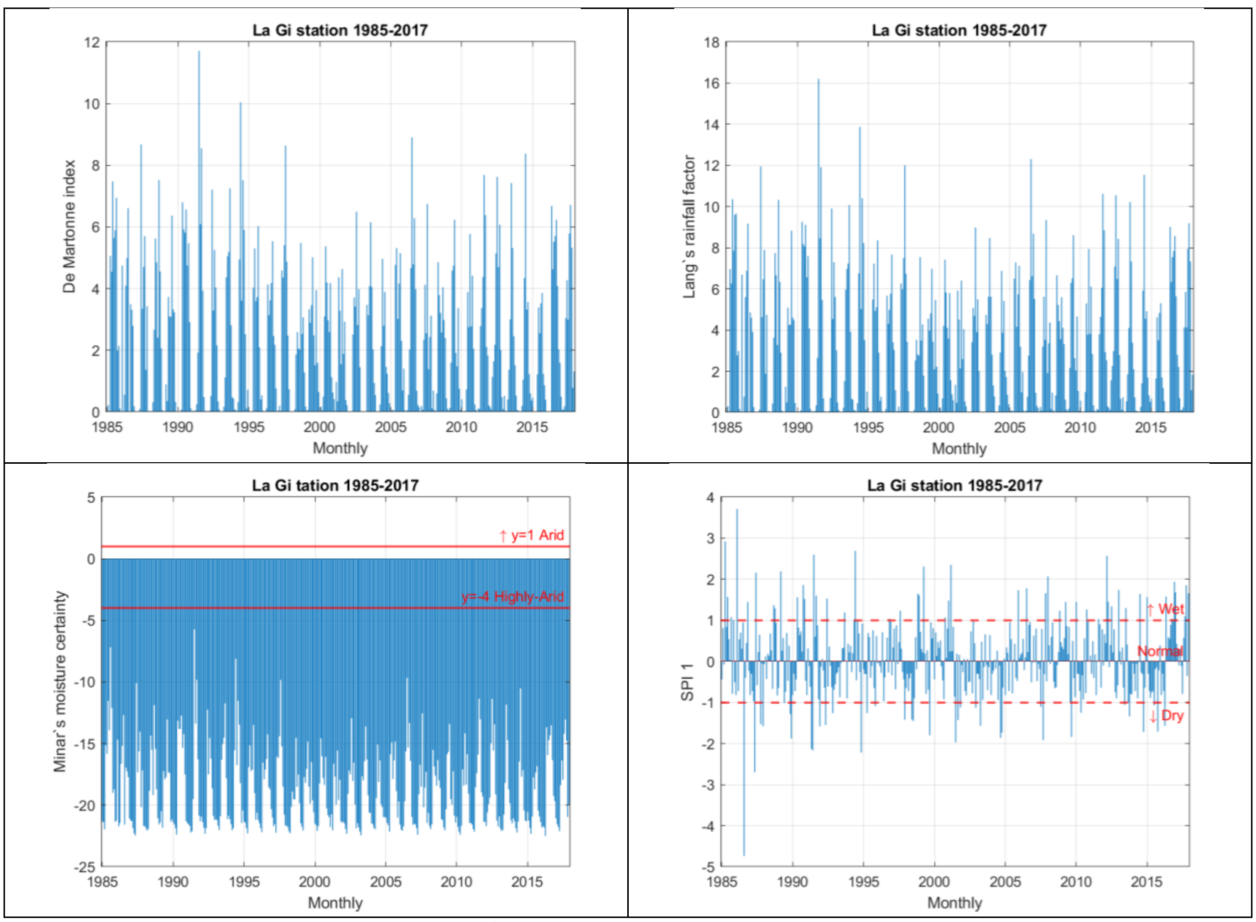


Figure 5. Computed monthly values of De Martonne's, Lang's, Minar's, and SPI 1 index at LaGi station.

The SPI 1, on the other hand, by using a wider range of positive and negative values to express dry conditions, is easier to determine anomalies in moisture stress. The fourth graph (lower right) in each figure 5, 6, and 7 illustrate variation of SPI 1 month. The SPI 1 negative values indicated some periods that were extremely dry referring occurrence of meteorological drought from moderate to extreme level (SPI < -1, see table 3 for reference). Based on the SPI values, the Northern coastal area, in which Lien Huong and Phan Thiet station are located, is much drier compared to the Southern part (La Gi station), and droughts occurred more frequently, especially in the period of 1990-2003. Therefore, in this examination of monthly moisture stress to predict dry conditions and drought occurrence, SPI 1 is more effective than the other arid indices.

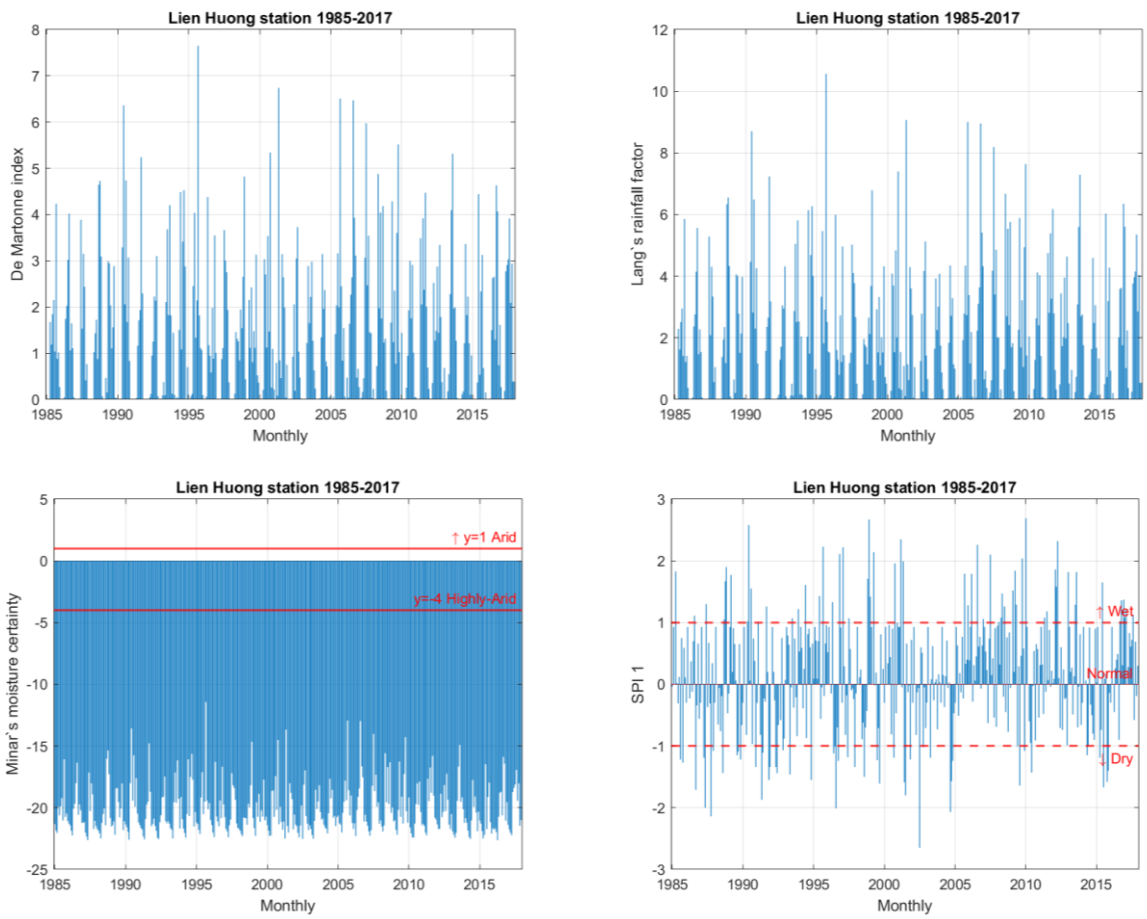


Figure 6. Computed monthly values of De Martonne's, Lang's, Minar's, and SPI 1 index at Lien Huong station.

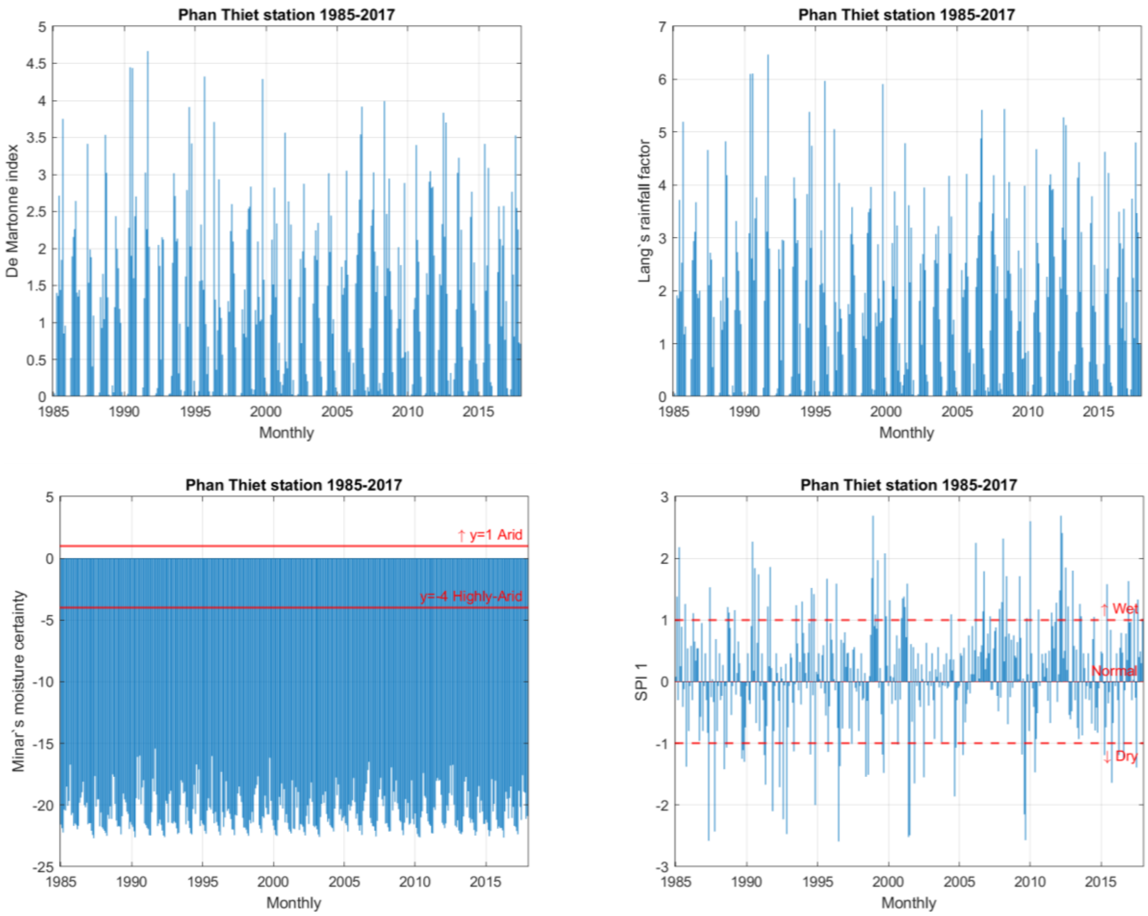


Figure 7. Computed monthly values of De Martonne's, Lang's, Minar's, and SPI 1 index at Phan Thiet station.

2. Drought indicated by annual arid indices

Values of five yearly arid indices and the SPI are charted and illustrated in figures 8, 9, and 10. Five indices including De Martonne's, Lang's, Minar's, Thornthwaite's, and Pinna's show semi-humid to humid conditions within the Southern coast (La Gi station), and arid to semi-arid condition in the Northern coast (Lien Huong and Phan Thiet). Local climate in Phan Thiet is the driest comparing to two other stations. The tremendously dry conditions recorded at Phan Thiet station were not only influenced by geographic and physiological characteristics but also by impacts of "urban heat island" effects. Phan Thiet is the central city of Binh Thuan province where its population is half that of one the entire province, industrialization and urbanization processes are developing speedily resulting "heat island" within higher surface temperatures and quicker evapotranspiration explaining why the De Martonne's and Lang's indices at Phan Thiet station are much lower than La Gi and Lien Huong.

In this examination, we investigated annual data for assessing conditions of "drier than normal" or drought-based arid indices to specify years of drought occurrence. In comparison to four indices (De Martonne's, Lang's, Thornthwaite's, and Pinna's), the Minar's moisture stress is much more effective in capturing anomalies in arid conditions as a wide deviation between computed and average values: the La Gi station recorded “drier than normal” condition in periods of 2000-2005 and 2013-2015; while at the Lien Huong station, records and computed data indicate that meteorological drought occurred more frequently, there are similar patterns between Minar’s index and SPI 12 showing occurrences of severe droughts during 1986-1989, 1992-1994, 2000-2005, and 2013-2015; the period of 2000-2005 also denoted frequent presence of drought recorded at Phan Thiet station.

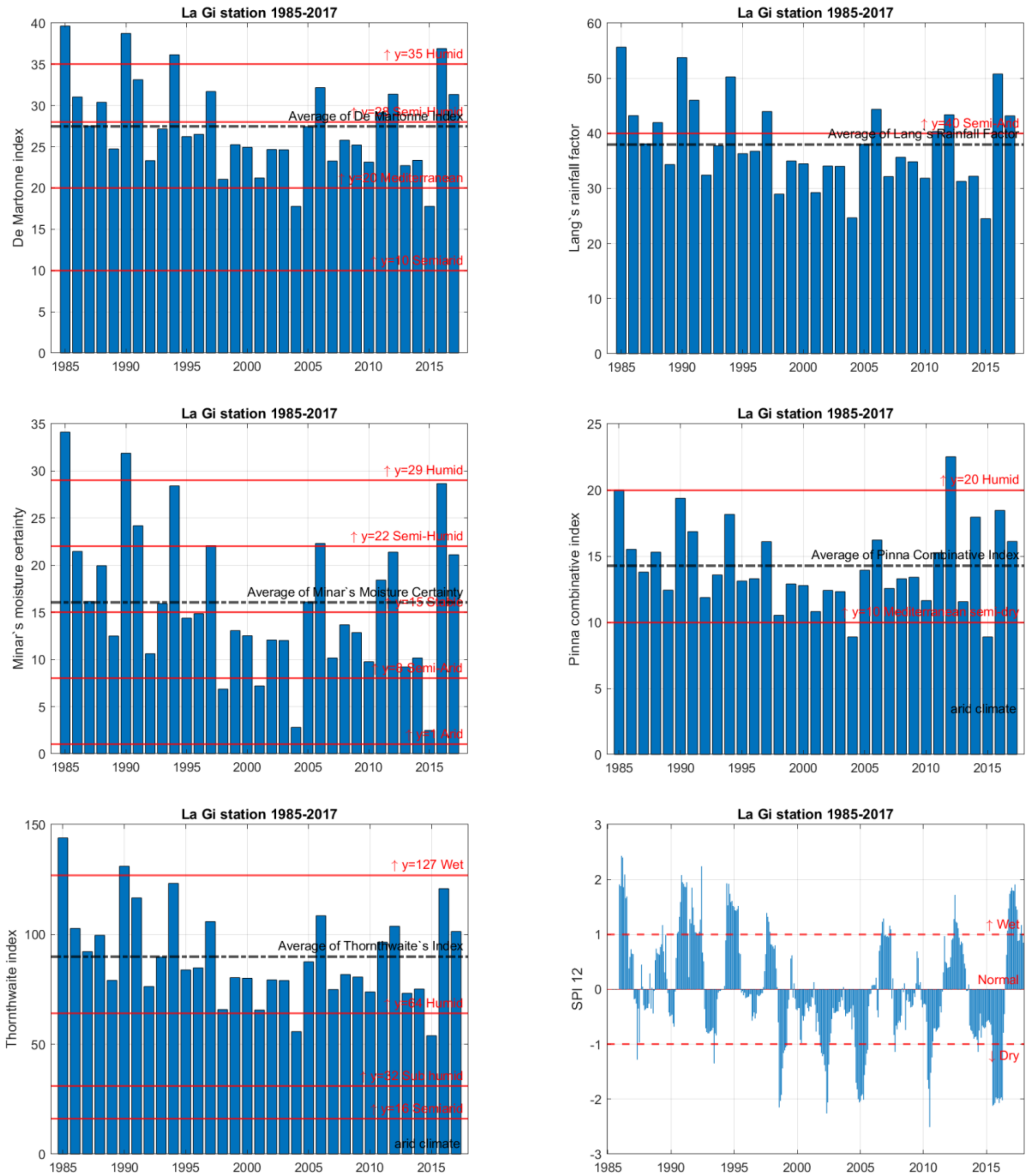


Figure 8. Computed yearly values of De Martonne’s, Lang’s, Minar’s, Pinna’s, and Thorthwaite and SPI 1 index at LaGi station

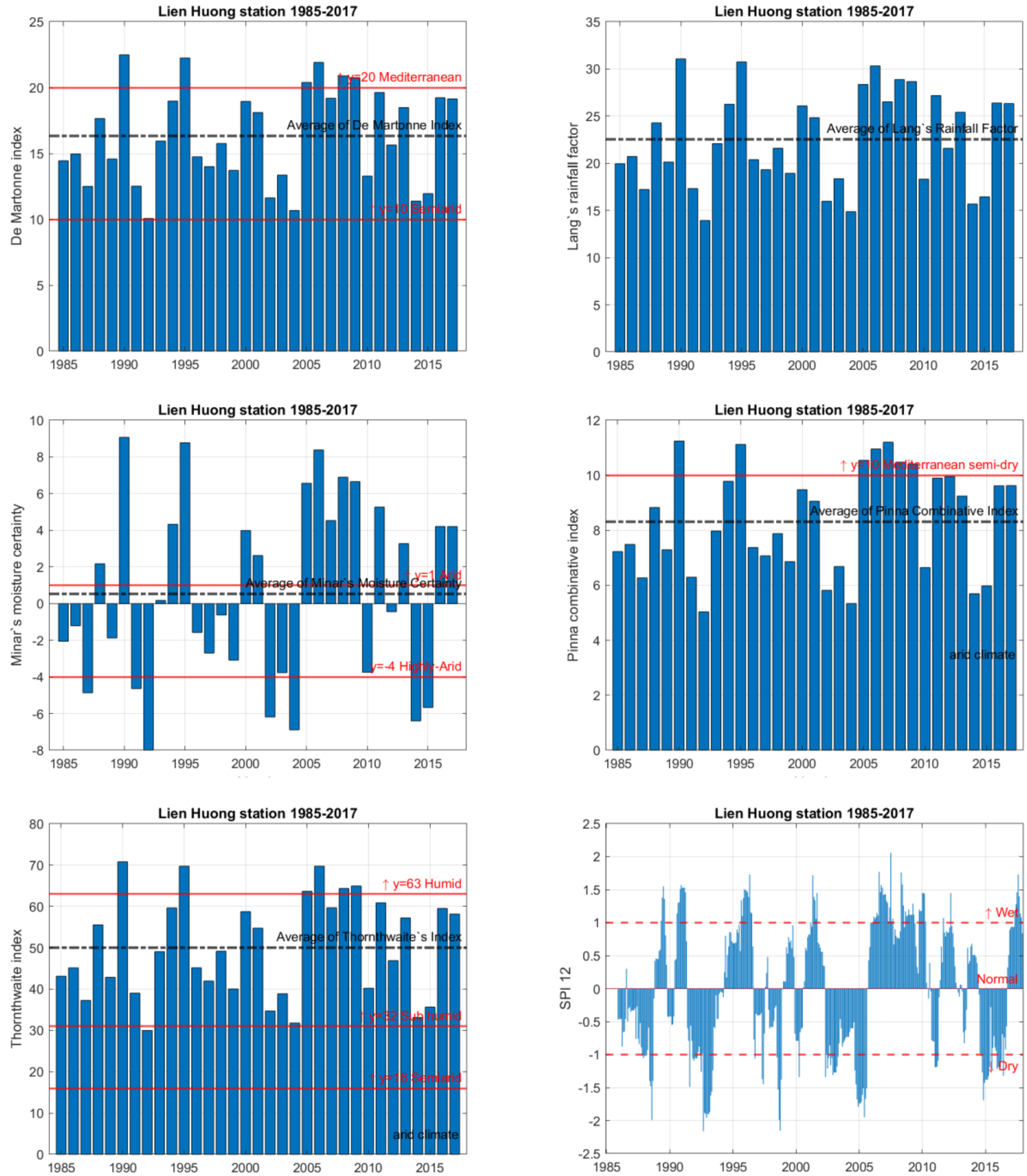


Figure 9. Computed yearly values of De Martonne's, Lang's, Minar's, Pinna's, and Thorthwaite's and SPI 1 index at Lien Huong station.

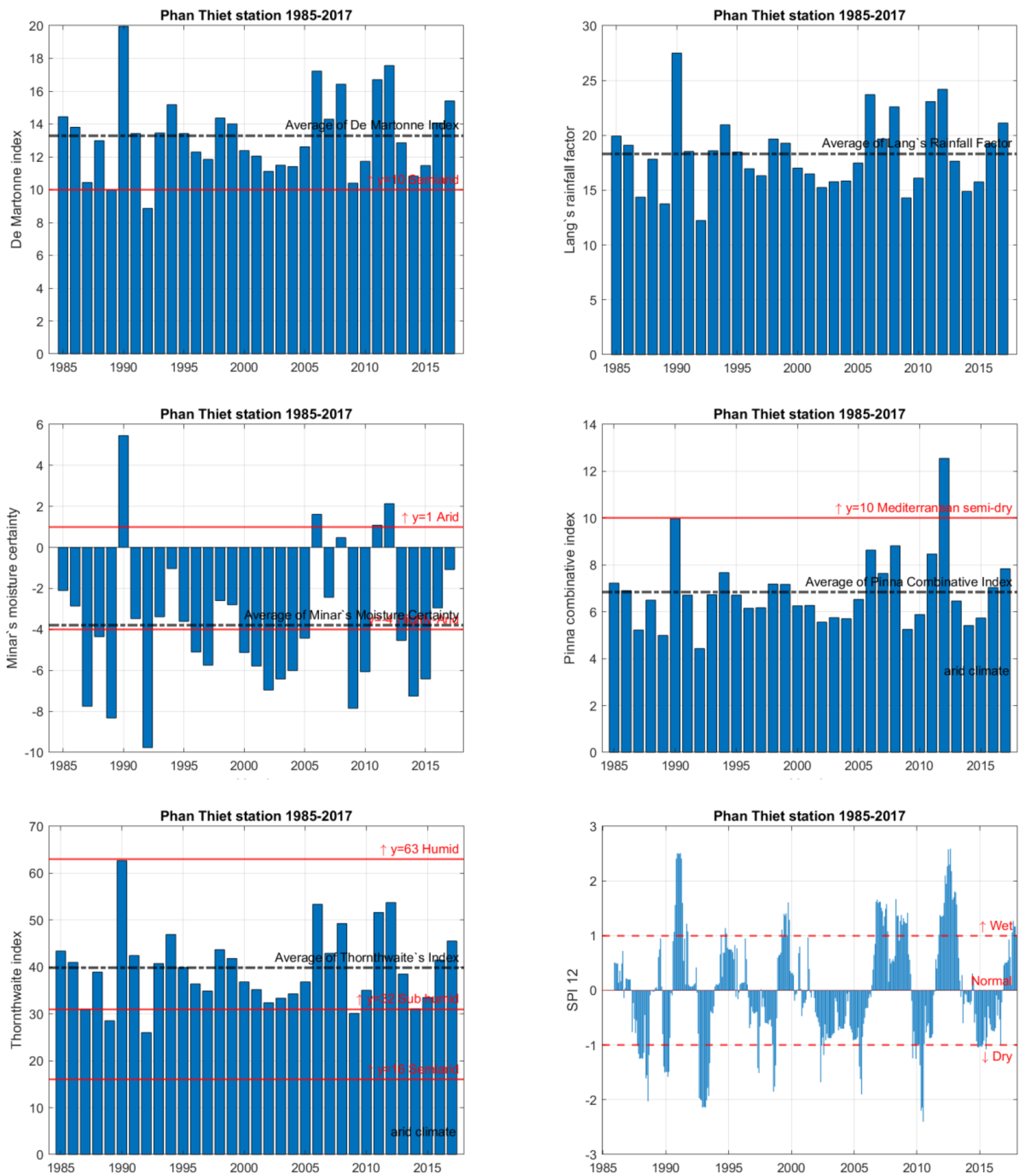


Figure 10. Computed yearly values of De Martonne's, Lang's, Minar's, Pinna's, and Thorthwaite's and SPI 1 index at Phan Thiet station.

Generally, by conducting both monthly and annual arid indices for testing "drier than normal" conditions based historical weather records, this study has shown that:

- Monthly arid indices possibly represent variation of dry conditions relating to precipitation and air temperature records. However, in order to reveal the stress of moisture condition and water unbalance, monthly intervals are not sufficient. In contrast, SPI 1 month is more effective in revealing short-term stress of moisture stresses relating to droughts.

- Yearly arid indices are probably effective in indicating occurrence of droughts based on a condition of “drier than normal”.
- All five arid indices illustrated years that were more arid compared to average. However, computed values of Minar’s moisture stress is more apparent. Additionally, SPI 12 showed similar patterns of dry condition as Minar’s index.
- Droughts occur more frequently and more severely at the Northern coast of Binh Thuan province as identified by comparing computed data of different stations.
- The SPI time scales are able to describe the condition of precipitation deficit in both frequency and duration (see the appendix for a comparison of different SPI time scales), but one of the disadvantages of this index is that the SPI model only use one single input dataset-precipitation. Thus, the relationship between rainfall and temperature are not credited. At yearly scale, the Minar’s moisture stress index may possibly alternate SPI 12 which computes both records of precipitation and temperature in its model.

The appendix presents three graphs of SPI values assessed in different time scales: SPI 3, SPI 6, and SPI 12 performing variations of drought occurrences and duration during 1985-2017. The shaded blue areas illustrated drought occurrence when SPI values were below -1 based on the table of SPI categories, the length of the shaded areas represented duration of drought within months. Within an interval of 3 months (SPI 3), the Lien Huong station recorded approximately 22 drought events which lasted from 1 to 5 months, while at LaGi and Phan Thiet, there were about 20 drought events. Within an interval of 12 months, drought events occurred more frequently recorded at Lien Huong station comparing to two other stations, but drought tended to last longer at LaGi.

CONCLUSION

Located at the border between the humid climate in the South, and the hot - dry climate in the North, the climate of Binh Thuan province is very distinctive, as represented by characteristics of long dry seasons within limitations of rainfall forming semi- arid to arid conditions in the coastal areas of the province. These areas, positioned in an arid zone, are much more at risk of drought due to insufficient water resources resulting mainly from sudden cut-off rainfall, and inefficient water management. Weather records support to quick assessment of drought occurrence and estimation of drought severity via precipitation indices. However, in order to evaluate drought severity more accurately, it is necessary to further study on other impacts of drought, such as impacts on vegetation, soil –water capacity, stream flows, and social-economic impacts.

REFERENCES

Alley, W. M. (1984). "The Palmer Drought Severity Index: limitation and assumptions." Journal of Climate and Applied Meteorology(23): 1100-11009.

Baltas, E. (2007). "Spatial distribution of climatic indices in northern Greece." Met. App **14**: 69-78.

Binh Vuong Ho, Hien Van Le, Thanh Hung Pham and T. D. Quach (1996). "Doi Kho Thuan Hai, Mot Dac Trung Co Ban ve Dia Chat, Dia Hoa o Vietnam can duoc Dau Tu Nghien Cuu Khai Thac Hop Li." Geology and Minerals **5**: 167-180.

Chen, C., Z. Lai, R. C. Beardsley, Q. Xu, H. Lin and N. T. Viet (2012). "Current separation and upwelling over the southeast shelf of Vietnam in the South China Sea." Journal of Geophysical Research: Oceans **117**(C3): n/a-n/a.

de Martonne, E. (1926). "Areism and aridity index." Comptes Rendus Hebdomadaires Des Seances De L Academie Des Sciences **182**: 1395-1398.

Emberger, E. (1932). "Sur uneformulecclimatiqueetses applications en botanique." La Meteorologie: 423-432.

Gamo, M., M. Shinoda and T. Maeda (2013). "Classification of arid lands, including soil degradation and irrigated areas, based on vegetation and aridity indices." International Journal of Remote Sensing **34**(19): 6701-6722.

Greve, P. and S. I. Seneviratne (2015). "Assessment of future changes in water availability and aridity." Geophysical Research Letters **42**(13): 5493-5499.

McKee, T. B., N. J. Doesken and and J. Kleist (1995). "Drought monitoring with multiple time scales. Ninth Conference on Applied Climatology." American Meteorological Society: 233-236.

McKee, T. B., N. J. Doesken and a. J. Kleist (1993). "The relationship of drought frequency and duration of time scales. Eighth Conference on Applied Climatology." American Meteorological Society: 179-186.

NDMC, N. D. M. C. "Types of Drought." from https://drought.unl.edu/Education/DroughtIn-depth/TypesofDrought.aspx.

Neira, F., K. Verbist, D. Gabriels, D. Lobo, I. Toro and Y. Carvajal (2010). "Assessment of climate idnices in dry lands of Columbia." Proceedings of the Int. Conf. Arif and Semi-arid devel. through Water(90).

Palmer, W. (1965). Meteorological drought Research paper. Washington DC, US Weather Bureau. **45**.

Sahin, S. (2012). "An aridity index defined by precipitation and specific humidity." Journal of Hydrology **444**: 199-208.

Sobisek, B. (1993). Meterological Lexicon, Prague: Acamedia.

Spinoni, J., J. Vogt, G. Naumann, H. Carrao and P. Barbosa (2015). "Towards identifying areas at climatological risk of desertification using the Koppen-Geiger classification and FAO aridity index." International Journal of Climatology **35**(9): 2210-2222.

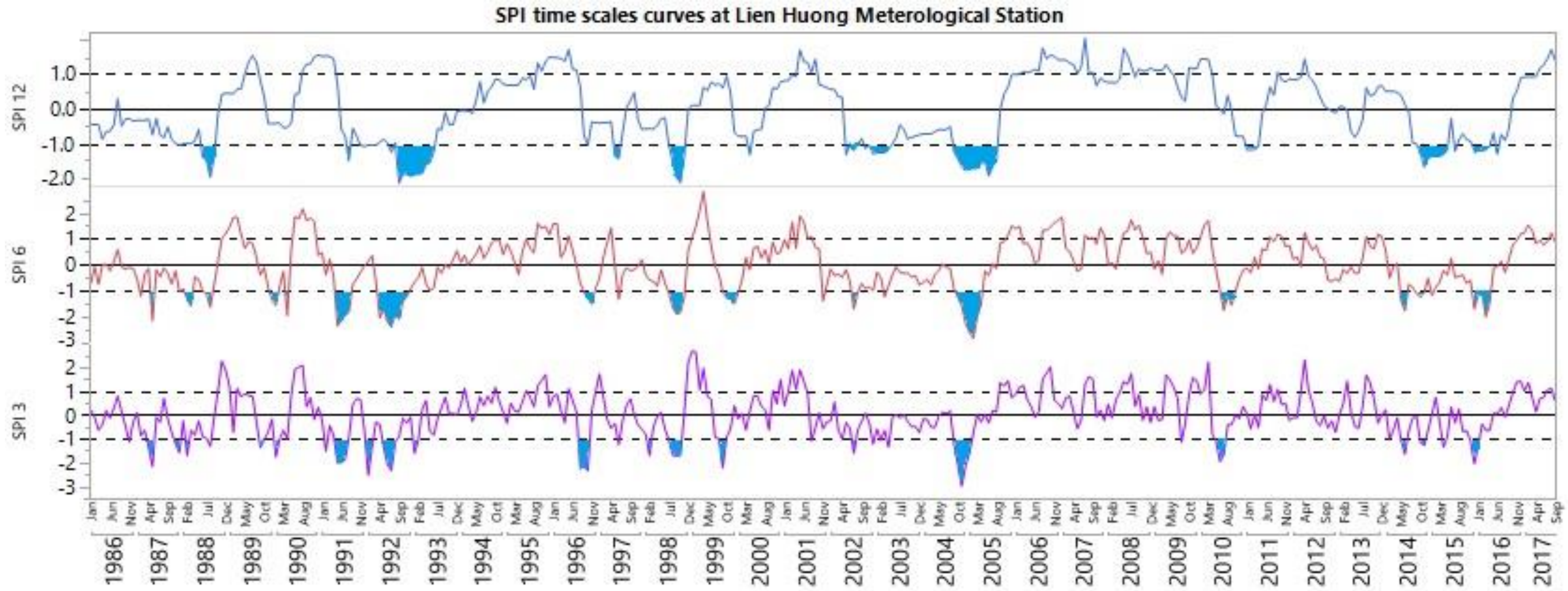
Thai, K. T., B. Cazelles, N. V. Nguyen, L. T. Vo, M. F. Boni, J. Farrar, C. P. Simmons, H. R. van Doorn and P. J. de Vries (2010). "Dengue dynamics in Binh Thuan province, southern Vietnam: periodicity, synchronicity and climate variability." PLoS Negl Trop Dis **4**(7): e747.

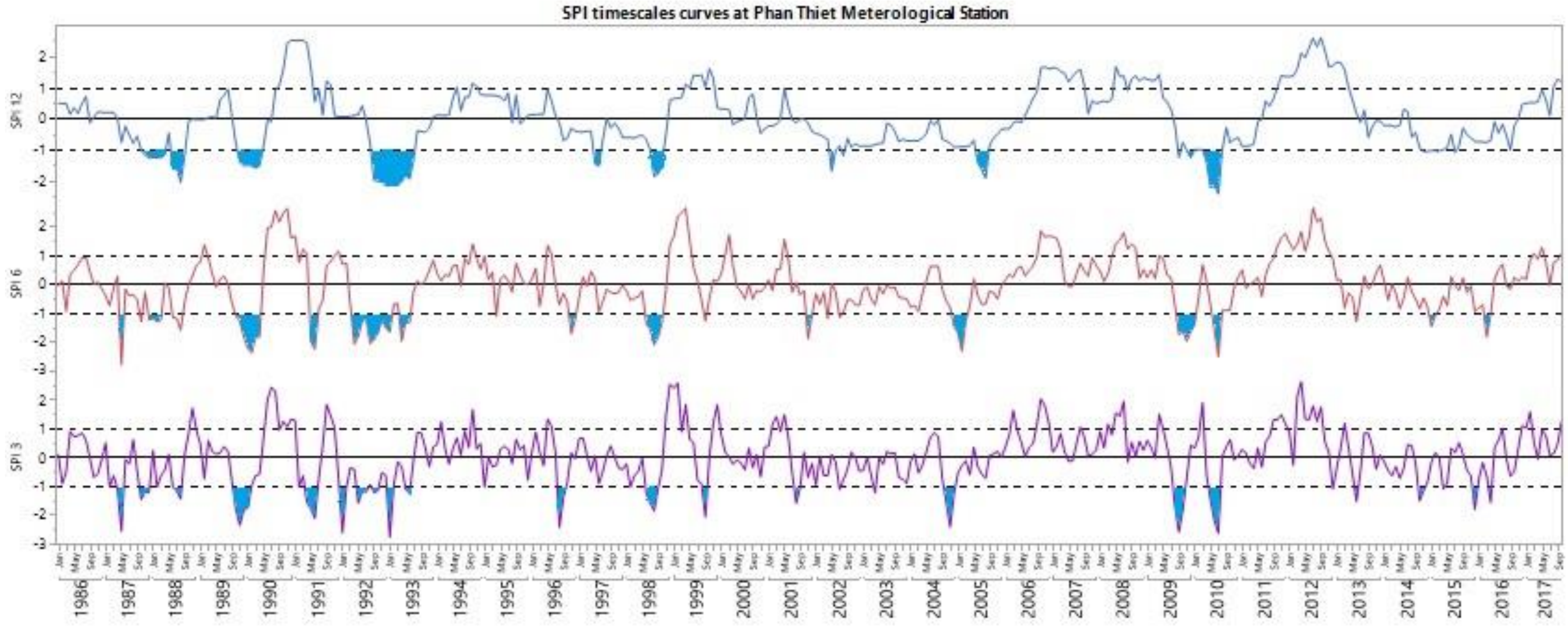
Thornthwaite, C. W. (1948). "An approach toward a rational classificatio of climate." Geo. Ev(38).

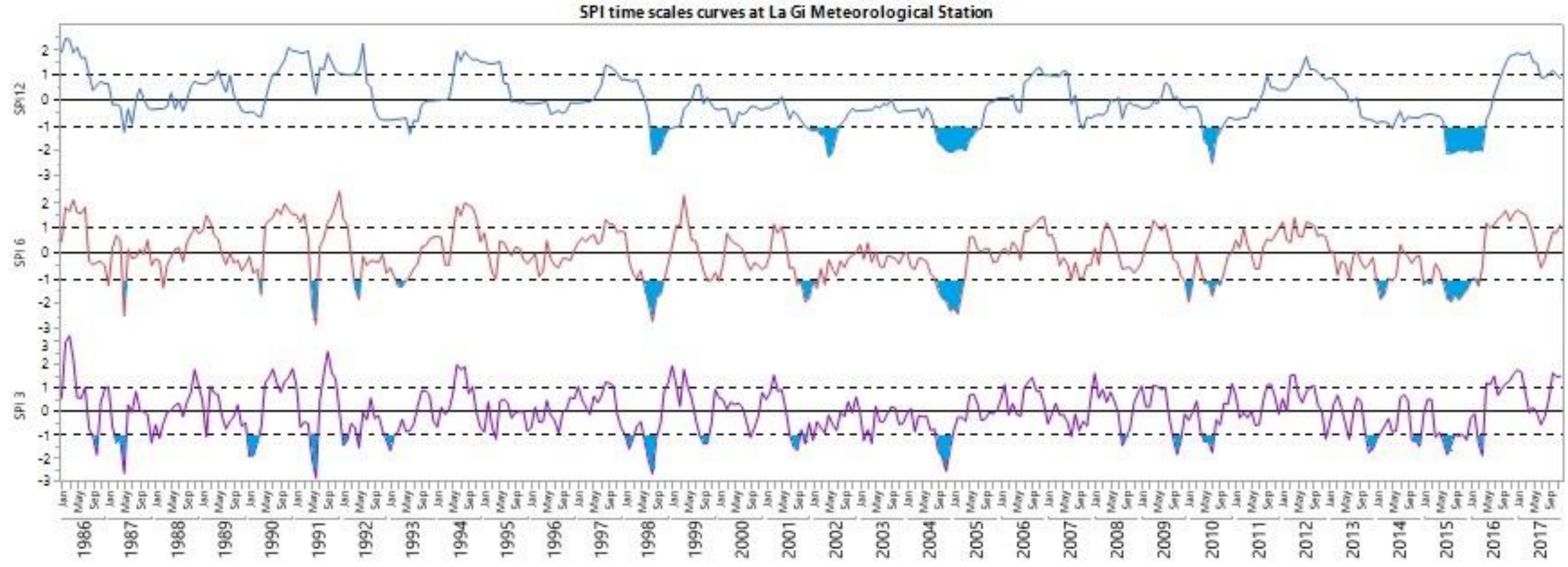
Vinh, P. Q., L. T. T. Hien, U. D. Khanh and N. H. Tu (2013). Anh Huong cua Bien Doi Khi Hau va Hoang Mac Hoa toi Moi Truong Tinh Binh Thuan. Ha Noi, Natural Sciences and Technologies Inc.

Yao, N., Y. Li, N. Li, D. Q. Yang and O. O. Ayantobo (2018). "Bias correction of precipitation data and its effects on aridity and drought assessment in China over 1961-2015." Science of the Total Environment **639**: 1015-1027.

Zarch, M. A. A., B. Sivakumar and A. Sharma (2015). "Assessment of global aridity change." Journal of Hydrology **520**: 300-313.

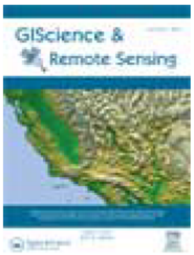

SPI time scales curves at Lien Huong Meterological Station
SPI 12
SPI 6
SPI 3
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


SPI timescales curves at Phan Thiet Meterological Station
SPI 12
SPI 6
SPI 3
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


SPI time scales curves at La Gi Meteorological Station
SPI12
SPI 6
SPI 3
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

Appendix 2

Hoa Thi Tran, James B. Campbell, Tri Dinh Tran & Ha Thanh Tran (2017). Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (Case Study: Tuy Phong, Binh Thuan, Vietnam). *GIScience & Remote Sensing*, 54:2, 167-184, DOI: 10.1080/15481603.2017.1287838



GIScience & Remote Sensing

ISSN: 1548-1603 (Print) 1943-7226 (Online) Journal homepage: http://www.tandfonline.com/loi/tgrs20

Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (Case Study: Tuy Phong, Binh Thuan, Vietnam)

Hoa Thi Tran, James B. Campbell, Tri Dinh Tran & Ha Thanh Tran

To cite this article: Hoa Thi Tran, James B. Campbell, Tri Dinh Tran & Ha Thanh Tran (2017): Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (Case Study: Tuy Phong, Binh Thuan, Vietnam), GIScience & Remote Sensing, DOI: 10.1080/15481603.2017.1287838

To link to this article: http://dx.doi.org/10.1080/15481603.2017.1287838

Published online: 09 Feb 2017.

GIScience & Remote Sensing, 2017
http://dx.doi.org/10.1080/15481603.2017.1287838

ARTICLE

Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (Case Study: Tuy Phong, Binh Thuan, Vietnam)

Hoa Thi Tran [a]*, James B. Campbell[a], Tri Dinh Tran [b] and Ha Thanh Tran [b]

[a]*Department of Geography, Virginia Polytechnic Institute and State University, 220 Stanger Street, Blacksburg, VA 24061, USA;* [b]*Department of Photogrammetry and Remote Sensing, Hanoi University of Mining and Geology, Duc Thang, Bac Tu Liem district, Hanoi, Vietnam*

(*Received 24 June 2016; accepted 22 January 2017*)

This study applies multispectral band ratios to examine vegetation density and vegetation health to assess drought conditions over nearly 30 years (1989–2016) in Tuy Phong district, Binh Thuan province, Vietnam using a sequence of Landsat imagery (TM and OLI). Our research area has a distinctive climate, characterized by arid and semiarid areas adjacent to Binh Thuan's coastline. Drought is likely intensified by rain shadow effects of the Central Highlands (part of the Truong Son- or the Annamese Cordillera, positioned immediately west of the province). The seasonal Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) were calculated to derive three other indices: Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI). Results show that approximately two-thirds of Tuy Phong district was influenced by mid-to-severe drought. During the dry season (November to the following April), severity of drought has increased both intensively and extensively toward the North. Hypotheses testing of correlation between LST and NDVI also revealed a significantly negative relationship – increasing surface temperature and decreasing NDVI. To validate our results, we applied the same procedure for generating the VHI from MODIS data. Despite the absence of historical datasets for our region, Landsat data shows many advantages in monitoring drought in remote and small areas compared to MODIS. Our research strategies may be effective in other regions without sufficient climatic records for conventional climatic analysis.

Keywords: Binh Thuan – Vietnam; Drought; NDVI; LST; VHI

1. Introduction

As a climatic abnormality originating from a period of usually low precipitation, drought can occur in every part of the Earth's surface, even in humid regions. Droughts can disrupt both ecological and economic systems, leading to population displacement. Furthermore, sustained drought also encourages desertification (Hirche et al. 2011), and land degradation, which are especially harmful for vulnerable landscapes bordering arid and semiarid areas (Pandey et al. 2013). When local climatic meteorological data are available, drought can be measured using integrated indices related to weather and soil conditions, such as atmospheric humidity, air temperature, rainfall, and soil moisture.

*Corresponding author. Email: hoatran@vt.edu

Although meteorological data do define drought status, they are not fully sufficient, especially in areas that lack robust, sustained, and adequate records at appropriate spatial and temporal scales. This study examines drought conditions within a small, but distinctive, region at the central coast of Vietnam characterized by serious drought, but lacking systematic climatic records – specifically, there are only 105 internationally and officially recognized weather stations within all of Vietnam – a country with 63 provinces. Additionally, due to the Historical Observing Metadata Repository system, within our study area, in Binh Thuan province (see Figure 1), there are two stations, located in Phan Thiet City, though there are no *in situ* weather stations within our specific study area. Therefore, it is very difficult to examine climate anomalies at monthly to yearly scales. On the other hand, broad-scale weather models, can only work well over larger areas, and be applied to predict general climatic trends, rather than specific drought episodes.

However, sequential satellite imagery can form a comprehensive method to observe and evaluate drought conditions within regions without records of systematic climate data. There are multiple forms of freely available remotely sensed imagery suitable for drought analysis, such as MODIS, LANDSAT, and ASTER imagery, together providing a wide range of resolutions and spectral channels (Cai, Mingyi, and Liu 2011). These data can be applied to land use assessment (Doi 2002), or to generate useful indexes for specific purposes, such as changes of surface temperature (Sobrino, Jiménez-Muñoz, and Paolini 2004; Valiente et al. 2010), and vegetation health, which can be considered as indicators of drought (Karnieli et al. 2010; Orhan, Ekercin, and Dadaser-Celik 2014).

NDVI is a proxy index applied to extract, and to estimate, vegetation cover in terms of proportion and density, which indirectly indicates vegetation health (Tucker 1979). In monitoring drought status, assessing vegetative cover and health is very important as an indicator of overall plant health, and specifically, temperature, and moisture stress. Thus, any sign of changing behavior of the prevailing NDVI time series of the vegetative cover

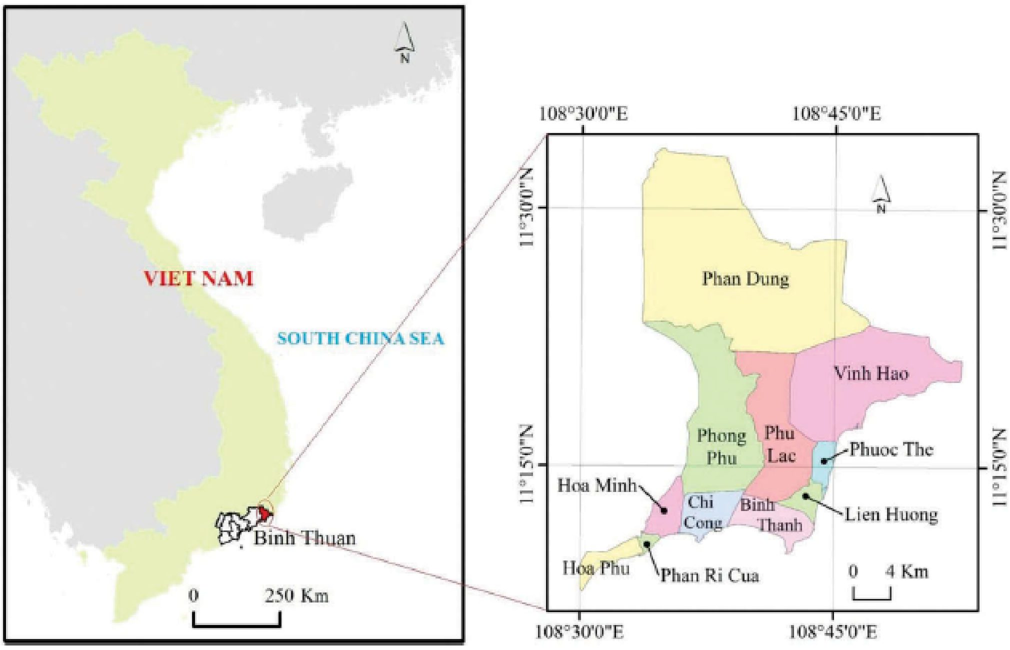


Figure 1. Location of case study, Northeastern Binh Thuan Province, Southern Coastal Vietnam. For full colour versions of the figures in this paper, please see the online version. Figure 1 should be shown in section 2.1. Case study.

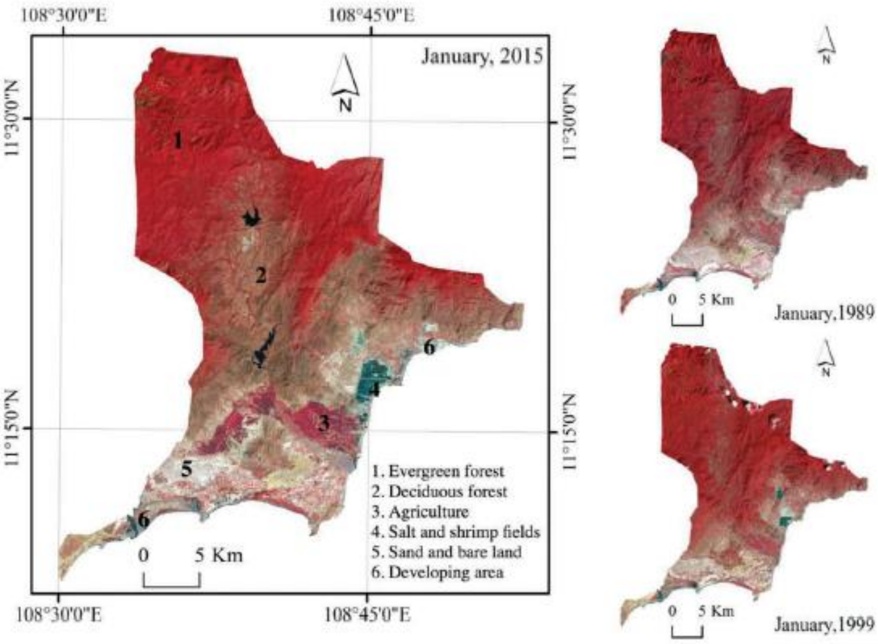


Figure 2. False color Landsat images of the study area from January 1989 to January 2015 show land use changes over 26 years, with the expansion of agriculture (3), shrimp fishing, and solar salterns (4).

can be attributed to variation of climatic measures, such as temperature or precipitation (Peters et al. 2002; Sun and Kafatos 2007; Bai and Dent 2009). Otherwise, in their study using datasets acquired by Advanced Very High Resolution Radiometer (AVHRR), Karnieli and his colleges found a negative correlation between surface temperature (LST) and NDVI that also can be considered as another indicator of drought monitoring in terms of water-limiting vegetation growth (Karnieli et al. 2010). Therefore, in our study, instead of working on NDVI separately, we investigate an integration of LST, and NDVI.

In that context, the Vegetation Health Index (VHI) has been used to monitor vegetation health according to drought impact (Kogan 1990, 1994). VHI is based upon the correlation between NDVI and LST derived from AVHRR-NOAA imagery. Basically, VHI, according to Kogan, is based on the three principles of environmental ecosystem analysis: the "law of minimum; the law of tolerance; and the law of carrying capacity" (Kogan 1990). To integrate NDVI and LST obtained over the long term, Kogan used two indices as components to derive the general index VHI: VCI and TCI. VCI is generated by NDVI time series analysis that measures percent change of the difference of current NDVI and range of historical NDVI values. VCI can be applied individually in advance to monitor impact of drought on vegetation health (Peters et al. 2002; Jiao et al. 2016), but it is insufficient because VCI only reflects impact of moisture condition. Therefore, TCI, which indicates the influence of thermal condition, was proposed. TCI measures the difference of current LST and range of historical LST values. Generally, VHI is a time series analysis of moisture and thermal impacts on vegetation. Kogan's results demonstrate the potential application of VHI in agricultural drought analysis. In the United States, USDA applies this index at monthly to yearly frequencies to monitor drought and crop health (www.star.nesdis.noaa.gov). However, application of the VHI estimation algorithm requires sequential imagery on a weekly basis over at least 32 years of

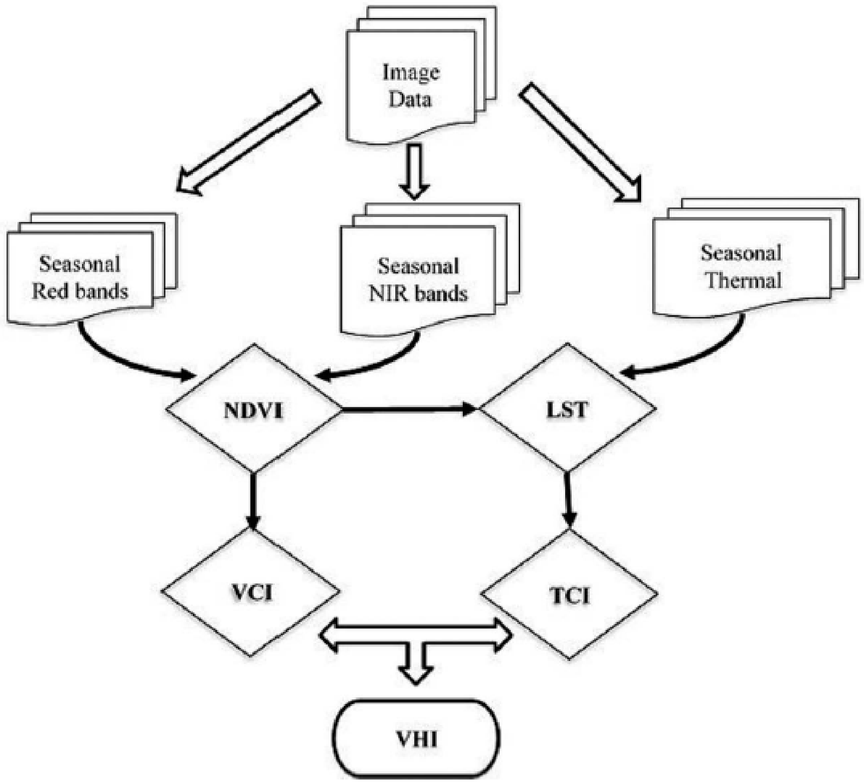


Figure 3. Flowchart of image processing and analyzing. Figure 3 should be shown in section 3.1. Image preprocessing.

observation. Thus, at coarse resolutions, or global scales, VHI seems to work well due to the huge image databases at that scale from NOAA or MODIS, for example. Otherwise, at moderate or high resolutions, applications of VHI are limited due to the lack of available sequential imagery, longer revisit times, and cloud cover, especially for areas near the Equator. As a result, there are few reports assessing influences of drought at local scales, in part because of the absence of long-term metrological records.

This study applies the basic VHI method using Landsat imagery (TM and OLI) for a small region within a tropical environment to assess its performance in characterizing drought severity and monitoring vegetation stress under drought conditions. Therefore, it contributes to an understanding of relationships between water shortages and high temperatures, and their effects upon vegetation health, which are essential for monitoring spatial and temporal impacts of drought upon local landscapes.

2. Materials and methods

2.1. Case study

District Tuy Phong is located in the Northeast of Binh Thuan Province, Southern Coast of Vietnam (centered at 11°11′43″N, and 107°31′34″ E), covering approximately 755 km^2, with a 2015 population of around 188,000 (Figure 1). Much of this region is characterized by a typical tropical wet and dry climate with a distinctive Monsoon summer wet season (May–October) and a winter dry season (November–the following April). However, a narrow zone parallel to the coastline gives this region's climate a distinctive arid character, uncharacteristic of the humid tropical climate of the majority of Vietnam. During summer months, the Southwest Monsoon brings moisture to Vietnam from the southwest, traversing the Truong Son through the Central Highlands, then descends the steep eastern slopes, likely with a rain-shadow effect reducing rainfall totals along Vietnam's central coast. In addition, upwelling related to the steep offshore topography near Binh Thuan's coastline likely creates cooler coastal currents (Jianyu et al. 2000; Chen et al. 2012), possibly stabilizing the lower atmosphere and further reducing opportunities for local summer rainfall. Annual rainfall here is often below 250 mm (mm) per year, concentrated mostly in the rainy season (May–October), while annual temperature is quite high, above 30°C. During the dry season, normally extending the six months from November to the following April, the precipitation is usually less than 50 mm per month, or even lower than 1-mm rainfall per month during 3–4 months. Such effects intensify the semiarid conditions prevailing over the broader region, accentuating aridity of the coastal zone, and leading to the distinctive coastal sand dunes, xerophytes, and desertification processes that are currently observed in this region.

One significant characteristic of Tuy Phong's climate is the occurrence of the Xiaoman in the end of dry season. The Xiaoman (or Soman) is the Chinese name that describes a special weather event in the East Asian region, which lasts around 2 weeks from the end of May to the middle of June. The Xiaoman is considered to be earliest sign of the beginning of the rainy (stormy) season due to the significant increase of rainfall that may occasionally lead to local flooding. The main stormy season will begin later, depending on the location. For example, in our study area, the stormy season usually starts in the end of August. The Xiaoman provides a very important freshwater resource for reservoirs, supplying a seasonal reserve of freshwater for agriculture, and households, in the interval before the rainy season starts.

During past decades, Tuy Phong has suffered several severe to extreme droughts. Prolonged drought has led to many environmental and social impacts in this district, such as the threat of water scarcity for agriculture and households, changes of land use (Figure 2) and of increased wildfire risk (Pham, Binh, and Huong 2012). The 2014–2015 dry season was the most severe recorded drought in Tuy Phong: all three of the largest local reservoirs experienced dramatic declines; water levels in Da Ba Lake fell dramatically to 800,000 cubic meters, compared to its 4.5 million cubic meter design capacity (a decline of 90%); local people in the communes of Vinh Hao, and Vinh Tan could not practice agriculture due to the water shortage. In Vinh Hao commune, available water resources could serve only 600 of the 1,800 households, forcing many to pay out-of-pocket costs at the relatively high rate of 90,000–250,000 VND (4–12 USD) per cubic meter of water.

In addition to impacts of drought, and declines in local food production, populations suffered other difficulties, such as pressure of population, which is increasing rapidly, doubling in just 13 years: from 90,000 in 2002 to 188,000 in 2015. Because freshwater is not sufficient for irrigation, the local population may face risk of food shortages. Additionally, a rapid rate of land use change with expansion of agriculture without parallel development of management and irrigation systems will accelerate processes of land degradation. Then, when drought happens, such processes increase rates of desertification, consequently degrading arable lands. While there are many studies of Binh Thuan province (Gobin et al. 2012; Tran, Hoa, Dinh, and Thanh 2015), and of neighboring districts – Bac Binh (Le and Dao 2015), there is little research, or reference data that provides insight on local drought, its effects upon the entire province, specifically for Tuy Phong, and how the local population of Tuy Phong has been reacting to this hazard. This present research can develop knowledge about role of drought episodes in promoting local desertification processes, and improving local knowledge to combat effects of drought. Our review of French, English, and Vietnamese research reveals only sparse meteorological and climatic records for this region, as might be expected for a locality peripheral to the nation's principal population, industrial, and agricultural concerns. Therefore, satellite image archives provide one of the few resources that can provide accessibility, continuity, and consistency for an inquiry into the nature and impacts of changing drought in this region.

2.2. Data resources

Available Landsat images (Path 123, Row 52) with less than 10% cloud cover, entirely covering the district, were selected and downloaded from GLOVIS (http://glovis.usgs.gov) for both dry and wet seasons of 1989, 1994, 1999, 2004, 2009, 2013, 2014, 2015, and 2016. Though all images were processed at Level 1, only 3 bands of each image were investigated in this research (red band, near-infrared (NIR) band, and the thermal band). Because of the 27-year interval, images from 1989–2009 were acquired by Landsat 5 TM, and others from Landsat 8 OLI-TIRS. Although Landsat 7 ETM+ imagery is available for this study site, to minimize the number of sensors employed for this study, only these two datasets were used here. We used bands 3–4-6 for Landsat 5 TM, and bands 4–5-10 for Landsat 8, as red-NIR-thermal, respectively. Thermal bands for both systems have coarser spatial resolutions than do the two other bands; at Level 1 processing, they were resampled by Cubic Convolution to match the 30 m pixel size as the red and NIR bands.

Otherwise, for validation, MODIS data also were collected. As mentioned on its original website of NASA, MODIS (Moderate Resolution Imaging Spectroradiometer) is "a key instrument aboard the Terra Satellite, and the Aqua Satellite (https://modis.gsfc.nasa.gov/about/)". These two satellites form the core of the Earth Observation Missions, which are also known as the EOS AM-1 (morning acquisition), and the EOS PM-1 (afternoon acquisition). MODIS data are acquired globally every 1 or 2 days in 36 spectral bands including visual spectral region, and the thermal bands at 250-m, 500-m, and 1-km resolution. Thus, applications of MODIS products are widespread in land assessment, ocean studies, atmospheric studies, environmental protection and management. Additionally, MODIS data can form the basis for accurate validation, and monitoring models of global variation of surface temperature, and vegetation dynamics. Other data products, which are commonly used for modeling global variation of temperature and vegetation, are derived from the Advance Very High Resolution Radiometer (AVHRR), and the Visible Infrared Imaging Radiometer Suite (VIIRS) at 4-km resolution. However, because of the disadvantages of coarser resolution of the VIIRS, and the lack of cloud-free AVHRR data, for our study area, we investigated MODIS Terra products as prospective validation for our study.

Because of the large number of MODIS images, we used 8-day Terra composite for Surface Temperature data, and 16-day Terra composite for vegetation index – NDVI, respectively. Our time range for data is dry seasons (November to April) from 2013 to 2016, approximately, 24 NDVI images, and 48 LST per season. Table 1 outlines the overall nature of Terra products as reference at https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table.

Table 1. MODIS data description.

ID of product	Name	Data description	Resolution (m)
MOD13A2	MODIS Vegetation Indices 16-Day	A gridded level-3 product in the Sinusoidal projection. Vegetation indices such as NDVI or Enhance Vegetation Index (EVI) was calculated by averaging NDVI or EVI values generated for each scene during a 16-day period	1000
MOD11A2	MODIS LST and Emissivity 8-Day	The level-3 MODIS global Land Surface Temperature (LST) and Emissivity 8-day data are average values of clear- sky LSTs during an 8-day period	1000
MOD13A3	MODIS Vegetation Indices Monthly	A gridded level-3 product in the Sinusoidal projection. In generating this monthly product, the algorithm ingests all the 16-day 1-kilometer products that overlap the month and employs a weighted temporal average if data is cloud free, or a maximum value in case of clouds	1000
MOD11C3	MODIS LST and Emissivity monthly (Version 004)	The products provide per-pixel temperature and emissivity values in a sequence of swath-based to grid-based global products, and configured on a 0.05°latitude/longitude climate modeling grid (CMG)	5600

3. Methodology

3.1. Image preprocessing

Because images were collected from different sensors (Landsat 5 TM, and Landsat 8 OLI), in order to obtain values of NDVI and LST, two sets of algorithms were applied to derive at-sensor reflectance (or Top of Atmospheric reflectance – TOA) of three bands: Red, NIR, and Thermal. Following the Landsat user guides for TM and OLI, the processing procedure for these images is similar, which requires several steps: co-registration, radiometric calibration, atmospheric correction, sun angle correction, topography, and normalization. Algorithms can be generally established by converting the digital number of each pixel to radiance, then from radiance to surface reflectance. Figure 3 shows the overall procedure to achieve final results.

3.2. NDVI calculation

During the early 1980s, the NDVI was defined and developed by scientists at NASA's Goddard Space Flight Center, Greenbelt, Md. for monitoring vegetation health based on the difference between absorption and reflectance of green leaves of red and near-infrared band of visible light, respectively (Tucker 1979). The value of NDVI of each pixel was estimated by dividing the reflectance difference by the sum between NIR and Red band; NIR ranges from 0.7 to 1.1 μm, while Red ranges from 0.58 to 0.68 μm. Normally, values of NDVI range from −1 to +1, with +1 indicating healthy vegetation cover, and lower values representing stressed vegetation, and negative values representing open water, or high moisture content respectively. The higher NDVI values are, the healthier vegetation is. The range value of NDVI in wet seasons is much wider than in dry seasons.

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{1}$$

In addition, NDVI also was used to extract Land Surface Emissivity (LSE), which is an adjustable parameter in correcting Land Surface Temperature in the next step. Values of LSE were calculated based on the proportion of vegetation (Sobrino, Jiménez-Muñoz, and Paolini 2004; Jiménez-Muñoz et al. 2014).

$$\mathrm{LSE} = 0.004P_v + 0.986 \tag{2}$$

Whereas, P_v is the proportion of vegetation, based on a normalized NDVI value of each pixel.

$$P_v = \left(\frac{\mathrm{NDVI} - \mathrm{NDVI_{min}}}{\mathrm{NDVI_{max}} - \mathrm{NDVI_{min}}}\right)^2 \tag{3}$$

3.3. Retrieval of LST

Land Surface Temperature (LST) was derived from the Top of Atmosphere Brightness Temperature (T) as formula (4) where K_1 and K_2 are Thermal conversion constants for band 6 for Landsat 5 TM and band 10 for Landsat 8 OLI (10.8 μm), and L_λ is spectral radiance.

$$BT = K_2/\ln\left(\frac{K_1}{L_\lambda} + 1\right) \tag{4}$$

There are algorithms applied to transfer BT for LST, such as "*single channel model*" (Sobrino, Jiménez-Muñoz, and Paolini 2004), "split window" (Yu, Guo, and Zhaocong 2014) or "*mono window*" (Wang et al. 2015). In this case study, the "single channel model" was investigated in conducting LST (unit: Celsius degree).

$$\mathrm{LST} = \mathrm{BT}/[1 + (\lambda \times E/\rho) \times \ln(\mathrm{LSE})] - 273.15, \tag{5}$$

Whereas, BT is Brightness Temperature (4) (Kevin) λ is the band wavelength (μm); ρ = 14380; LSE is Land Surface Emissivity (2). Here, ρ = h*c/ς, with h is Plank's constant ($6.626*10^{-34}$Js), c is light velocity ($3*10^8$ m/s) and ς is the Boltzmann constant ($1.38*10^{-23}$ J/K).

3.4. VHI estimation

The VHI was established by the contribution of two indices derived from NDVI and LST for all observed years (27 years from 1989 to 2016 in this case). Two indices are related to moisture conditions – Vegetation Condition Index, and thermal conditions – Temperature Condition Index (Kogan 1995). The equations are below:

$$\mathrm{VCI} = 100\times \frac{\mathrm{NDVI} - \mathrm{NDVI_{min}}}{\mathrm{NDVI_{max}} - \mathrm{NDVI_{min}}} \tag{6}$$

Table 2. Categorizing drought severity upon VHI values (Kogan 1995; Le Hung and Hoai 2015).

No	VHI value	Drought severity
1	0–10	Extreme drought
2	10–20	Severe drought
3	20–30	Moderate drought
4	30–40	Mid drought
5	>40	No drought

$$\mathrm{TCI} = 100 \times \frac{\mathrm{LST_{max}} - \mathrm{LST}}{\mathrm{LST_{max}} - \mathrm{LST_{min}}} \tag{7}$$

$$\mathrm{VHI} = a \times \mathrm{VCI} + (1 - a)\mathrm{TCI} \tag{8}$$

While, NDVI: value of NDVI at time of observation
$\mathrm{NDVI_{min}}$ = 27-year absolute maximum NDVI
$\mathrm{NDVI_{max}}$ = 27-year absolute minimum NDVI
LST: value of LST at time of observation
$\mathrm{LST_{max}}$ = 27-year absolute maximum LST
$\mathrm{LST_{min}}$ = 27-year absolute minimum LST
"a" is the coefficient of different weighting between VCI and TCI. The value of "a" depends on differencing conditions of moisture and temperature. In case of unknown moisture conditions, "a" is set to 0.5, which signifies that VCI and TCI are equally weighted for VHI estimation.

Values of VHI rank from 0 to 100 indicating extreme stress of vegetation condition to healthy vegetation. When drought happens, its severity can be categorized from extreme to no drought according to VHI values (see Table 2).

3.5. MODIS data processing

Methods to process MODIS imagery are similar to the Landsat procedures for generating the three main indexes: VCI, TCI, and VHI. Maximum and minimum values of NDVI, and LST were statistical values from the monthly values retrieved from monthly composite products starting from February 2000. One of the difficulties processing composite images of surface temperature from MODIS is the presence of gaps from prevailing cloud cover. Figure 4 shows gaps between pixels on the 22 March image (on the right), and 1 November 2015 image (on the left). When the gap is too large, that image will be removed from the procedure, but retained when the gap is small enough (missing fewer pixels, such as 5 to10 pixels, for example), in such instances, we applied nearest neighbor interpolation to generate values of the missing pixels.

4. Results and discussion

4.1. Correlation between NDVI and LST

A linear regression model was constructed to survey the relationship between LST and NDVI across dry and wet seasons. Results demonstrate that the various distributions of LST–NDVI correlations depend on seasonal conditions. Figure 5 shows that in wet season (September), there were more variables compared to dry season (January and March), and

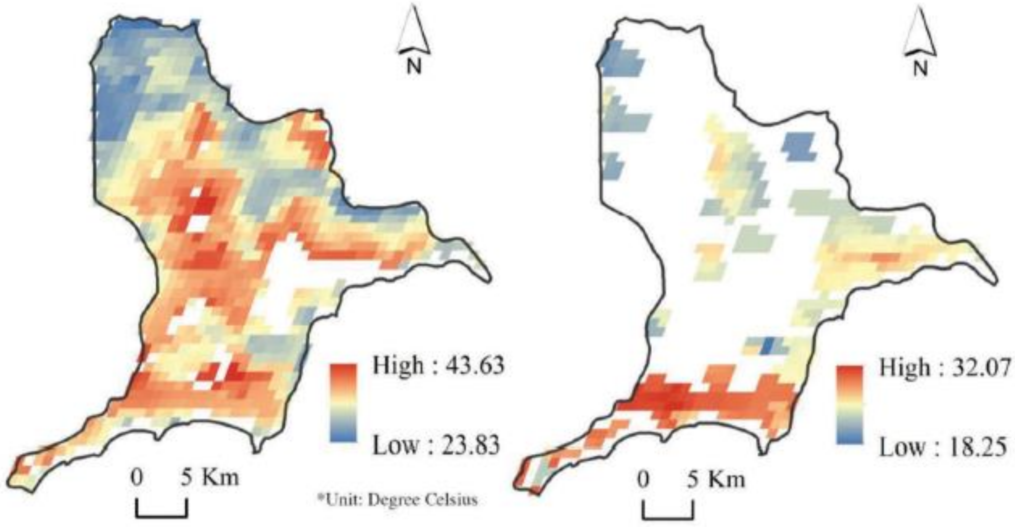


Figure 4. MODIS surface temperature captured on 03/22/2015, and 11/01/2015. The white color inside the border shows gaps due to missing pixels of composite products. Figure 4 should be shown in section 3.5. MODIS data processing

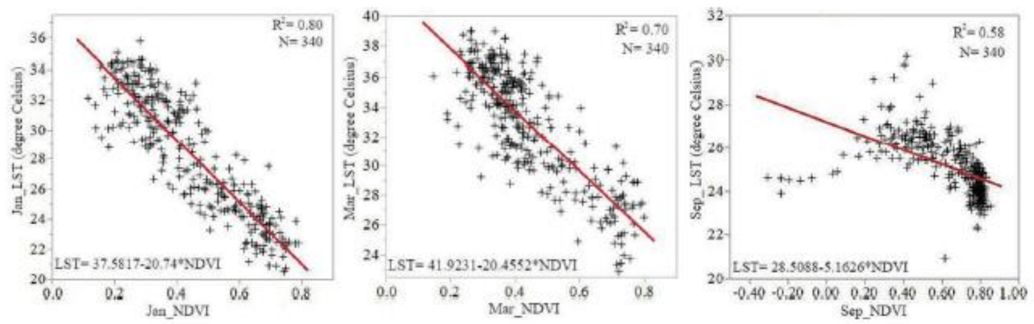


Figure 5. LST–NDVI correlations during dry to wet season, 2015 (from left to right: January, March and September). Note: there is a significant increase of the slope from −20.74 (Jan) to −5.16 (Sep). There are outliers in the March graph, caused by clouds (NDVI values can be affected by some conditions such as clouds, snow, or ice).

the slope of the fitted line also increased across the seasonal transition from dry to wet. R^2, on the other side, dropped from near 0.8 to 0.58 (from January to September), which means that in the wet season, due to increases of moisture and air temperature, relationships between LST and NDVI were not significant, so the vegetation responses (NDVI) are only loosely related to thermal conditions (LST). Conversely, during the dry season, temperature can be effective in explaining and in predicting the stress of vegetation health, and it can potentially estimate effects of vegetation drought when temperature is high, and rainfall is low.

Overall, there was a significant negative relationship between LST and NDVI. This result is because likely Tuy Phong is located at 11°N (a lower latitude), where weather is hot and humid. Soil and atmospheric moisture have distinctive impacts on the response of vegetation to changes in temperature (Sun and Kafatos 2007).

Other research investigating the relationships between LST and NDVI also showed that, at higher latitudes, the slope will gradually change from negative to positive (Karnieli

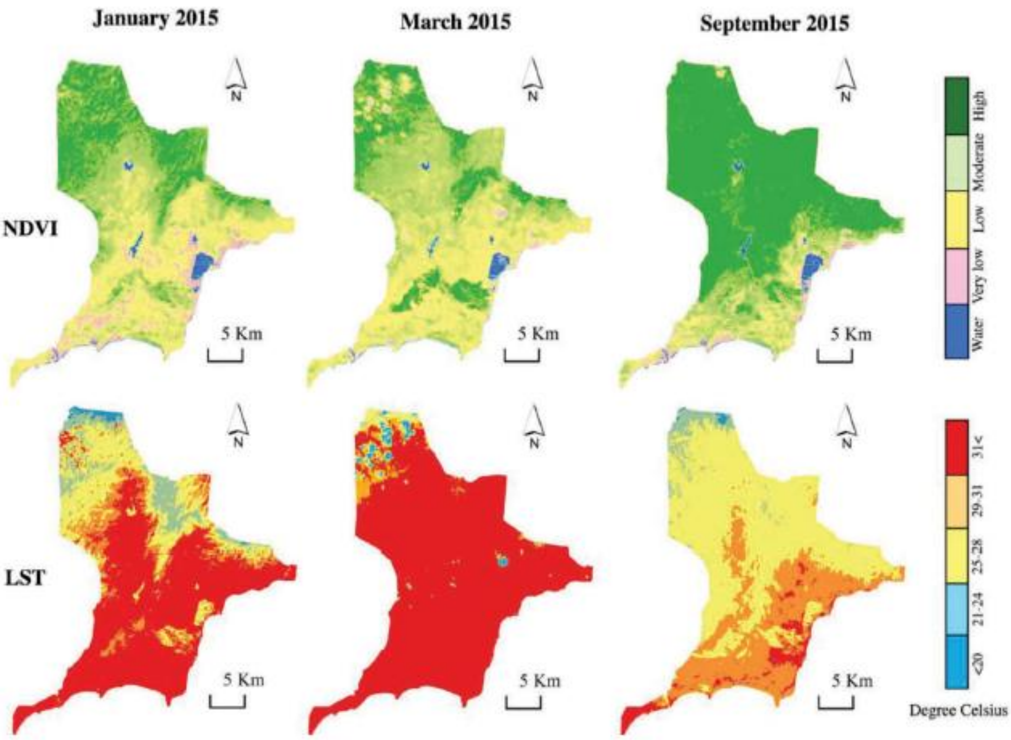


Figure 6. Simply classified NDVI (top) and LST (bottom) in January, March and September in 2015 (from left to right). Throughout a year, coastal areas, where there are low NDVI vales, and high temperatures, are potentially impacted by drought.

et al. 2010). The spatial relationships between LST and NDVI are represented in Figure 6. During the dry season, density of vegetation declined, and temperatures were very high, and during the middle dry season, the vast majority of the area had surface temperatures higher than 31°C (red color). During wet season, vegetation was denser, the surface temperature was down, but varied. There was also a higher temperature even in highly dense vegetated areas.

4.2. Spatial distribution of drought severity

Based on statistical data of 27 years of NDVI and LST in both dry and wet seasons, the maximum and minimum values of both LST and NDVI were selected (see Table 3) for the three recent dry seasons from 2013 to 2016, and for calculation of VCI, and TCI. Monthly

Table 3. Selected values of NDVI and LST used to calculate VCI and TCI.

Type of values	2013–2014	2014–2015	2015–2016
NDVI	Mean value	Mean value	Mean value
$NDVI_{min}$	−0.61	−0.92	−0.92
$NDVI_{max}$	0.84	0.84	0.86
LST (Celsius degree)	Mean value	Mean value	Mean value
LST_{max}	42.48	42.48	42.48
LST_{min}	4.48	4.48	4.48

Table 4. Selected values of NDVI and LST for MODIS data.

Types of values	2013–2014	2014–2015	2015–2016
NDVI	Mean value	Mean value	Mean value
$NDVI_{min}$	−0.19	−0.19	−0.2
$NDVI_{max}$	0.94	0.98	0.98
LST (Celsius degree)	Mean value	Mean value	Mean value
LST_{min}	46.63	46.79	48.05
LST_{max}	15.87	15.87	15.87

values of NDVI and LST in both dry and rainy seasons of each year give a comprehensive sense of the wide range of values and variations of both NDVI and LST (Figure 8). Monthly records during dry season in 2014 and 2015 showed the highest temperatures, which were over 42°C, while the lowest temperatures were recorded in mountainous area in 1994. The values of NDVI were difficult to obtain because of fluctuations of vegetation responses each month. Generally, high values of NDVI were recorded in wet seasons, while lowest values were in dry seasons. Figure 7 is the graph of monthly mean NDVI and LST values from November 2013 to April 2016, which show increasing trend of temperatures from early to end of season, and the negative response (declination) of vegetation indexes. In order to estimate VHI, the "a" coefficient selected as 0.5, equally contributing to VCI and TCI. Table 3 shows selected statistical values of NDVI and LST for the three recent dry seasons.

Maps shown on Figure 7 represent spatial distributions of VCI, TCI and VHI. Values of VCI and TCI range from 0 to 100, revealing the stress of reduced water availability, and temperature increases upon vegetation during dry season (the smaller the values are, the greater the stress upon vegetation health is). The VHI maps were categorized simply into five levels of drought severity, from no drought to extreme (green to red, respectively). During dry season 2014–2015, approximately two-thirds of Tuy Phong district was under drought condition (from mid-to-severe drought – Figure 9). During the 2015–2016 dry season, the drought-affected areas declined, severe drought areas increased, which means that areas vulnerable to drought increased, and droughts were more intensive. Furthermore, drought impacts were especially serious in communes near the coast (in the East), such as Hoa Phu, Binh Thanh, Phong Phu, Phu Lac, Vinh Hao. Vinh Hao commune was the most severely influenced area. We did not observe any extension of agricultural drought into the beginning of wet seasons because of the regular occurrence of the Xiaoman, marking the start of growing season.

4.3. MODIS–VHI validation

The six maps of drought severity that were generated by the VHI values from MODIS and Landsat data of three dry seasons 2013–2014, 2014–2015, and 2015–2016 (see Figure 10), illustrate the same intensification of drought-influenced areas. And the 2014–2015 dry season is the period when drought occurred, and affected the largest area, especially areas near the coast. In addition, that period was also recorded as severe, and widespread drought in local, and governmental reports. Table 4 shows selected values of NDVI and LST extracted from MODIS data for calculating the VHI.

Nevertheless, for the 2015–2016 dry season, although MODIS imagery depicted a significant declining pattern of drought severity, we observed a slight decrease in affected

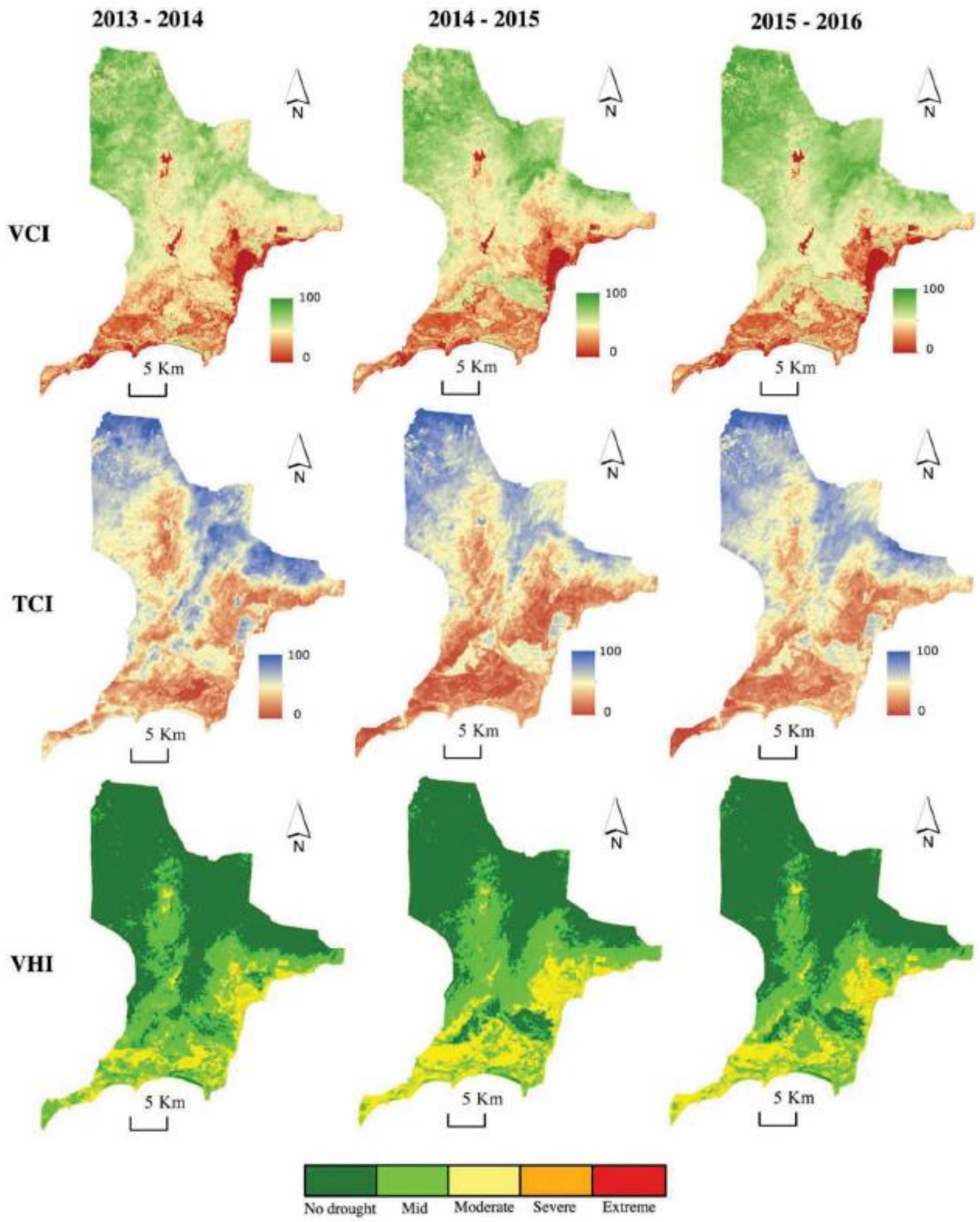


Figure 7. From upper to lower: Vegetation Condition Index, Temperature Condition Index and Vegetation Health Index of three dry seasons (November to April), from left to right: 2013–2014, 2014–2015, and 2015–2016. All show increases of moisture and thermal stress in vegetation near the coast of the study area, where land is used for crop production. The combination of those stresses accelerated drought severity, and consequently increased to risks of agricultural losses. Figure 7 should be shown in the section 4.2. Spatial distribution of drought severity.

area comparing to the 2014–2015 from the Landsat data. That difference arises from some missing MODIS temperature data due to the big gap of pixels, and accuracy can be affected by the nearest neighbor resampling procedure. Otherwise, the MODIS maps only show general patterns of drought effects, which are moderate, and mid drought. However,

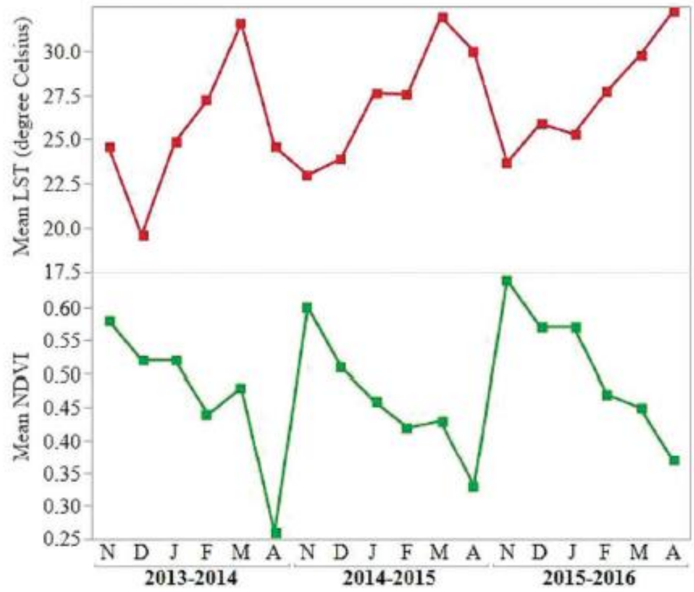


Figure 8. Graphs of mean NDVI (green) and mean LST(red) during three recent dry seasons.

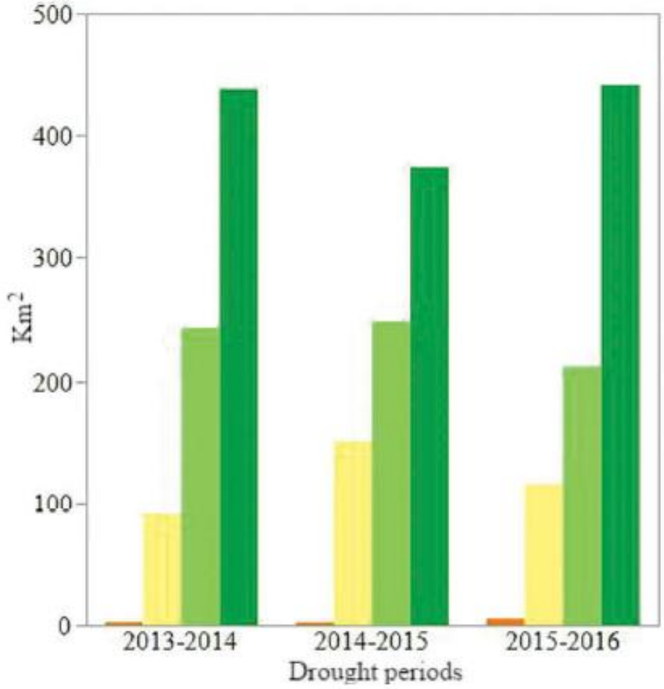


Figure 9. Areas influenced by drought within vulnerable categories.

Landsat data permits not only assessment of areas at severe drought level (orange color in the map), but also assessment of drought patterns (both severity and duration) monitored with identification of specific location. Thus, applying Landsat data is an appropriate method to monitor drought vulnerability in small and remote areas.

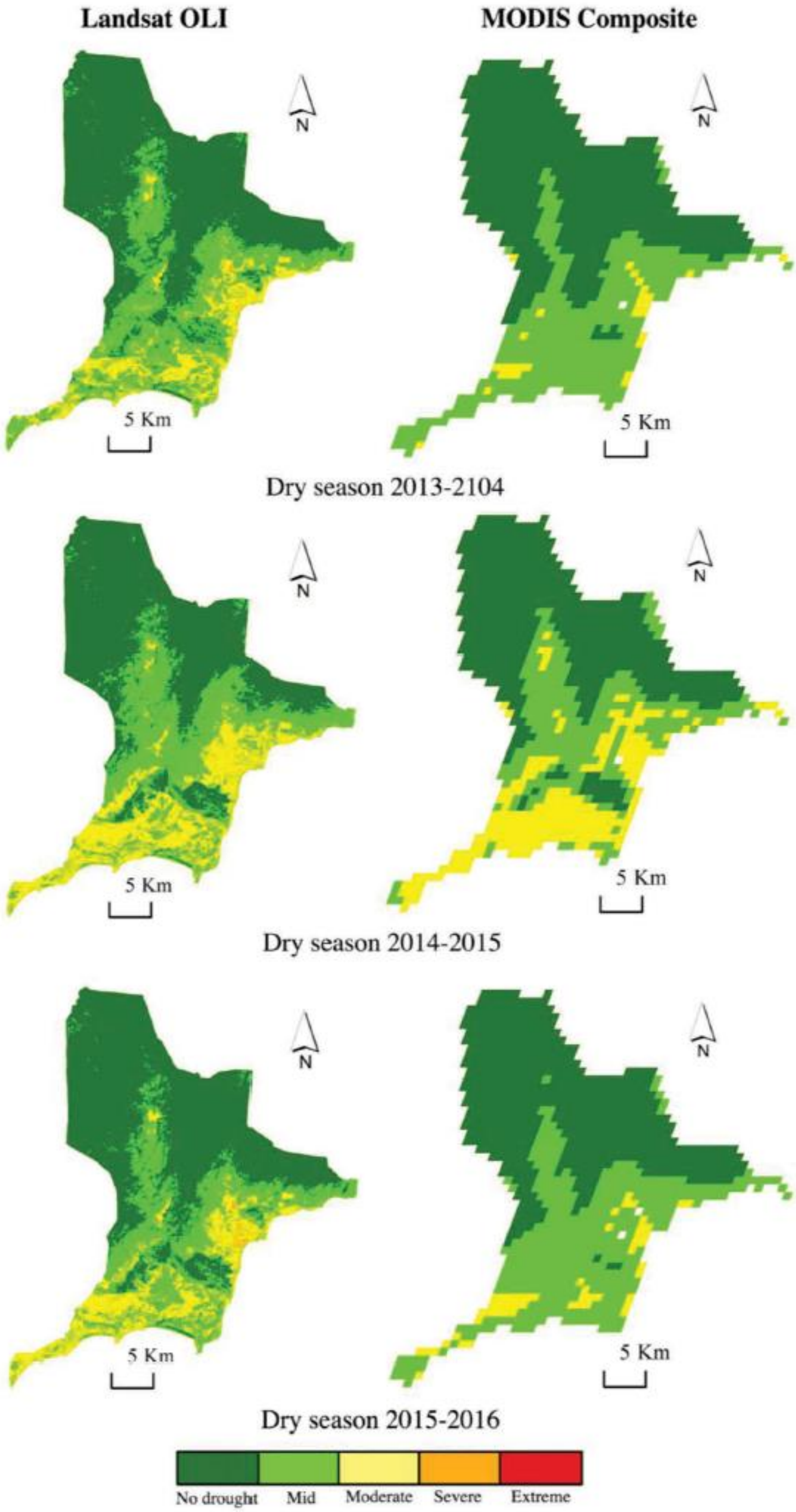


Figure 10. Maps of drought severity upon the VHI values of Landsat OLI, and MODIS data.

5. Conclusion

This study examined drought conditions within a relatively small rural region of the Central Coast of Vietnam. This region, within Binh Thuan Province, has a distinctive climate, characterized by pronounced aridity adjacent to the coastline, but diminishing with increasing distance inland. Because this region lacks the history of climate records that would normally support investigation of recent climatic trends, analysis of sequential multispectral satellite imagery provides an opportunity to both document impacts of recent drought conditions, and to highlight the value of such imagery in remote regions lacking suitable weather and climate records.

Our results confirm that data collected at relatively fine spatial detail, acquired at relatively long temporal intervals, such as LANDSAT data, are useful for recording and monitoring vegetation health. A further analysis to cross-validate these findings with MODIS data, which are acquired more frequently, but at coarser resolution, shows the same patterns that we observed from Landsat data of our study area.

However, it is necessary to take into account additional parameters to indicate drought severity, such as water capacity and rainfall, not used in this study. Finally, studies such as this one need to consider local policies, management, and carrying capacity. These factors play important roles in understanding behavior of local people when drought occurs. Because drought is very closely linked to processes of land degradation, and desertification, land that is heavily impacted by drought, without local management, will be gradually degraded. The recent Belgian-Vietnamese project (for a larger area within our region) (Gobin et al. 2012) used meteorological data to consider global climate change in its development of a climate change model that involved drought as a climatic abnormality. Testing that model using recent weather records can be used to validate our results. We expect to investigate applicability of our remote sensing approach to study drought vulnerability for the entire province.

Acknowledgments

We acknowledge with thanks the Vietnamese Government, and the Vietnam International Education Development for their funding support for Hoa Tran to pursue a PhD program at Virginia Tech. We are very much thankful to Virginia Tech – Graduate School and the Interdisciplinary Graduate Education Program (IGEP) for their contributions to our research. We express our thanks to Dr. Randolph H. Wynne (Department of Forest Resources and Environmental Conservation, Virginia Tech), Dr. Steve C. Hodges (Department of Crop and Soil Environmental Sciences, Virginia Tech), Dr. Yang Shao (Department of Geography, Virginia Tech), and Dr. Winston Chow (Department of Geography, National University of Singapore) for their suggestions, and encouragement to the evolution of our research ideas. We are grateful to the Guest Editor of the GIScience Remote Sensing, and reviewers for their thorough recommendation, and suggestions for revising our paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Hoa Thi Tran http://orcid.org/0000-0002-1742-0226

Tri Dinh Tran http://orcid.org/0000-0002-1742-0226

Ha Thanh Tran http://orcid.org/0000-0002-1742-0226

References

Bai, Z., and D. Dent. 2009. “Recent Land Degradation and Improvement in China.” *Ambio* 38 (3): 150–156. doi:10.1579/0044-7447-38.3.150.

Cai, G., D. Mingyi, and Y. Liu. 2011. *Regional Drought Monitoring And Analyzing Using Modis Data — A Case Study In* Yunnan Province. *Regional Drought Monitoring And Analyzing Using Modis Data — A Case Study In*: Li D., Liu Y., Chen Y. (eds) *Regional Drought Monitoring And Analyzing Using Modis Data — A Case Study In* Agriculture IV. *Regional Drought Monitoring And Analyzing Using Modis Data — A Case Study In* 2010. IFIP Advances in Information and Communication Technology, vol 345. Springer, Berlin, Heidelberg. doi:10.1007/978-3-642-18336-2_29

Chen, C., R. C. Zhigang Lai, Q. X. Beardsley, H. Lin, and N. T. Viet. 2012. “Current Separation and Upwelling over the Southeast Shelf of Vietnam in the South China Sea.” *Journal of Geophysical Research* 117. doi:10.1029/2011JC007150.

Doi, R. D. 2002. *Remote Sensing and Its Application: A Monograph Monitoring Vegetal Landcover and Desertification*. Jaipur: University Book House.

Gobin, A., L. T. Hai, P. H. Linh, L. Hens, P. Ozer, L. T. T. Hien, N. T. Binh, and P. Q. Vinh. 2012. *Impact of Global Climate Change and Desertification on the Enivronment and Society in the Southern Centre of Vietnam (Case Study in Binh Thuan Province)*. Belgium, Vietnam.

Hirche, A., M. Salamani, A. Abdellaoui, S. Benhouhou, and J. M. Valderrama. 2011. “Landscape Changes of Desertification in Arid Areas: The Case of South-West Algeria.” *Environ Monit Assess* 179 (1–4): 403–420. doi:10.1007/s10661-010-1744-5.

Jianyu, H., H. Kawamura, H. Hong, and Q. Yiquan. 2000. “A Review on the Currents in the South China Sea: Seasonal Circulation, South China Sea Warm Current and Kuroshia Intrusion.” *Journal of Oceangraphy* 56: 607–624. doi:10.1023/A:1011117531252.

Jiao, W., L. Zhang, Q. Chang, F. Dongjie, Y. Cen, and Q. Tong. 2016. “Evaluating an Enhanced Vegetation Condition Index (VCI) Based on VIUPD for Drought Monitoring in the Continental United States.” *Remote Sensing* 8 (3): 224. doi:10.3390/rs8030224.

Jiménez-Muñoz, J. C., J. A. Sobrino, D. Skokovic, C. Mattar, and J. Cristóbal. 2014. “Land Surface Temperature Retrieval Methods From Landsat-8 Thermal Infrared Sensor Data.” *Ieee Geoscience and Remote Sensing Letters* 11 (10).

Karnieli, A., R. T. Nurit Agam, M. A. Pinker, M. L. Imhoff, G. G. Gutman, N. Panov, and A. Goldberg. 2010. “Use of NDVI and Land Surface Temperature for Drought Assessment: Merits and Limitations.” *Journal of Climate* 23 (3): 618–633. doi:10.1175/2009jcli2900.1.

Kogan, F. 1994. “Drought Monitoring from NOAA Polar-Orbiting Satellites - Principles, Development, and Verification.” *Soviet Journal of Remote Sensing* 11 (8): 575–593.

Kogan, F. N. 1990. “Remote-Sensing of Weather Impacts on Vegetation in Nonhomogeneous Areas.” *International Journal of Remote Sensing* 11 (8): 1405–1419. doi:10.1080/01431169008955102.

Kogan, F. N. 1995. “Application of Vegetation Index and Brightness Temperature for Drought Detection.” *Natural Hazards: Monitoring and Assessment Using Remote Sensing Technique* 15 (11): 91–100.

Le, H. T., and K. H. Dao. 2015. “Drought Risk Evaluation Using Remote Sensing: A Case Study in Bac Binh District, Binh Thuan Province.” *Scientific Journal of Educational University of Ho Chi Minh City* 5: 70.

Le Hung, T., and D. K. Hoai. 2015. “Drought Risk Evaluation Using Remote Sensing: A Case Study in Bac Binh District, Binh Thuan Province.” *Scientific Journal of Ho Chi Minh Educational University* 5.

Orhan, O., S. Ekercin, and F. Dadaser-Celik. 2014. “Use of Landsat Land Surface Temperature and Vegetation Indices for Monitoring Drought in the Salt Lake Basin Area, Turkey.” *Scientific World Journal* 2014: 1–11. doi:10.1155/2014/142939.

Pandey, P. C., M. Rani, P. K. Srivastava, L. K. Sharma, and M. S. Nathawat. 2013. ““Land Degradation Severity Assessment with Sand Encroachment in an Ecologically Fragile Arid Environment.” *A Geospatial Perspective.” Qscience Connect* 2013: 43. doi:10.5339/connect.2013.43.

Peters, A. J., A. Elizabeth, L. J. Walther-Shea, A. Vina, M. Hayes, and M. D. Svoboda. 2002. “Drounght Monitoring with NDVI-Based Standardized Vegetation Index.” *Photogrammetric Engineering & Remote Sensing* 68 (1): 71–75.

Pham, Q. V., N. T. Binh, and B. T. T. Huong. 2012. “Drought Zoning for Binh Thuan Province in Vietnam Based on Eto Calculator and GIS.” *Geoinformatics for Spatial-Infrastructure Development in Earth and Allied Sciences.*

Sobrino, J. A., J. C. Jiménez-Muñoz, and L. Paolini. 2004. “Land Surface Temperature Retrieval from LANDSAT TM 5.” *Remote Sensing of Environment* 90 (4): 434–440. doi:10.1016/j.rse.2004.02.003.

Sun, D., and M. Kafatos. 2007. “Note on the NDVI-LST Relationship and the Use of Temperature-Related Drought Indices over North America.” *Geophysical Research Letters* 34: 24. doi:10.1029/2007gl031485.

Tran, Hoa, J. B. C., T. T. Dinh, and H. T. Thanh. 2015. “Detecting Sand Movement: A NDVI Time Series Analysis (Binh Thuan Case Study).” In *Vietname - Poland International Conference*. Hanoi.

Tucker, C. J. 1979. “Red and Photographic Infrared Linear Combinations for Monitoring Vegetation.” *Remote Sensing of Environment* 8 (2): 127–150. doi:10.1016/0034-4257(79)90013-0.

Valiente, J. A., R. Niclos, M. J. Barbera, and M. J. Estrela. 2010. “Analysis of Differences between Air-Land Surface Temperatures to Esitimate Land Surface Air Temperature from MSG Data.” *Spanish Ministerio De Ciencia E Innovación (CONSOLIDER-INGENIO 2010 CSD2007-00067).*

Wang, F., Z. Qin, C. Song, T. Lili, A. Karnieli, and S. Zhao. 2015. “An Improved Mono-Window Algorithm for Land Surface Temperature Retrieval from Landsat 8 Thermal Infrared Sensor Data.” *Remote Sensing* 7 (4): 4268–4289. doi:10.3390/rs70404268.

Yu, X., X. Guo, and W. Zhaocong. 2014. “Land Surface Temperature Retrieval from Landsat 8 Tirs—Comparison between Radiative Transfer Equation-Based Method, Split Window Algorithm and Single Channel Method.” *Remote Sensing* 6 (10): 9829–9852. doi:10.3390/rs6109829.

Appendix 3

Tran, Hoa T.; Campbell, James B.; Wynne, Randolph H.; Shao, Yang; Phan, Son V. 2019. "Drought and Human Impacts on Land Use and Land Cover Change in a Vietnamese Coastal Area." *Remote Sens.* 11, no. 3: 333.DOI: 10.3390/RS11030333

remote sensing

Article

Drought and Human Impacts on Land Use and Land Cover Change in a Vietnamese Coastal Area

Hoa Thi Tran [1,2,†,‡,*], **James B. Campbell** [1,‡], **Randolph H. Wynne** [1,‡], **Yang Shao** [1,‡] and **Son Viet Phan** [2,‡]

1 Virginia Polytechnic Institute and State University (Virginia Tech), Blacksburg, VA 24061, USA; jayhawk@vt.edu (J.B.C.); wynne@vt.edu (R.H.W.); yshao@vt.edu (Y.S.)
2 Hanoi University of Mining and Geology, Hanoi, Vietnam; phanvietson_humg@yahoo.com.vn
* Correspondence: hoatran@vt.edu or tranthihoa@humg.edu.vn; Tel.: +1-540-449-8146
† Current address: Geography Department, Virginia Tech, Blacksburg, VA 24061, USA.
‡ These authors contributed equally to this work.

Received: 11 December 2018; Accepted: 5 February 2019; Published: 8 February 2019

Abstract: Drought is a dry-weather event characterized by a deficit of water resources in a period of year due to less rainfall than normal or overexploitation. This insidious hazard tends to occur frequently and more intensively in sub-humid regions resulting in changes in the landscape, transitions in agricultural practices and other environmental-social issues. The study area is in the sub-humid region of the northern coastal zone of Binh Thuan province, Vietnam—Tuy Phong district. This area is indicated as a subject of prolonged droughts during 6-month dry seasons, which have occurred more frequently in recent years. Associated with economic transitions in agricultural practicing, urbanization, and industrialization, prolonged droughts have resulted in rapid changes in land use and land cover (LULC) in Tuy Phong, especially in three coastal communes: Binh Thanh, Lien Huong, and Phuoc The. A bi-temporal analysis using high-resolution data, the 2011 WorldView2 and the 2016 GeoEye1, was examined to assess LULC changes from observed severe droughts in those three communes. Results showed a dramatic reduction in the extent of hydrological systems (about 20%), and significant increases of tree canopies in urban areas and near the coastal areas (approximately 76.8%). Paddy fields declined by 51% in 2016; such areas transitioned to inactive status or were alternated for growing drought-tolerant plants. Shrimp farming experienced a recognizable decrease by approximately 44%. The 2014 map and field observations during summer 2016 provide references for object-based classification and validation. Overall agreement of results is about 85%.

Keywords: Vietnam; Binh Thuan; sub-humid region; drought-human impacts; LULC; high-resolution images; object-based classification

1. Introduction

Drought is defined as an extended period of precipitation deficiency, which leads to severely arid conditions during dry seasons [1]. Drought has considerable impacts on ecosystems, environment, and society. For example, drought may cause changes in landscapes as a formation of dry area, and grassland, and a promotion of aeolian processes. Otherwise, drought also leads to a reduction of water quality and quantity [2,3], soil moisture, and soil productivity. Reduction of soil moisture cannot guarantee soil microbial activities, which play an essential role in organic matter decomposition and synthesis to create soil fertility. Therefore, soil is very sensitive, and easily desiccated. Fresh water is very important not only for domestic uses, farming, and grazing, but also for preserving natural habitats. Sudden decreases of water in hydrological systems due to severely arid conditions can affect both biotic and abiotic components of the ecosystem [4]. Plants and vegetation are vital components that create biomass for the ecosystem, but under drought conditions, loss of soil moisture, and infertile soils, survival is not secured. There will be a risk of bare land and aeolian landscapes, which, coupled with unsustainable land management, promote desertification, complicating land productivity recovery. Drought also has substantial impacts upon societal and economic priorities, including increased budgeting for fresh water, reduction of crop yields, losses from businesses, families, and government [2]. Migration from dry areas is often forced by drought, which can drive land use transitions and changes in LULC [5]. However, water overuse, overpopulation, and mitigation have certain impacts of deficits of both surface and ground water resources resulting in more severe hydrological drought [3,6].

Dry areas in the tropics are characterized by prolonged dry seasons under conditions of low humidity, high air temperatures, and drying up of seasonal rivers and streams. Instead of precipitation deficits, known as a cause of meteorological and agricultural drought, there is here a linkage between drought and human activities [7]. Humans, via their activities, have created negative influences on water cycles, such as deforestation, urbanization, and intensified/extensified farming [8]. Such activities increase transpiration, evaporation, and reduce water-holding capacities of soil. Otherwise, dam construction to regulate hydrologic systems, to mitigate floods, to produce hydro-electric power, and to irrigate farmlands is, on one hand, necessary with respect to sustainable land management; on the other hand, it has unfortunate impacts on downstream surface water flow, and creates higher demands upon water supply [3]. Generally, a long drought duration, and its interactions with human activities, has directly or indirectly responded to changing landscape and changes of LULC. Understanding impacts of drought-human interaction is very important to govern water restrictions and preserve soil quality in the condition of drier-than-normal conditions. Furthermore, clarifying drought impacts on LULC changes can help to support sustainable land management in dry lands.

In this study, we examine changes in LULC upon drought events and human activities in three coastal communes of Tuy Phong district, Binh Thuan, Vietnam. The study area is shown in Figures 1 and 2 covering three communities: Phuoc The (in the north) , Lien Huong (in the middle), and Binh Thanh (in the south). We were seeking answers of our three research questions regarding LULC changes during drought periods: (1) How has LULC changed during drought events of our study's five-year inquiry, 2011–2016? (2) How did drought events affect specific land uses, such as agriculture, or shrimp farming? (3) How did local inhabitants manage land use during those drought events? Thus, to reveal both impacts of drought and humans on LULC in general, and some specific types of land use in particular, we proposed applying high-resolution images in LULC change assessment at two levels of detail. The first level is land cover, which observes any change in seven main types: built-up land, open water, agriculture, salterns and shrimp farming, vegetation, bare land, and sand. The second level is more detailed, consisting of 13 classes, and focuses on specific land use types that reveal human impacts by adding five more classes: (a) active and (b) inactive agriculture (paddy fields, orchards and inactive fields); (c) active and (d) inactive shrimp farming; and (e) vegetation on sand. Descriptions of imagery data and land types are represented in Tables 1 and 2 in Section 3.2; imagery datasets are shown in Figure 2, and training samples for each land type are in Appendix A.

2. Study Area

2.1. Study Area Background

Tuy Phong is a Northeastern district of Binh Thuan province, south-central coast of Vietnam. Although Tuy Phong is positioned in the tropical wet–dry climate following the Köppen-Geiger classification characterized [9], annual precipitation is quite low compared to other parts of Binh Thuan. Northern districts, such as Tuy Phong and Bac Binh, are much drier than other regions; Southern districts such as Ham Tan and Ham Thuan Nam are wetter [10]. Figure 3 shows annual rainfall in our study area in comparison to other part of Vietnam which is considered to be one of two driest regions in the whole country. Annual precipitation of the Northern area is less than 800 mm per year; in some years, it can be less than 250 mm; the driest period is from January to March (monthly rainfall less than 4 mm—see Figure 3, top right chart, data were collected at Lien Huong weather station). There is a distinction of rainfall distribution between wet and dry seasons in Tuy Phong: rainfall mostly occurs during wet season (from May to October), while there is less than 50 mm or no rain during the 6 months of dry season (from November to April). Thus, preserving water storage and practicing irrigation in this district during dry season needs to be taken seriously. However, in the Southern part, annual precipitation is on average 1700 mm per year, and can exceed 2500 mm per year, which is one beneficial condition for high water demand crops such as rice.

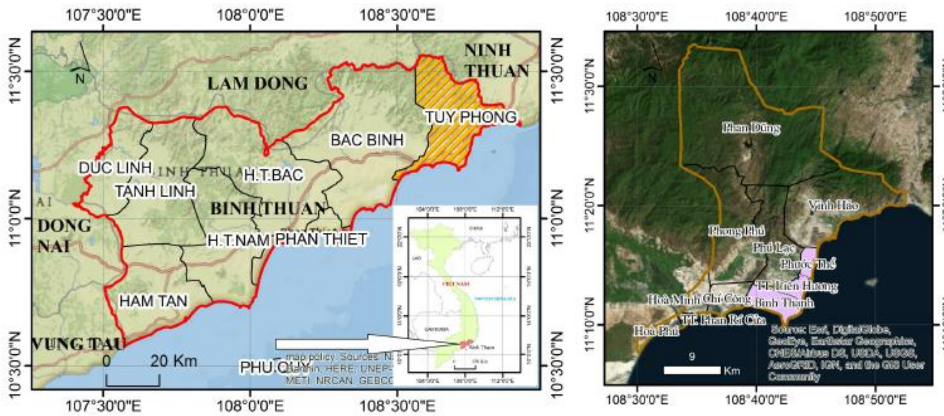


Figure 1. The case study is covering three coastal communities Binh Thanh, Lien Huong, and Phuoc The of Tuy Phong District which are highlighted in pink on the right map.

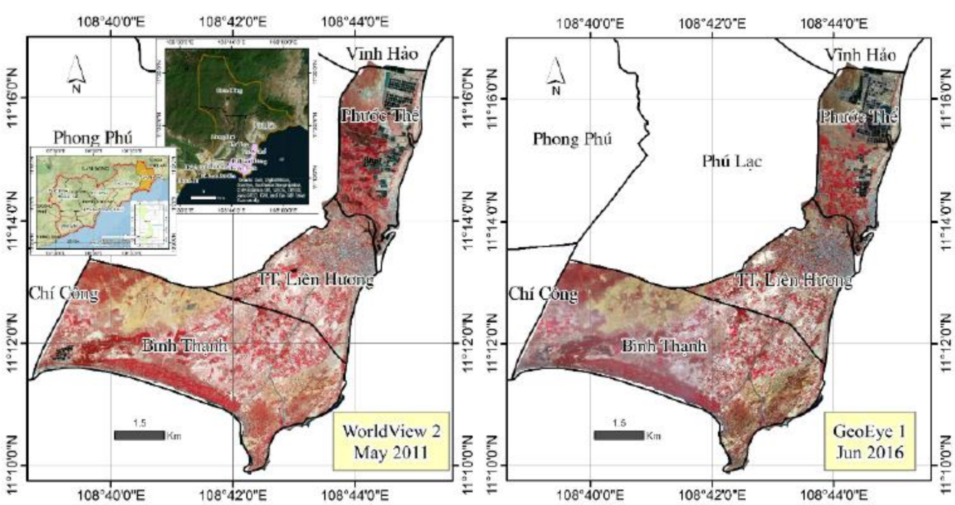


Figure 2. False color band combination for two-image datasets used for the research area: the 2011 WorldView2 (NIR2, R, G as R,G,B), and the 2016 GeoEye1 (NIR, R, G as R,G,B). See Table 1 for the sensor-specific band number designations along with bandwidths

Population of this district has been increasing rapidly, doubling in the 13 years from 90,000 in 2002 to 188,000 in 2015. High population creates pressure for local food production, demand for fresh water, health care, and education, but on the other hand, it can provide an abundant labor force for the local labor market. However, most of the local labor force in Tuy Phong is involved in farming and in salt production, which produce less economic value [11], and brings lower family income. Furthermore, farming and salt production are water and climatic dependent. As a result, droughts and water shortages may directly threaten local people.

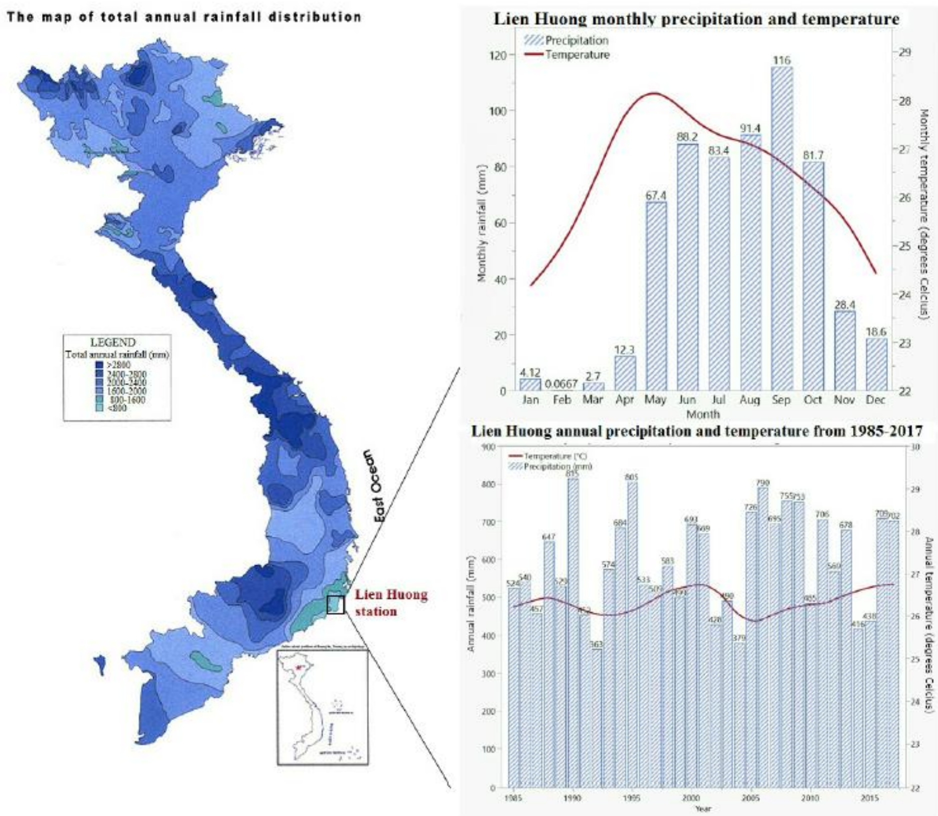


Figure 3. Map of total annual rainfall distribution of Vietnam (source: *The center of database establishment for Environmental resources in Vietnam, Geography institute (1999)* [12]; and charts of monthly and annual precipitation and temperature report at Lien Huong station during 1985–2017 (meteoblue.com [13]).

Water shortage is one of major issues in Tuy Phong, due to the occurrence of prolonged meteorological drought regarding rainfall deficits during dry seasons, and overuse of local residents [14,15]. The lower right chart in Figure 3 illustrates fluctuations of annual precipitation and annual temperature acquired at Lien Huong station during 1985–2017; this station is in Lien Huong commune, one of three coastal communes involved in this study. Average precipitation of this 32-year observation is 612 mm per year. During 1990–2005, most of yearly rainfall is less than this value, most significantly in 1992 (363 mm), 2002 (428 mm), and 2004 (379 mm), respectively. Otherwise, in recent years, such as 2010, 2012, 2014, and 2015, annual precipitation also denoted lower values than the average one. These meteorological data were collected at meteoblue.com. Upon local reports, during the 2014–2015 dry season, there was a significant decline of water in the main reservoirs; in 2015, Da Bac Lake lost 90% of its fresh water [16]. Our recent study of agricultural drought severity in Tuy Phong district under a scenario of rainfall shortage indicated that those coastal communes are sensitive subjects to drought at moderate to mild levels [17], which are shown in light green to yellow in Figure 4. The analysis of that study was based on an idea of using the Vegetation Health Index (VHI) extracted from satellite images [18], which are Landsat time series data to access spatial and temporal agricultural drought patterns in Tuy Phong.

Another consequence of frequent drought events is LULC changes. Due to water shortages, irrigated and rain-fed lands for paddy fields or rice production in Tuy Phong have transitioned to inactive status. Additionally, high temperatures associated with drought may disturb shrimp farming. Figure 2 shows a significant reduction of agricultural lands in Phuoc The commune; a majority of agricultural lands occurred in a reddish color on the WorldView2 image was replaced by dry lands (brownish color on the GeoEye1). Furthermore, there was an expansion of dry salterns and dry shrimp fields in this northern commune's coastline on the 2016 GeoEye1 image shown in tan color. Drought also promotes advances of mobile sands, and creation of land degradation processes, through removal of top soil, and decreasing soil fertility. Advances of sand dunes also influences local people's normal life as it buries roads, buildings, and vegetation; the right image in Figure 5 shows that one part of Lien Huong communal roads was dominated by red and yellow sand. On images (Figure 2), mobile sand shown in white color dominants areas between Binh Thanh and Lien Huong communes, and coastal areas.

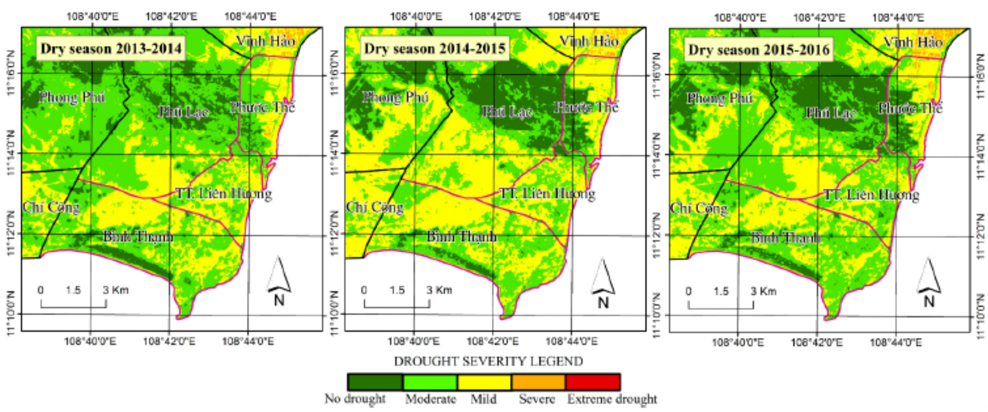


Figure 4. Agricultural drought severity during dry seasons from 2013 to 2016 in the study area (red color border) in Tuy Phong district, Binh Thuan. The study area was indicated under moderate to mild impact of drought. The analysis was based on assessing spatial and temporal Vegetation Health Index distribution via Landsat images over 27 years [17].

In addition to drought impacts, local residents in Tuy Phong have significant influences on LULC changes via land-economic transition, and drought-adaptive mitigated practices. Many policies have been designed to protect land, and prevent salinization, such as constructing man-made dams and lakes for water storage and irrigation improvement, or cultivating unused land, or separating agriculture from salt-shrimp production areas. Da Bac Lake was built in 1990 just about 2 km away from salt production; it has played an important role in storing and governing fresh water for irrigation in Vinh Hao commune. The Long Song Dam, one of the biggest man-made dams in Viet Nam, was constructed in 2000 in Phong Phu commune [19] to irrigate more than 4000 ha of cultivated land, to supply fresh water for households, and mitigate food in lower areas. Other cultivated land near the coast is mainly rain-fed. Urbanization and industrialization mainly occur in Tuy Phong's coastal area. New power plant construction includes: the Vinh Tan thermal power plants in 2010 in Vinh Hao commune, and Binh Thanh's wind power plants to use an abundant ocean wind resources in 2008. Tourism, factories, and marine fishing have encouraged local residents to migrate to the coast.

2.2. Agricultural Practicing During Drought Period

Agricultural areas of Tuy Phong are mainly located near water resources and the coastline as flat terrain. However, due to dramatic weather (long dry seasons, lack of rainfall, high temperatures, and high wind speeds), infertile soil, insufficient irrigation, and aeolian erosion, local agriculture has faced many difficulties. Many of the surface soils of coastal areas of Tuy Phong and Binh Thuan province contain minerals and heavy metals, such as iron, which are visible as yellow and red surface soils. Ocean winds also displace topsoil and transport sand from coastlines and dunes to inland sites. As a result, such soils are now largely infertile, unable to support agriculture. Furthermore, such soils are very sensitive to land degradation and desertification. For example, the left image in Figure 5, acquired in summer 2016, shows a cassava field—one type of drought-tolerant plant in Binh Than commune grown on orange soil representing the high amount of iron contamination. Near the coast, there are wind farms which have been established since 2011. Wind power fields were used to practice agriculture in the past; currently they are bare and unused. On the research images, those soil types are located mainly in the Northwest and Southeast of Binh Thanh shown in a yellowish color (Figure 2).

Figure 5. Cassava field in Binh Thanh commune (**left**); and sand-covered road near the coast in Lien Huong commune (**right**).

Dramatic reductions of supplies during prolonged droughts, infertile soils, and land degradation have changed status of both irrigated and rain-fed fields from active to inactive, both temporarily and permanently. Local residents here have applied crop rotation, planted cover crops, and installed new irrigation systems to mitigate increasing aridity. There are replacements of paddy fields by orchards, salterns, and shrimp fields. Dragon fruit (pitaya), grape, and cassava replace the rice base on their drought-tolerant characteristics, and their higher economic value. However, many fields have maintained their inactive status for many years, especially rain-fed fields in Binh Thuan and Lien Huong commune. Transitioning agricultural land to salterns or shrimp fields on one hand may bring higher income to farmers, but on the other hand, it can affect soil fertility (salinity intrusion), promote soil erosion, and indirectly enhance sand-dominant and land degradation processes in neighborhood areas. Furthermore, under long-term aridity, without sustainable practices or cultivation, inactive fields near the coast are directly subject to land degradation and desertification.

3. Materials and Methodologies

3.1. Datasets

To carry out this research, we acquired WorldView2 and GeoEye1 satellite images—both providing high-resolution multi-spectral imagery of our region which are shown in Figure 2. The WorldView2 image was captured on 22 May 2011 providing eight spectral bands, and one panchromatic band, at 1.84 m and 0.46 m spatial resolutions, respectively. The GeoEye1 image, on the other hand, was recorded on 16 June 2016 with four spectral channels and one panchromatic band at 1.65 m and 0.41 m spatial resolution. Table 1 shows the numbers and range of wavelengths of each spectral channel of two images using in this study. Prior to classification, images were calibrated and enhanced. Digital Globe Courtesy kindly contributed their image datasets for this research.

Table 1. WorldView2 and GeoEye1 bands.

No	Band	WorldView2	Geoeye1
1	Coastal	400–450 nm	NA
2	Blue	450–510 nm	450–510 nm
3	Green	510–580 nm	510–580 nm
4	Yellow	585–625 nm	NA
5	Red	630–690 nm	655–690 nm
6	Red Edge	705–745 nm	NA
7	NIR1	770–895 nm	780–920 nm
8	NIR2	860–1040 nm	NA

3.2. Image Analysis Procedures

The procedure of image processing and analysis is represented shortly in the flowchart—Figure 6. Generally, the preprocessing procedure carried out processes of image calibration, radiometric—spectral enhancement, pan-sharpening, and sub-setting, then images were classified to match land use classes, and, finally LULC maps were generated and validated. The 2014 map made by the government, Google Earth images, and several land types' samples of 2016 field research are used for selecting the training samples, and decision making for the manual editing (shown in Figure 6). To validate our results, we used Google Earth images and ground reference points collected during our field study in 2016.

To classify the image data, we applied object-based image classification method, which is commonly applied for high-resolution images [20,21]. This method is based on distinctive characteristics of each object, such as color, shape, size, and relationships to others to define LULC [22–24]. As mentioned in the Introduction, there are two categorized systems used to classify LULC types at two detailed levels, Table 2 describes those two systems and identities of land types. In this research, training datasets were sampled mainly based on each object's characteristics. Besides, we investigated some band indices that supported decision rules of assigning classes. These indices are tremendously supportive for making decisions on feature assignment procedure [25–28].

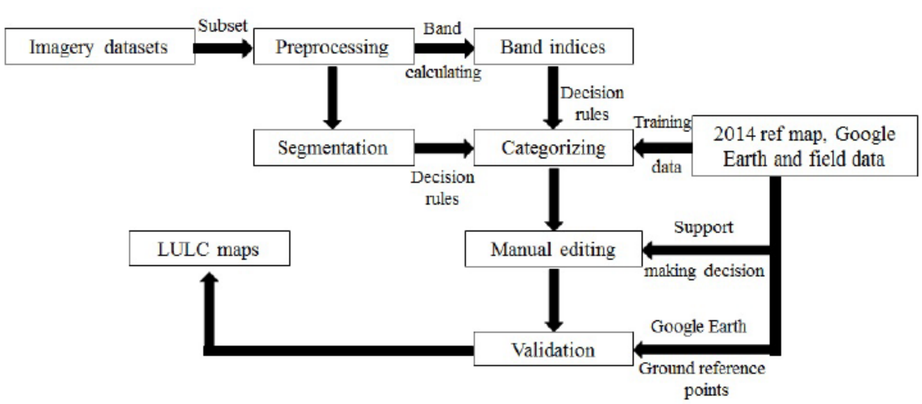


Figure 6. Flowchart of image analysis and maps generalization procedure.

Four band indices—Normalized Difference Vegetation Index (*NDVI*), Normalized Difference Water Index (*NDWI*), Normalized Difference Soil Index (*NDSI*), and *NHFD* (Non-Homogenous Feature Difference)—were involved in the procedure of classifying the WorldView2 dataset using its 8 spectral channels in advance. The *NDVI* was approached to classify the GeoEye1 as its four available spectral bands (shown in Table 1). Formulas * to calculate those indices are presented below. *NIR*1 and *NIR*2 are two Near Infrared channels, their wavelengths are shown in Table 1.

$$NDVI = \frac{Red - NIR2}{Red + NIR2} \quad \text{or} \quad NDVI = \frac{Red - NIR}{Red + NIR} \tag{1}$$

$$NDWI = \frac{Coastal - NIR2}{Coastal + NIR2} \tag{2}$$

$$NDSI = \frac{Green - Yellow}{Green + Yellow} \tag{3}$$

$$NHFD = \frac{RedEdge - Coastal}{RedEdge + Coastal} \tag{4}$$

* *These formulas are suggested for a World View 2 object-based classification by Antonio Wolf, Digital Globe Foundation [29].*

Training samples, suggested band indices and typical characteristics of each class are described in the Appendix A—Table A1.

Table 2. Description of land use and land cover categorized system in this research at two detailed levels.

ID	Level 1 Land Type	ID	Level 2 Land Type	Description
1	Built up	1	Built up	Urban area, transportation, mining and windpower.
2	Salterns and shrimp farming	2	Salterns	Used for sea salt production; near coastline; different shape
		3	Active shrimp farming	Square objects; used for shrimp cultivation, well organized.
		4	Inactive shrimp farming	Square shapes; no practice at time of observation.
		10	Land in shrimp farming	Normally linear object;bright color (tan); used for transportation.
3	Water	5	water	Lakes, ponds, streams, rivers.
4	Agriculture	6	Rice production /paddy fields	In different shape (rectangular); smooth surface; still practicing.
		11	Orchards	Drought-tolerant plants; normally in rectangular; clear rows, and pots; mixing urban (single buildings or roads).
		12	Inactive agriculture	No/sparse vegetation; normally rectangular; clear/sharp borders.
5	Vegetation	7	Vegetation	Near urban area, or fields; dense; rough surface.
6	Bare land	8	Bare land	Bare soil, no/sparse vegetation (small and low bush).
7	Sand	9	Sand	No vegetation;yellow, or white; near the coastline.
		13	Vegetation on sand	Small and low bush; near. coastline; dense or sparse.

3.3. Recommendations on Object-Based Classification Procedure

While executing the image classification procedure applying the object-oriented method, there were several emerging issues resulting in a lot of time consumption. For example, reselecting train samples was attempted several times to replace unsatisfactory old ones. Finding optimistic numbers of pixels for the segmentation procedure also required trials on differentiated objects. Some objects share similar characteristics such as color or shape, so an additional procedure needed approaching. Figure 7 is an example of how the classification procedure was conducted based on the object-oriented method. There are several classes that need to be reclassified due to an issue of "mixed pixel"—pixels belonging to built-up areas were categorized into water, for instance. In this circumstance, to resolve the mixed-pixel problem, a rule that all areas that were less than 1000 pixels should be built up was derived. Instead of using the area of objects, other characteristics can be used, such as color, associated index (*NDVI*), or training samples. Involving each object's characteristics rather than isolatedly using each pixel's value in the classification procedure is one of significant advantages of the object-oriented method compared to the general supervised classification. However, there are some highlighted points that should be considered, which are represented below:

- Shadowed areas: On GeoEye 1 image, we observed shadows of vegetation and low buildings. In this circumstance, this shadow effect was not significant, so no further procedure was applied. However, if shadow effects are obvious (mainly in urban or forested areas), an object—spatial relationship (nearest neighbor, for instance) will be applied in the decision rules.

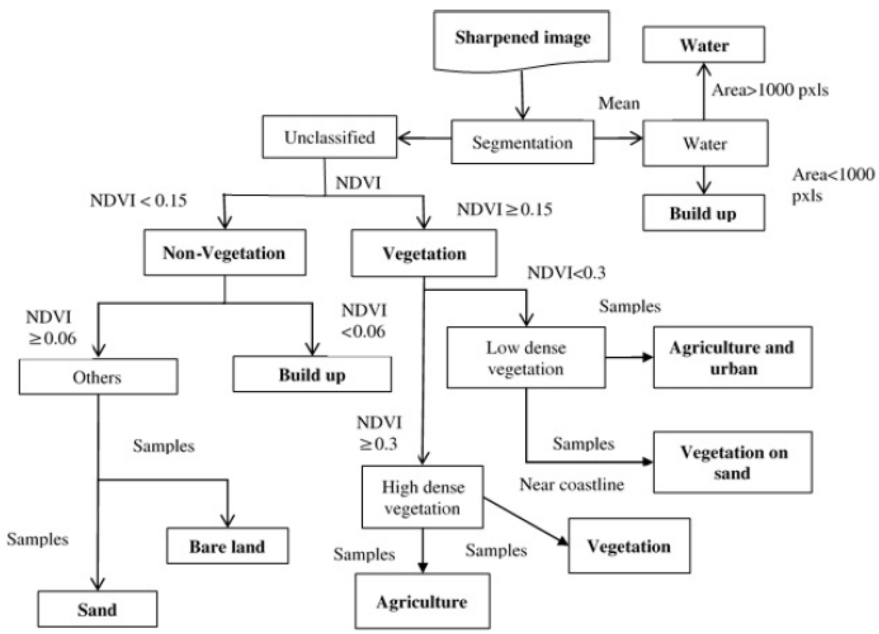


Figure 7. An example of classification hierarchy (decision tree) to categorize objects into classes of the Lien Huong GeoEye1 image.

- Band indices: Using different band indices is a good approach to derive effective rules of decision tree to assign classes. It required less time to categorize classes on the Worldview2 image than the GeoEye1 one, especially when it is effective to differentiate roads from water layer. On images, road and water surfaces often appear as similar colors—dark blue. Nevertheless, these indices are quite sensitive, so in each case, the selected range of values of each index designated to each class are different. The image preprocessing step is very important before calculating band indices.
- Segmentation procedure: This procedure requires a lot of time, computer RAM storage, and analyst experience. Sub-divided regions that are too small or too large may increase processing time, or lead to missing data or mixed classes.
- Decision tree: Constructing rules for the decision tree to categorize objects into classes is very important, and obviously not an easy mission. Each object has its own typical characteristics,

and shares some with others. The more indicators there are, the more supportive and successful decision rules are. However, there is another constraint of cost and time consumption.

- Subset images helps to save time to generate classified rules and decision trees. We divided the study area into three parts regarding the administrative boundary.
- Manual editing is a necessary step to approach a better result. A significant difference between object-based classification and supervised classification is the smallest object. A pixel is the smallest object in a supervised method, so "salt and pepper" errors exist on the classified image. An object that may cover at least 50 or 100 pixels, depending on segmentation methods is the smallest one in the object-based classification. Thus, it is easier to detect mis-classified objects on results, and bring them to their true class. Ecognition Developer software allows users to process segmentation, and manual editing very conveniently.

4. Results and Discussion

4.1. Land Use—Land Cover Classification

To execute this research, the 2011 and 2016 LULC maps were generated at two levels: (1) Level 1 within seven classes assessing general trend of LULC changed during 2011–2016, and cross validating with the 2014 map; and (2) Level 2 with 13 classes assessing drought-human impacts on agricultural and vegetating lands. Our maps, statistical data, and validation results are shown in Figures 8–10, Tables 3–5.

To validate our final results, we conducted contingency tables for LULC maps 2011 and 2016 (summary of the classification accuracy at level 2 is shown at Table 3) by using 521 random points including 460 automatically generated points and 61 ground reference points collected in the 2016 field research of land sampling. Furthermore, Google Earth images was used to cross-validate our images and final maps. Overall accuracies of two-image classification at level 2 are 85% (WorldView2), and 87.3% (GeoEye1). According to the contingency tables, class 7 and class 13, which are urban vegetation and sandy vegetation, respectively, are less accurate in comparison to others. The reasons are: firstly, the segmentation method resulted in a different size of polygon that could not perfectly isolate objects; secondly, some vegetated areas were mixed with agricultural lands, or buildings, or vegetation—sand mixing, so it is not easy to differentiate them correctly. Accuracy of water layers is very low because there are several random points belonging to the water layer (see Table 3). At level 1 classification, the overall accuracies of those two classified images are much higher than 90% as there are fewer categories, and less ambiguity between classes. Thus, in the classification procedure, designed numbers of classes, and class assignment methodologies are the main factors that affect overall accuracy.

4.2. Overall Changes in LULC during 2011–2016

At level 1 of image classification, we occupied an overall trend of LULC changes in the case study within seven classes: built up, salterns and aquaculture (shrimp farming), surface water, agriculture, bare land, and sand. Figure 8 and the data Table 4 below show our findings of LULC changes during the interval 2011—2016. Generally, there was a dramatic increase of vegetation cover, especially in urban areas from 475.1 ha (2011) to 839.8 ha (2016), an increase of about 76.8%. Sand and water declined 20% after 5 years, while other land types such as bare land, agriculture, and shrimp farming rose slightly, about 3%. Built-up land decreased by approximately 3% because we only counted impervious surface (buildings, single blocks, or roads). Several types of vegetation cover such as urban vegetation, bushes and plants grown on sandy lands (near the coast) are both categorized into the same class. On the maps shown in the Figure 8, vegetation (dark green) increased both in urban areas (red) and near the coast, replacing sandy lands (light blue). These types of vegetation play important roles to reduce urban heat islands in urban areas, to stabilize sand dunes near the coast, and to protect agricultural lands from sand-dominant processes as a windbreak solution during drought periods and dry seasons.

Table 3. Statistical summary from contingency tables generated to assess accuracy of two land use maps in 2011 and 2016. Unit:%.

ID	Land Types	2011 Map's Accuracy		2016 Map's Accuracy		Overall
		User's	Producer's	User's	Producer's	
1	Built up	86.2	92.6	98	84.5	2011's overall = 85%
2	Salterns	100	100	100	93.8	2011's kappa= 82.9%
3	Active shrimp farming	100	100	100	100	2016's overall = 87.3%
4	Inactive shrimp farming	90	100	83.3	90.9	2016's kappa=85.6%
5	Water	66.7	66.7	100	66.7	Total points = 521
6	Rice production	74.5	87.2	84	100	
7	Vegetation	84.2	61.5	79.1	89.5	
8	Bare land	76.9	81.1	87	88.9	
9	Sand	93.3	79.5	100	77.1	
10	Land for aquaculture	100	83.3	92.3	92.3	
11	Orchards	91.7	64.7	83.3	71.4	
12	Inactive agriculture	78.5	93.9	92.7	93.6	
13	Vegetation on sand	83.5	94.7	71.8	87.1	

Table 4. Changes in different LULC types.

No	Land Types	Area in 2011 (ha)	Area in 2014 (ha)	Area in 2016 (ha)	Difference 2011–2016 (ha)	% of Difference
1	Built up	418.8	725.3	406.5	↓ 12.3	↓ 2.9
2	Salterns and shrimp farming	311.9	321.9	322.4	↑ 10.5	↑ 3.4
3	Water	30.8	17.2	24.8	↓ 6	↓ 19.5
4	Agriculture	1229.4	2293.3	1269.3	↑ 39.9	↑ 3.2
5	Vegetation	475.1	517.9	839.8	↑ 364.7	↑ 76.8
6	Bare land	291.7	156.3	300.6	↑ 8.9	↑ 3.1
7	Sand	1992.5	755	1592.5	↓ 400	↓ 20.1

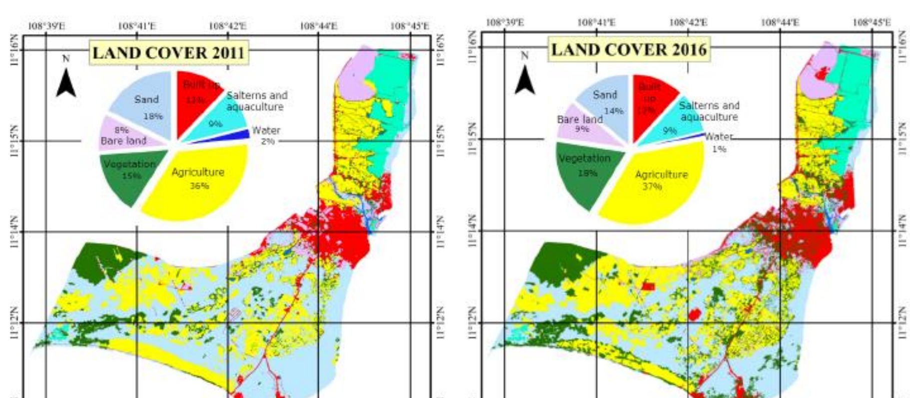


Figure 8. Land cover maps pie charts of 2011 and 2016.

4.3. Impacts of Drought and Human on LULC Change during 2011–2016

The second level of classification was focusing on revealing the human role on LULC change under prolonged drought occurrences in the study area. We investigated specific land types such as agriculture, salterns, urban vegetation, and sandy vegetation, which were under high impact of local people via land practicing. Figure 10 is an overall report of LULC change by local resident influence.

4.3.1. Agricultural Land Transition

Droughts have had impacts on the environment and society [7,30,31]. They can disturb agricultural activities via fresh water shortages; they may interrupt shrimp farming because higher water surface temperatures simulate evaporating processes. However, high air and surface temperature, lack of rainfall, and more solar radiation, which are climatic characteristics of droughts, stimulate water-vaporing processes, and as a result, marine salt production may get more benefits. Humans, via their land practicing methods, also change use purposes of land to adapt to the change of weather both in the long term and short term depending on the duration of extreme weather (drought) and irrigation conditions. Figure 9 illustrates desiccated paddy fields in Phuoc The due to insufficient irrigation; the image was taken in July 2016 in the middle of wet season. To understand how droughts and humans affect LULC, we accounted for changes in agriculture and shrimp farming by defining more precise land use classes: rice production, inactive agriculture, orchards, salterns, active shrimp farming, and inactive shrimp farming (level 2 in Table 2). A further analysis applied to Phuoc The commune in Section 4.4 shows a "closer look" on these influences.

From Table 5, from 2011–2016, the area devoted to rice production declined by more than 50%. Inactive agriculture (increased 32%), bare land, and orchards replaced this 50% decrease. The area devoted to orchards was 76.9% greater in 2016 than in 2011. The transition from rice to dragon fruit, grape, and cassava is one of the examples of applying adaptive methods under drought impacts of local residents. Those types of plants require less water consumption than rice. Moreover, dragon fruit and grapes are more valuable than rice, and can reproduce over many years. Inactive agricultural area was divided into two types: (1) temporal interruption due to water shortage (mainly found in Phuoc The); and (2) permanent interruption (other communes).

Figure 9. Lack of fresh water for irrigation created these desiccated lands in the commune of Phuoc The.

Long-term inactive agriculture is one of risks of land degradation, which is found mostly in Binh Thanh and Lien Huong communes where fields are mainly rain-fed. Because of the lack of precipitation and insufficient irrigation, these lands cannot support agriculture, based on our field observation, and using Google Earth time series, they have not been cultivated for more than 20 years. Those inactive agricultural lands are typically orange in appearance on standard false color composites, which reveal the occurrence of iron in the soil. Characteristics of soil and water shortages due to frequent droughts are two main factors that lead to land degradation or desertification in the study area.

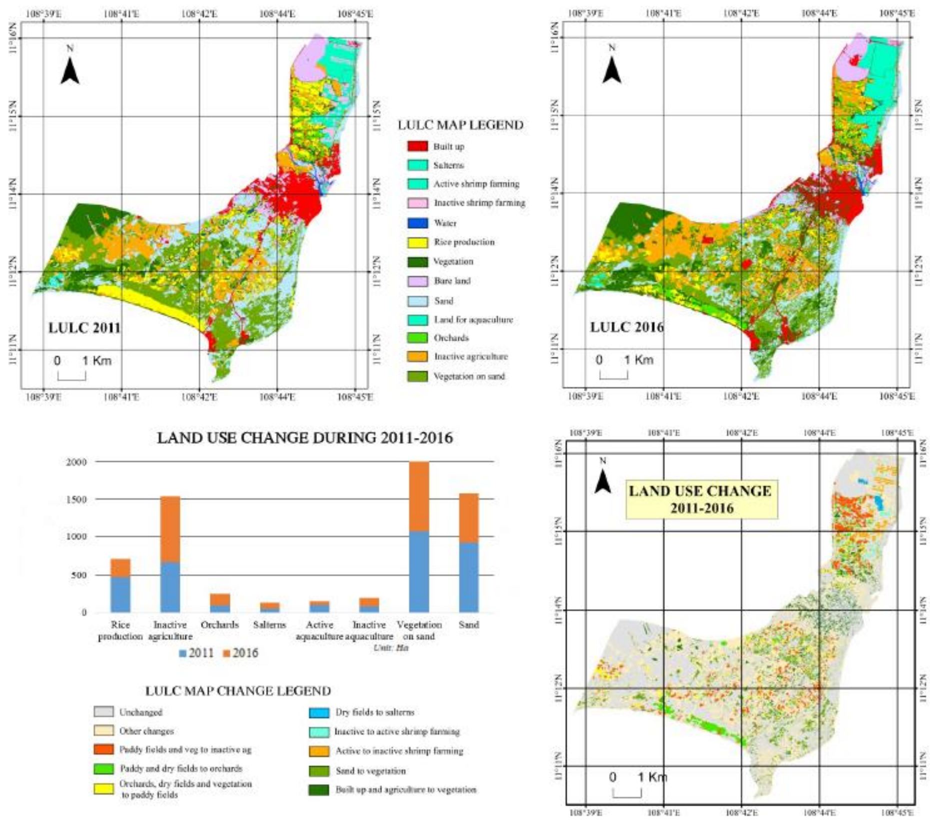


Figure 10. Maps of land use and land cover change during 2011–2016 .

Table 5. Changes of specific land types regarding to agriculture and shrimp farming during 2011–2016.

No	Land Types	Area in 2011 (ha)	Area in 2016 (ha)	Area of Difference (ha)	% of Difference
1	Rice production	474.6	228.5	↓ 246.1	↓ 51.9
2	Inactive agriculture	662.2	877	↑ 214.8	↑ 32.4
3	Orchards	92.6	163.8	↑ 71.2	↑ 76.9
4	Salterns	50.4	80.4	↑ 30	↑ 59.5
5	Active shrimp farming	99.8	55.8	↓ 44	↓ 44.1
6	Inactive shrimp farming	79.5	114.7	↑ 35.2	↑ 44.3
7	Vegetation on sand	1071.9	937.7	↓ 134.2	↓ 12.5
8	Sand	920.6	654.8	↓ 265.8	↓ 28.9

4.3.2. Salterns and Shrimp Farming

Shrimp is more valuable, but it requires a big investment in prawn shrimp, food, and cleaning, etc. Moreover, shrimp is sensitive to environmental conditions, such as water temperature, water quality, and diseases. Shrimp farming in Tuy Phong is mainly based upon individual operators, so farmers have faced many difficulties, especially finding markets for their products, and reinvestment after losses. In the study area, salterns and shrimp farming are located in Phuoc The commune (cyan color on LULC maps—Figure 10). During the period 2011–2016, there was a slight increase in salterns and shrimp farming. From Table 5, it can be seen that active shrimp fields declined by nearly 40% in 2016 compared to 2011; they were replaced by dry fields. A local report described this disruption: regarding the Tuy Phong agricultural office, in 2016, the area of shrimp farming was about 60% due to climatic impacts as prolonged drought during the dry season, and more rainfall during wet season changed the water environment and temperature [32]. Long-term inactive fields dedicated for shrimp farming can create some environmental impacts, such as an increase in saline tolerance in soils, which can disperse and infect other land types, especially agricultural land in case of deficient irrigation systems, and inadequate land planning. Furthermore, because of proximity to the coastline, dry fields are considered to be sources of sand formation, based on changes in soil structure under severe conditions (such as prolonged high temperature, and oceanic winds). Such processes have dispersed sand from the coast inland.

Oceanic salt production started in Vietnam during the period of French colonization at the beginning of the 20th century. However, in Tuy Phong, it began in 1989, to take advantage of flat terrain, less rainfall, high levels of solar radiation, more than 300 sunny days per year, and local labor resources. Tuy Phong is one of four districts of Binh Thuan that has salterns. Salterns are in Vinh Hao commune, which covers 567.5 ha over 960 ha of total salt production in Binh Thuan [16]. Only a small portion of salterns was practiced in a small area of Phuoc The commune in 2001. Most lands currently used for salterns and shrimp fields were bare land and agricultural practicing in the past. Despite high yields from salt production, salt does not ensure higher incomes for salt farmers, generally a monthly income from 0.1 ha salt production is about $50 [16]. Figure 11 was taken at the area used for marine salt production in Phuoc The commune.

Figure 11. Salt production in Phuoc The commune.

Despite negative impacts of drought on sand spreading and land degradation, stimulation of salt production is a positive one of prolonged drought to the coastal area. Areas of salterns increased by nearly 60% after transitions of inactive agricultural lands to salt production. However, in similarity to shrimp farming, conversions to salterns may lead to significant environmental impacts. Without a commitment to sustainable practices, conversions to salt production can promote adverse effects such as saline intrusions into residential areas. This effect was found in Vinh Hao commune [11], where there were reports from local residents concerning influences of occurrence of salterns near their houses. Another drawback of salt production is economic value. Income from salt production is less than that from rice production, while its impacts on environment and human life are significant. Thus, there is more bias than gain.

4.3.3. Vegetative Areas

Impacts of human on land changes during drought events are both negative and positive. Permanently inactive agricultural land, deficit irrigation systems, unsustainable practices of salterns, and shrimp farming can affect local environments and soil. Despite negative effects, there are recognizable efforts of local residents and government, which were approached to support mitigation of drought, and expansion of sandy terrain. The most significant effort is vegetating bare soil and sand. Our findings show that vegetated area increased more than 70% (Table 4 and Figure 8), especially ones located in urban and around agricultural land. In Phuoc The, this type of vegetation increased about 305 (bar graph in Figure 12). Plants can help to reduce urban heat islands and protect land from salinity process. Furthermore, vegetating sand can help to stabilize sand dunes near the coastline and prevent sand tracking. From our land survey in 2016, casuarina (Australian pine) is a common plant found along the study area's coastline, which can grow on salt-tolerant sand, and it can be constructed as a windbreak to prevent advances in sand.

4.4. Agricultural Practicing in Phuoc The Commune

Phuoc The commune experienced many changes in land use. The areal extent of Phuoc The commune is about 978 ha. In 2011, the agricultural area of Phuoc The was 288.87 ha covering 29.5% of total area, while salt and shrimp farming was 21% (approximately 206 ha). In 2016, there was a decrease in agricultural land, and a slight increase of salt and shrimp farming, 242.6 ha and 227.28 ha, respectively. During 2011–2016, vegetation cover increased from 60.8 ha to 90.59 ha, and a sandy plantation was 1ha larger in 2016 than in 2011 (17.29 and 18.15 ha), see table A2 in the Appendix B for more details. Figure 12 comprises LULC change map in Phuoc The with a bar graph reporting changes in some specific land types, and pie charts showing land proportions of agricultural, salterns and aquacultural lands

Drought led to a decline in agriculture and shrimp farming in this commune in 2016. In comparison to 2011, in 2016, areas of rice paddies reduced by 30% to change their active status to inactive because of reduced irrigation water. There is a significant increase in inactive shrimp farming due to drought, as higher surface temperatures have indirectly altered aquatic environments.

In Phuoc The, local residents transitioned paddies to orchards of dragon fruit or cassava in response to reductions in surface water. Although areas of orchards only rose 4% from 22% to 26% of total agricultural area, it can be shown that local people acknowledged drought impacts, and were trying to derive solutions for practicing agriculture under this adverse event, and to reduce economic losses. Furthermore, there was a transition from paddies to salterns. Most of those paddies were dry, distant from water resources, and close to industrial salt production areas. Transition to salterns is necessary to guarantee income for farmers in the case that no plants could be cultivated in neighborhood of salterns, and irrigation was not sufficient to prevent saline intrusions.

4.5. Limitations of the study

While conducting our analysis and validation, we have observed several issues, such as the time gap between images, or disagreements between our results and the 2014 governmental map. Although there is three-week difference between two imagery datasets, the influence of acquisition time was not significant as a start of growing season (monsoon season). The 2014 map (shown in the Appendix C, Figure A1) is involved in our study to select training samples and validate our final results as a referenced map. Because we focus on drought and human impacts on some specific land types, such as agriculture (paddy fields, orchards or inactive agriculture). Thus, there is a significant difference of details on final maps compared to the reference map. This is an explanation for why, compared to 2014, built-up areas in 2011 and 2016 account for three fifths of 2014; 2014 agricultural area doubled, while its sand and water covered half in comparison to 2011 and 2016 (shown in Table 4).

Our findings are based on bi-temporal analysis using high-resolution data, a 2016 land survey, and Google Earth time series. They showed the changes in LULC in the study area of three coastal communes Binh Thanh, Lien Huong and Phuoc The, which are significant in agricultural lands and vegetated areas. Our findings attempted to reveal a prospectively undergoing story of LULC change in coastal areas in the North of Binh Thuan which were excluded in previous research [14,15,33]. We have discovered that there is a linkage of human and a dry condition (prolonged droughts) resulting in land transitions, especially in agricultural lands which were addressed in other similar studies [7,34]. However, because of bi-temporal analysis, the influence of drought is not significant; there could be a fluctuation on using land year by year. There is a study on drought impacts on LULC using time series satellite data represented an argument that "no significant relationship between drought variations" and LULC change [35]. Nevertheless that study only carried out the meteorological drought (lack of rainfall) analysis, and excluded agricultural or hydrological drought. Meteorological drought may not affect agricultural lands if irrigation is proficient and sufficient [30] while agricultural and hydrological droughts have very close relationships to LULC upon available content of moisture, water resources and vegetation behavior during drought period. Further analysis will investigate identification of the main factors driving LULC changes in the study area; it is necessary to involve additional analysis and extension of time observation, such as monitoring available surface water during dry season, or a multiple temporal analysis for sequential images.

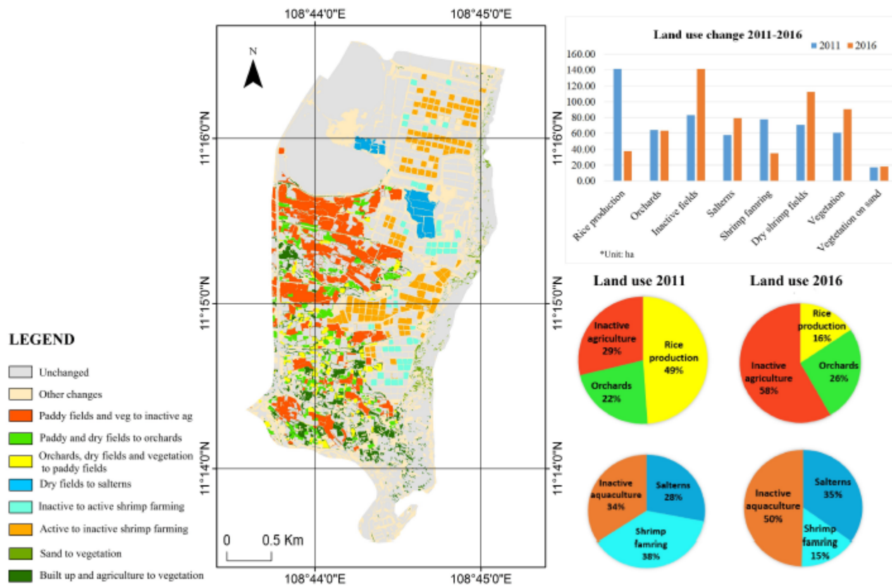


Figure 12. Land use change map of Phuoc The commune during 2011–2016. Bar graph and pie charts describe changes of eight specific classes regarding agriculture, shrimp farming and vegetation layers.

5. Conclusions

Prolonged drought can lead to many environmental and social impacts to affected areas. Tuy Phong, Binh Thuan is in a semi-arid area oriented parallel to a long coastline subject to severe droughts. This research is conducted to reveal impacts of drought on LULC changes in recent years (2011–2016), and to document some of these processes. In summary, recalling our research questions in the Introduction, our results have shown that:

(1) During drought periods, surface water resources reduced by one fourth, resulting in water shortage for irrigated and rain-fed rice fields, and a slight increase of bare land (unused land);
(2) To quantify impacts of drought, and water shortage on agricultural and aquacultural lands, we conducted a higher detailed image analysis; results showed a dramatic decrease of those land types (more than 50% and 44% , respectively). The extent of inactive agriculture and dry shrimp fields may promote land degradation, a spreading of sand into land, and desertification processes;
(3) Assessing interaction of local residents and droughts on LULC change, we observed local efforts to alternate rice and dry field by orchards growing drought-tolerant plants, such as dragon fruit or pitayas. Those plants not only adapt the prolonged dry conditions of the study area, but also bring higher income. Additionally, local residents and authorities were also active in promoting LULC transitions by vegetating bare soil and sand with stabilizing covering crops. Vegetating and crop rotation are examples of adaptive methods to combat drought.

Nevertheless, there are several limitations in our study, such as time gap between datasets that may result in vegetation variation in the beginning of growing season; a bi-temporal analysis cannot assess LULC variability regarding drought occurrence patterns; and there were discrepancies in our results compared to the map established by the local authorities in categorizing those fields as they were shown active status in the 2014 map. Therefore, a multi-temporal analysis will be the approach in our further research for improving our understandings of local land management in the study area under a scenario of prolonged drought. Accessing land management will include a procedure to quantify and qualify available water resources and effectiveness of irrigation systems, which secure fresh water to the entire study area during a drought period. During our summer field studies in 2016, we observed most agricultural lands near the coast shown as inactive in 2011 and 2016 maps were unable to support crop production. Reasons for the inactive status of those fields were long-term shortage of water, poor soil fertility, and soil salinity intrusion which resulted in land degradation, and promoted desertification in the study area. Thus, it is necessary to continue research to gain insight on human impacts on LULC, and on broader environmental processes during drought events. Such initiatives will support the development of solutions for land management and protection under threat of climatic hazards.

Author Contributions: H.T.T., J.B.C., R.H.W., and Y.S. conceived and designed experiments. H.T.T. performed the experiments, and analyzed data. S.V.P. contributed field research and reference materials. H.T.T., J.B.C., R.H.W. and Y.S. wrote the paper.

Funding: This research was sponsored by: (1) Imagery Grant by the Digital Globe Foundation, (2) Field study funded by Geography Department, Graduate School and the Interdisciplinary Graduate Education Program at Virginia Tech.

Acknowledgments: We would like to thank Digital Globe Courtesy for their imagery grant that provided valuable data to conduct this research. We acknowledge the Virginia Tech Graduate School, Virginia Tech's IGEP-RS (Interdisciplinary Graduate Education Program in Remote Sensing), and the Department of Geography for funding support for the summer 2016 field research. We acknowledge funding support by the Virginia Agricultural Experiment Station and the McIntire-Stennis Program of NIFA, United States Department of Agriculture. We are thankful to VT OASF (Virginia Tech Open Access Subvention Funding) support in our published article. We credit Virginia Tech's faculty—Steven Hodges, and National University of Singapore's faculty—Winston Chow as members of Hoa Tran's dissertation committee for their contributions to our research. We also recognize Devon Libby, the Digital Globe representation who supported us during our grant application process and his excellent communication during our project. We credit the Meteoblue team for providing free historical weather data of three locations: Lien Huong, Phan Thiet, and La Gi. We appreciate our field assistants: Ngoc Tran, and Ha Tran, who served as co-workers during the field research in Binh Thuan province. Lastly, we credit reviewers and the Remote Sensing journal's staff for their support during the processing procedure.

Conflicts of Interest: This research continues the previous study on drought severity monitoring and contributes to a Ph.D. dissertation. There are no conflicts of interest among authors.

Appendix A. Training Sample

Table A1 describes characteristics of each class involved in the image classification procedure. Here we show samples of each land type from each sensor used in our study, displayed at consistent scales. Training samples were selected from the 2011 WorldView 2 (WV2), and the 2016 GeoEye 1 (GE1) images, at a scale of 1: 25,000. Some specific samples, such as buildings or roads, were at finer scale as noted under each image. Samples for the reference image were chosen from 2016 Google Earth scenes (Ref img).

Table A1. Training samples for WorldView 2 and GeoEye 1's classification procedures.

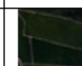
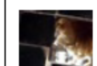
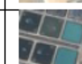
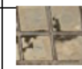
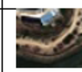
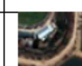
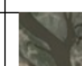
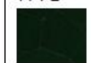
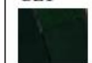
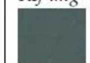
Land Types				Descriptions			Imagery Samples		
Level 1		*Level 2*		*Shape & distribution*	*Color*	*Indices*	*WV2*	*GE1*	*Ref img*
1	Built up	1	Build up	Rectangle,dense, near main roads or coastlines.	White or light blue or red rooftops.	NDWI NHFD	 *1:5000		
2	Salterns and shrimp farming	2	Salterns certain size.	Rectangle,but white or brown.	Blue, dark blue NDWI	NDVI	 	 	 
		3	Active shrimp farming	Square, certain size. 65 by 65 m.	Blue, dark blue.	NDVI	 *1:10 000		
		4	Inactive shrimp farming	Square, certain size 65 by 65 m.	Tan, brown, white.	NDSI			
		10	Others land for aquaculture	Routes or rectangle.	Brown, tan.	NDSI NHFD	 *1:5000		
3	Water	5	Water	Undefined shape.	Dark blue or green.	NDVI			

Table A1. *Cont.*

Land Types		**Descriptions**			**Imagery Samples**		
Level 1	*Level 2*	*Shape & distribution*	*Color*	*Indices*	*WV2*	*GE1*	*Ref img*
4 Agriculture	6 Rice production	Undefined shape, smooth surface.	Dark to light green (natural color). Dark to bright red (false color).	NDVI	 	 	
	11 Orchards	Rectangle, rows& and columns,mixed with built up.	Green and/or mixing brown as soil background.	NDVI			
	12 Inactive agriculture	Rectangle or undefined shape.	Brown, tan with some greenness	NDSI	 	 	 
5 Vegetation	7 Vegetation	Undefined shape, narrow like borders.	Green to dark green	NDVI			
6 Bare land	8 Bare land	Undefined shape, no or very spare vegetation.	Brown, tan, some greenness.	NDSI			
7 Sand	9 Sand	Undefined shape, near coastlines,or dried fields.	Yellow or white, tan, some greyness.	NDVI	 	 	 
	13 Vegetation on sand	Undefined shape, near coastlines.	Green	NDVI			

Appendix B. Land Use Change in Phuoc The community

Statistical data for analyzing LULC change in Phuoc The community—Table A2.

Table A2. Land use transition of Phuoc The from 2011 to 2016 (unit: ha) of 13 land use types. Gray represents unchanged land types; other colors refer to significant changes of some specific land types shown in Figure 12.

2011 \ 2016	1	2	3	4	5	6	7	8	9	10	11	12	13
1	46.95	0.65	0.01	0.03	0.49	0.48	11.92	7.09	0.9	1.35	1.90	2.04	0.69
2	0.72	47.91	1.13	1.71	0.41	0.02	0.46	1.178	0.1	2.62	0.9	0.04	0.11
3	0.26	0.9	10.01	53.89	0.06	0	0.96	0.54	0.04	9.97	0	0.11	0.15
4	0.22	0	18.28	39	0.02	0	0.79	0.25	0.15	12.01	0	0.01	0.05
5	0.35	0.09	0.02	0.04	6.9	0.22	2.41	1.8	0.13	0.38	0.06	0.23	0.12
6	2.39	0.21	12	0.05	0.008	18.8	11.44	2.55	0	0.12	15.77	89.69	0
7	6.68	0.89	0.27	0.73	0.52	3.46	25.16	6.15	0.02	2.02	5.74	9.1	0.06
8	16.12	1.3	0.11	0.04	1.97	0.32	5.46	140.	2.62	0.31	0.72	1.43	0.44
9	6.88	0.36	0.26	0.12	0.41	0	1.22	1.29	47.5	0.85	0.02	0.04	5.94
10	3.86	11.06	4.047	16.38	0.42	0	2.27	3.16	0.52	38.79	0.01	0.02	0.89
11	2.65	0	0	0.02	0	8.08	20.04	2.12	0	0.03	26.51	5.12	0
12	1.83	15.05	0.66	0.76	0.02	6.42	7.79	4.18	0	1.02	11.89	33.46	0
13	0.52	0.05	0.09	0.04	0.11	0	0.67	0.15	5.77	0.17	0	0.02	9.7

Appendix C. The 2014 Land Use Land Cover Map

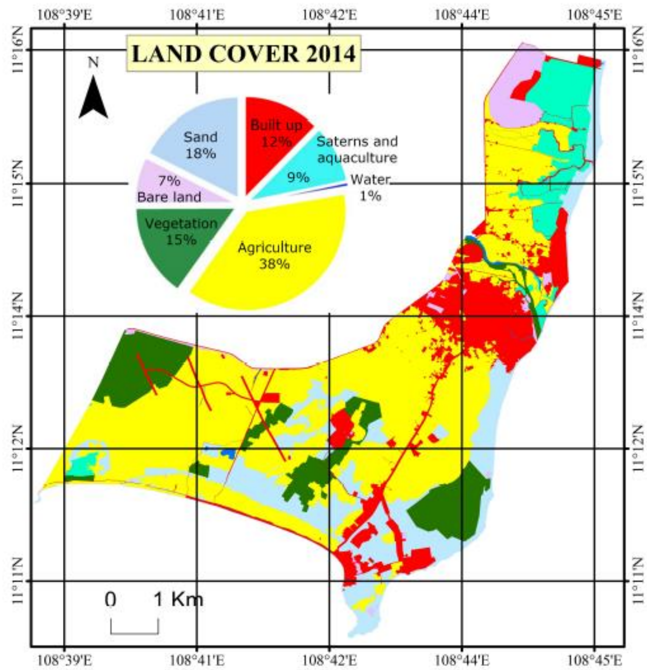


Figure A1. The governmental map of land use in the study area in 2014.

References

1. Wilhite, Donald A.; Glantz, Michael H. Understanding the Drought Phenomenon: The Role of Definitions; Drought Mitigation Center Faculty Publications. 1985. Available online: http://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1019&context=droughtfacpub (accessed on 8 February 2019).
2. Descroix, L.; Moussa, I.B.; Genthon, P.; Sighomnou, D.; Mahe, G.; Mamadou, I.; Vandervaere, J.-P.; Gautier, E.; Maiga, O.F.; Rajot, J.L.; et al. Impact of Drought an Land—Use Changes on Surface-Water Quality Quantity: The Sahelian Paradox. In *Current Perspectives in Contaminant Hydrology and Water Resources Sustainability*; IntechOpen: London, UK, 2013; Chapter 10, pp. 243–271, doi:10.5772/54536.
3. Li, Y.; Change, J.; Luo, L. Assessing the impacts of climate and land use land cover changes on hydrological droughts in the Yellow River Basin using SWAT model with time-varying parameters. In Proceedings of the 2017 6th International Conference on Agro-Geoinformatics, Fairfax, VA, USA, 7–10 August 2017, pp. 1–6, doi:10.1109/Agro-Geoinformatics.2017.8047045.
4. Gutierrez-Velez, V.H.; Uriarte, M.; DeFries, R.; Pinedo-Vasquez, M.; Fernades, K.; Ceccato, P.; Baethgen, W.; Padoch, C. Land cover change interacts with drought severity to change fire regimes in Western Amazonia. *Ecol. Appl.* **2014**, *24*, 1323–1340.
5. Raja Rao, G; Visweswara Reddy, B; Tammi Naidu, G; Hema Malini, B. Impact of Drought on Land Use/Land Cover Changes in Srikakulam District of Andhra Pradesh—A Study Through Remote Sensing and GIS. *Int. J. Multidiscip. Educ. Res.* **2013**, *2*.
6. Findell, K.L.; Berg, A.; Gentine, P.; Krasting, J.P., Lintner, B.R.; Malyshev, S.; Santanello, J.A; Sheliakova, E. The Impact of Anthoropogenic Land Use and Land Cover Change on Regional Climate Extremes. *Nat. Commun.* **2017**, *8*, doi:10.1038/s41467-017-01038-w.
7. Biazin, B.; Sterk, G. Drought Vulnerability Drives Land Use and Land Cover Changes in the Rift Valley Dry Lands of Ethiopia. *Agric. Ecosyst. Environ.* **2013** *164*, 100–112, doi:10.1016/j.agee.2012.09.012.
8. Hisdal, L.; Tallaksen, L.M. Drought Event Definition. In *Assessment of Regional Impacts of Droughts in Europe*; Technical Report; University Oslo: Oslo, Norway, 2000.

9. Kottek, M.; Grieser, J.; Beck, C.; Rudolf, B.; Rubel, F. World Map of the Köppen-Geiger climate classification updated. *Meteorol. Z.* **2006**, *15* , 259–263, doi: 10.1127/0941–2948/2006/0130.
10. Pham, Q.V.; Nguyen, T.B.; Bui, T.T.H. Drought Zoning for Binh Thuan Province, in Viet Nam base on ETo Calculator and GIS. In Proceedings of the GeoInformatics for Spatial-Infrastructure Development in Earth and Allied Sciences (GIS-IDEAS) 2012, Ho Chi Minh City, Vietnam, 16–20 October 2012.
11. Duong, H.L. San Xuat Muoi o Vinh Hao Gay O Nhiem Moi Truong. 2009. Available online: Mard.gov.vn (accessed on 8 February 2019).
12. The Center of Database Establishment for Environmental Resources in Vietnam, Geography Institute. *The Map of Total Annual Rainfall Distribution*; Geography Institute: Ha Noi, Vietnam, 1999.
13. Weather Data Archive at Lien Huong Station. Available online: www.meteoblue.com (accessed on 8 February 2019).
14. Gobin, A.; Le, T.H.; Pham, H.L.; Hens, L.; Ozer, P.; Le, T.T.H.; Nguyen, T.B.; Pham, Q.V. *Impact of Global Climate Change and Desertification on the Environment and Society in the Southern Centre of Viet Nam (Case Stuty in the Binh Thuan Province)*; Technical Report; The Belgian Federal Science Policy Office: Brussels, Belgium, 2012.
15. Le, Trinh Hai; Gobin, A.; Hens, L. Select Indicators and Prioritize Solutions for Desertification and Drought in Binh Thuan, Vietnam. *Chin. J. Pop. Resour. Environ.* **2016**, *14*, 123–132, doi:10.1080/10042857.2016.1177315.
16. VNA. Binh Thuan Province Dries up in Severe Drought. 2016. Available online: vietnamplus.vn (accessed on 8 February 2019).
17. Tran, H.T.; Campbell, J.B.; Tran, T.D.; Tran, H.T. Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (Case Study: Tuy Phong, Binh Thuan, Vietnam). *GISci. Remote Sens.* **2017**, *54*, 167–184, doi:10.1080/15481603.2017.1287838.
18. Kogan, F.N. Remote sensing of weather impacts on vegetation in non-homogeneous areas. *Int. J. Remote Sens.* **1990**, *11*, 1405–1419, doi:10.1080/01431169008955102.
19. Pham, T.H. Long Song Dam. 2009. Available online: vncold.vn (accessed on 8 February 2019).
20. Al-Kofahi,S.D.; Steele, C.; VanLeeuwen, D.; St Hilaire, R. Mapping Land Cover in Urban Residential Landscapes using Fine Resolution Imagery and Object-Oriented Classification. *Hortscience* **2010**, *45*, 93–94.
21. Cao, X.; Ke, C.Q. Land Use Classification with QUICKBIRD Image Using Object-Oriented Approach. *IEEE Int. Geosci. Remote Sens. Symp.* **2006**, *1*, 3255–3258, doi:10.1109/Igarss.2006.836.
22. Billo, R.E.; Bidanda, B. Representing Group Technology Classification and Coding Techniques with Object-Oriented Modeling Principles. *IIE Trans.* **1995**, *27*, 542–554, doi:10.1080/07408179508936770.
23. Gao, Y.; Mas, J.F.; Maathuis, B.H.P.; Zhang, X.M.; Van Dijk, P.M. Comparison of Pixel-based and Object-Oriented Image Classification Approaches—A Case Study in a Coal Fire Area, Wuda, Inner Mongolia, China. *Int. J. Remote Sens.* **2006**, *27*, 4039–4055, doi: 10.1080/01431160600702632.
24. Hebbar, R.; Ravishankar, H.M.; Trivedi, S.; Subramoniam, S.R.; Raj, U.; Dadhwal, V.K. *ISPRS Tech. Comission VIII Symp.* **2014**, *40*, 745–749, doi:10.5194/isprsarchives-XL-8-745–2014.
25. Chen, M.J.; Sui, W.; Li, L.; Zhang, C.; Yue, A.Z.; Li, H.X. A Comparison of Pixel-Based and Object-Oriented Classification using SPOT5 Imagery. *WSEAS Trans. Inf. Sci. Appl.* **2008**, *6*.
26. Hermosilla, T.; Almonacid, J.; Fernandez-Sarria, A.; Ruiz, L.A.; Recio, J.A. Combining Features extracted from Imagery and Lidar data for Object-Oriented Classification of Forest Areas. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2010**, *38–4-c7*.
27. Hong, L.; Liu, C.; Yang, K.; Deng, M. Object-Oriented Markov Random Model for Classification of High Resolution Satellite Imagery based on Wavelet Transform. In Proceedings of the Fifth International Conference on Digital Image Processing (Icdip), Beijing, China, 19 July 2013; Volume 8878, doi:10.1117/12.2031103.
28. Zhang, X.; Sun, Y.L.; Shang, K.; Zhang, L.F.; Wang, S.D. Crop Classification based on Feature Band Set Construction and Object-Oriented Approach using Hyperspectral Images. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2016**, *9*, 4117–4128, doi: 10.1109/Jstars.2016.2577339.
29. Wolf, A. Using World View 2 Vis-NIR MSI Imagery to Support Land Mapping and Feature Extraction using Normalized Difference Index Ratio. Proceedings Volume 8390, Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XVIII, Baltimore, MD, USA, 14 May 2012.
30. Cole, R. The Definition of Drought. In *Measuring Drought and Drought Impacts in Red Sea Province*; Publishing House: Oxford, UK, 1989; Volume xvii, 304p.

31. Healthcote, R.L. *Drought and the Human Story: Braving the Bull of Heaven*; Ashgate: Farnham, UK, 2013; Volume xvi, 301p, ISBN 9781409405016.
32. Duong, A. Tuy Phong: Dien Tich Tha Nuoi Tom The Chan Trang Giam. 2017. Available online: Baobinhthuan.com.vn (accessed on 8 February 2019).
33. Hountondji , Y.C.; De Longueville, F.; Ozer, P. Land Cover Dynamics (1990–2002) in Binh Thuan Province, Southern Central Vietnam. *Int. J. Asian Soc. Sci.* **2012**, *2*, 336–349.
34. Mercy, M.W. *Assessment of the Effects of Climate Change on Land Use and Land Cover Using Remote Sensing: A Case Study form Kenya*; Dresden Nexus Conference Working Paper Series; United Nations University Institute for Integrated Management of Material Fluxes and of Resources (UNU-FLORES): Tokyo, Japan, 2015; DNC2015/03.
35. Mokhtari, A.; Mansor, S.B; Mahmur, A.R.; Helmi, Z.M. Monitoring the Impacts of Drought on Land Use/Cover: a Developed Object-based Algorithm for NOAA AVHRR Time Series Data. *J. Appl. Sci.* **2011**, *11*, 3089–3103.