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Regional drought risk assessment in the Central Highlands and the South of Vietnam

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ABSTRACT

This study contributes to a proof-of-concept comprehensive drought risk assessment for Vietnam by (i) incorporating drought exposure and vulnerability based on specific socio-economic conditions of the regions; and (ii) using satellite data including World Meteorological Organization (WMO) Space-based Weather and Climate Extremes Monitoring (SWCEM) products, and The National Aeronautics and Space Administration (NASA)-Enhanced U.S Department of Agriculture (USDA)'s Soil Moisture Active Passive (SMAP) Global Data for drought hazard assessment. Drought risk assessment which incorporated hazard, exposure and vulnerability components was conducted for 27 provinces from four administrative areas in Vietnam. Drought Hazard Index (DHI) was derived using the Standardised Precipitation Index (SPI), the Vegetation Health Index (VHI), and surface soil moisture (SSM) to take into account the impact of both meteorological and agricultural drought. Drought Exposure Index (DEI) and Drought Vulnerability Index (DVI) were calculated using statistical data of land use and socio-economic characteristics obtained from Vietnam's statistical yearbooks. By combining DHI, DEI and DVI, a composite Drought Risk Index (DRI) was derived for drought risk assessment in the selected provinces for 2020. It was shown that the highest at-risk provinces were in the Mekong River Delta, the agricultural production centre of Vietnam. The South East regions were less impacted by drought compared to other regions. The proposed comprehensive approach to drought risk assessment in Vietnam has potential to contribute to improving drought preparedness and resilience of communities at-risk.

1. Introduction

Drought is a critical water shortage resulted from prolonged absence or marked deficiency of precipitation that affects vegetation growth, river flows, water storages and ultimately communities (IPCC 2007; WB 2019). It is one of the most complex

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climate-related natural disasters that causes detrimental impact on a wide range of sectors, especially agricultural production, human health, public water supply as well as on biodiversity and natural ecosystems (Vogt et al. 2018). Vietnam has been identified as one of drought-prone areas in South East Asia, being severely affected by El Niño-induced drought in 2015–2016 (MONRE 2019; UNESCAP 2019; MONRE 2020; WB 2020). Agricultural sector accounts for about one fifth of Vietnam's GDP and employs more than half of labour force. As such, economic losses caused by drought are substantial. According to the report of the United Nations Development Program (UNDP) Vietnam, during drought period in 2015–2016 an estimated 2 million people experienced acute water shortages and required humanitarian assistance; total economic losses in 18 severely affected provinces were estimated at approximately US$674 million (0.35% of country's GDP in 2015) (UNDP 2016). In 2019–2020, drought continued to be reported as a serious problem in the Mekong Delta region and Central Vietnam (Khoa 2020; Quoc 2020; UNESCAP 2020). Under impact of climate change, drought frequency and severity are projected to increase and cause detrimental impact on population and economy. Therefore, developing a comprehensive methodology for drought risk assessment in Vietnam is important to support the preparedness and resilience for drought in the agricultural sector (S. Pulwarty and Sivakumar 2014; CFE-DM 2018; MONRE 2020)

In recent years, drought risk assessment research has progressed and shifted away from traditional approach that was merely focused on the physical aspects of drought, to a comprehensive approach that as well considers socio-economic factors. This acknowledges growing understanding that evaluation of drought hazard risk alone would be insufficient for understanding drought impacts on population and economy, which in turn brings little benefit for drought risk response and management. Therefore, drought risk assessment must consider both the hazard and the existing socio-economic conditions of a particular region.

A comprehensive approach to risk assessment has been developed considering three key elements – hazard, exposure, and vulnerability – to assist with decision-making and prioritizing higher risk areas in disaster management. Applying this approach to drought, Drought Risk Index (DRI) which combines drought hazard index (DHI; the potential for drought conditions and/or a drought hazard event to occur), drought exposure index (DEI; the whole population, its livelihoods and resources in a place where a drought event may occur), and drought vulnerability index (DVI; the likelihood of exposed factors to suffer adverse effects when a drought event occurs) is now commonly used for drought risk analysis (Naumann et al. 2014; Tánago et al. 2016; Vogt et al. 2018; WB 2019).

This index-based approach is widely applied as an effective tool for drought risk management. At a national scale, by investigating the ranking of drought risk across provinces, the government can determine the areas of focus for implementing effective drought response and adaptation strategy. For example, using the Standardised Precipitation Index (SPI) as drought hazard indicator and several drought vulnerability indicators such as climate, topography, waterway density, land use and groundwater resources, drought risk map of Iran was derived (Alamdarloo et al. 2021). The same conceptual approach was used in drought risk assessment for South Korea and

Kazakhstan; however, different indicators for drought hazard, exposure, and vulnerability were selected (Kim et al. 2021). These earlier studies emphasized importance of using both physical and socio-economic indicators to assess drought risk.

In Vietnam, drought risk assessment studies have been mainly focused on investigating drought hazards considering spatio-temporal characteristics of drought and trends in drought occurrences (Tran et al. 2017; Du et al. 2018; Le P et al. 2019; Long et al. 2019; Phan et al. 2020; Stojanovic et al. 2020). Only a limited number of studies have assessed drought risk by combining hazard, exposure, and vulnerability components. For example, Nguyen et al. (2019) investigated the climatic, socio-economic conditions and local experience of past drought impacts using questionnaire survey. However, this study was confined to a small area and thus did not provide regional scale analysis. Specifically, drought risk has been assessed for local communities in two provinces. Furthermore, SPI was the only index used for drought hazard assessment and its data was obtained from surface-based meteorological observation stations. This could be considered as a limitation as rain gauge network in Vietnam is sparse and does not provide an adequate coverage to accurately reproduce spatial variability of rainfall. Study of Le VT et al. (2019) derived DRI for 18 Southern provinces of Vietnam considering hazard, exposure, and vulnerability components. However, no adequate justification was provided for the selection of 22 different socio-economic indicators used as inputs to derive exposure and vulnerability components. Similar to Nguyen et al. (2019), SPI was the only input into DHI, and its data was also obtained from low-density surface-based rain gauge network. Precipitation is highly variable, spatially and temporarily, and use of a single index such as SPI derived from a limited number of in-situ data may result in inadequate representation of drought conditions over a large region, and could in turn result in incorrect drought risk assessment (WB 2019). As such, an approach to drought risk assessment in Vietnam requires further improvement.

This study aims to address the limitations of drought risk assessment in Vietnam through two key contributions. First, it fills the gap of drought risk assessment in Vietnam by combing physical hazard and socio-economic conditions over the region. Specifically, it provides a quantification method of a composite DRI (hazard, exposure, and vulnerability) to compare drought risk level across provinces and regions in Vietnam. Second, it improves the accuracy of drought hazard assessment by incorporating satellite precipitation estimates to complement and enhance drought risk assessment methodology outlined in earlier studies, which relied on surface-based rainfall data to assess drought hazard.

The SPI, the Vegetation Health Index (VHI), and the surface soil moisture (SSM) data were utilized for calculating DHI. The SPI and VHI data were derived from the Space-based Weather and Climate Extremes Monitoring (SWCEM) project established by the World Meteorological Organization (WMO) (Kuleshov et al. 2019); whereas the SSM was obtained from The National Aeronautics and Space Administration (NASA)-Enhanced U.S Department of Agriculture (USDA)'s Soil Moisture Active Passive (SMAP) Global Data, using Google Earth Engine (GEE) tool (JD Bolten et al. 2010; J Bolten and Crow 2012; Sazib et al. 2018). Space-based observations of precipitation provide global coverage and has potential to complement in situ rainfall
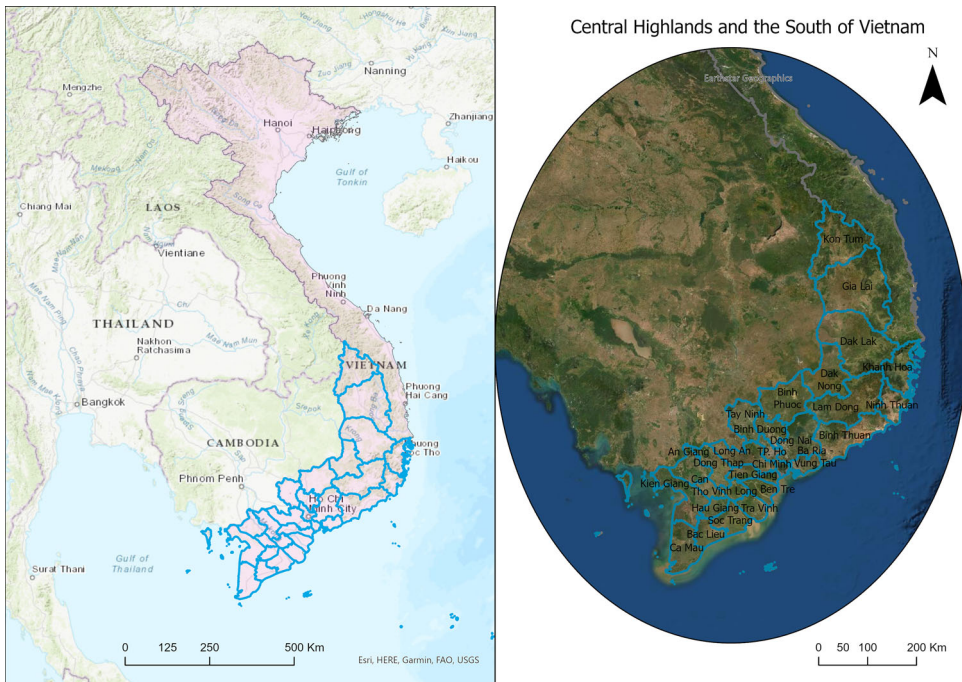
Figure 1. The study area in Vietnam showing regions and provinces.

measurements (Kuleshov et al. 2016; 2019). Earlier studies for Australia and Papua New Guinea demonstrated value of using SWCEM satellite precipitation estimates and derived products such as SPI and VHI for drought risk assessment (Kuleshov et al. 2019; Sun et al. 2020; Chua et al. 2020a; 2020b; Aitkenhead et al. 2021; Bhardwaj et al. 2021). Enhanced USDA's SMAP Global Data soil moisture data was also validated in a number of agricultural drought research (Mladenova et al. 2019; 2020; Sazib et al. 2020). Using the combination of SPI, VHI, and SSM to calculate DHI is the novelty of this study for drought risk assessment in Vietnam.

The paper is organized as follows. Section 2 describes the study area while section 3 discusses data and methodology used in this study. Results are presented in section 4, and discussed in section 5.

2. Study area

The Southern part of Vietnam which was severely affected by drought in 2015–2016 and 2018–2020 (UNDP 2016; UNESCAP 2020), was selected as the study area (Figure 1). It includes 27 provinces from four administrative regions: the South Central Coast (Khanh Hoa, Ninh Thuan, and Binh Thuan); the Central Highland (Kon Tum, Gia Lai, Dak Lak, Dak Nong, Lam Dong); the South East (Ho Chi Minh, Ba Ria – Vung Tau, Binh Duong, Binh Phuoc, Dong Nai, Tay Ninh); and the Mekong Delta region (Long An, Tien Giang, Ben Tre, Tra Vinh, Vinh Long, Kien Giang, Hau Giang, Soc Trang, Bac Lieu, Ca Mau, Can Tho, An Giang, and Dong Thap).

The study area lies within the South Central, Central Highlands and the South climate sub-regions of Vietnam; this part of Vietnam has a moderate tropical climate and is affected by the South West monsoon which causes substantial rainfall from May to October. The dry conditions usually occur in this area from November to April (MONRE 2019; Stojanovic et al. 2020; WB 2020).

The topography of the study area is complex. The Central South Coast including Ninh Thuan, Binh Thuan, and Khanh Hoa have mountainous topography along the border with the Central Highlands; and a flat topography toward the East Sea (Tran et al. 2017). By contrast, the Central Highlands are characterized by Plateau topography with high mountains in the West that range from 1,000 m to 2,500 m (Vu MT et al. 2015). Located on a large and wide plain, the South East is the transition region from South Central plateau to Mekong River Delta, with the elevation terrain changes from 200 m to 2,000 m. The Mekong Delta region is in the Southwestern part of Vietnam and the ending part of the Mekong River Basin. Except for a mountainous area in the North, the region has rather flat terrain and is at low altitude above sea level (Phan et al. 2020).

The South Central Coast is considered as having an average economic development status compared with the entire nation thanks to its advantages of coastline position. The population density in three provinces of this region is relatively high, with an average number of 190 persons/km^2. The Central Highland provinces, on the other hand, encounter socio-economic difficulties due to poor infrastructure, skilled labour shortage, low standard of living, and possibilities of ethnic-group conflict. However, the area has the advantages of natural resources with the biggest national reserve of fertile soil suitable for industrial crops such as coffee, tea, cocoa, pepper, and mulberry. The South East is the most economically developed region in Vietnam, with its leading index in export value, industrial production, foreign investment, and GDP. The total population in this area in 2019 was almost 18 million accounting for 18.5% total population of the whole country. Finally, the Mekong Delta is the largest centre of agricultural, fishery and fruit production in Vietnam. The region's rice production accounts for 50% of the country's production and the GDP of the Mekong Delta as of June 2019 is 7.8%. The area has a population of approximately more than 17 million people, accounting for 18% of the national population (2019).

3. Data and method

3.1. Drought hazard, vulnerability and exposure indicators

While SPI is recommended by the WMO (Svoboda and Fuchs 2016) and widely used for drought monitoring, it is acknowledged that the index alone may be insufficient to adequately assess reduced soil moisture and stress on crops which is associated with agricultural drought (UNESCAP 2020). For drought hazard assessment, we use a combination of SPI, VHI, and SSM as indicators; both SPI and VHI indices were derived from WMO SWCEM satellite precipitation estimates (Kuleshov et al. 2019), while the SSM was obtained from NASA-Enhanced USDA's SMAP Global Data. The SPI, developed by McKee and co-workers (McKee et al. 1993; McKee 1995), is a main meteorological drought indicator, used to identify a precipitation shortage by

Table 1. Indicators and data sources used for calculating DHI, DEI, and DVI.

Index	Indicator	Description	Correlation to overall drought	Data source[1]
DHI	SPI	SWCEM-CMORPH-BLD, 90 day, SPI, 0.25*0.25 degree, monthly satellite images 2020.	Negative	WMO SWCEM https://ftp.cpc.ncep.noaa.gov. . . . .
	VHI	SWCEM VHI, 0.25*0.25 degree, monthly satellite images 2020.	Negative	WMO SWCEM https://ftp.cpc.ncep.noaa.gov. . . . .
	SSM	NASA-USDA Enhanced SMAP Global SSM data, 10-km spatial resolution, 2020	Negative	NASA-USDA Enhanced SMAP https://developers.google.com/earth-engine/datasets/catalog/NASA_USDA_HSL_SMAP10KM. . . . . .
DEI	Percentage of agricultural land area	The percentage of agricultural production land area to the total land of each province, %	Positive	Provincial statistical yearbook, 2019
	Agricultural population density	Number of people with agricultural occupation kilometer of land, Persons/km^2	Positive	Provincial statistical yearbook, 2019. *The data in Tra Vinh and Dak Nong is taken in 2018.*
DVI	Agriculture, forestry and fishing values added (as a percentage of GDP)	Percentage of GDP, %	Positive	General statistic office of Vietnam, 2019
	Multi-dimensional poverty rate (%) 2019*	The multi-dimensional poverty line is defined upon two criteria, including income-based criteria and basic-social-service-based criteria, %	Positive	Provincial statistical yearbook, 2019
	The adult literacy rate	The literature rate of people aged from 15, %	Negative	General statistic office of Vietnam, 2019
	Percentage of monthly average income per capital based on agriculture, forestry and fishery (2019)	Percentage of total per-capital average income, %	Positive	General statistic office of Vietnam, 2019

comparing the total precipitation during certain months (i.e. 1, 3, 12, 48 months). The VHI is the result of work done by Kogan (Kogan 1990, 1997, 2001). VHI combines both the Vegetation Condition Index and the Temperature Condition Index and thus evaluates the severity of drought based on vegetation health and impact of air temperature on plant conditions. Low values of VHI (e.g., 40 and lower) would indicate stressed vegetation conditions and over a longer period would be indicative of drought (FAO 2018; Bhardwaj et al. 2021). SSM is the relative water content of the topmost layer, which has been proved useful for monitoring vegetation health and considered as an effective indicator of agricultural drought. SSM's values are typicaly in a range from 0 to 25 mm. This drought indicator was developed, modified and corrected from the Palmer two-layer soil moisture model (Entekhabi et al. 2010; JD Bolten et al. 2010).

Selecting appropriate indicators for calculating drought exposure and vulnerability indices, we applied the following three criteria: (i) indicators are relevant to agricultural sector; (ii) data for these indicators are quantitative and publicly available, and (iii) indicators are specific to Vietnam's socio-economic conditions.

Based on these criteria, we selected the following two exposure indicators: (i) 'agricultural population density' (the number of people working in the agriculture sector per unit of land area): higher agricultural population density reflects higher level of exposure of population at risk to drought, and (ii) 'percentage of agricultural land per total provincial land area': as agricultural activities are most likely to be affected by drought due to water shortage, higher percentage of agricultural land area means higher exposure to drought.

For drought vulnerability assessment, four key indicators were selected considering various socio-economic factors: (i) 'The percentage of agricultural, forestry and fishing value added per GDP', which is directly associated with the value of primary agricultural production; (ii) 'Multi-dimensional poverty rate', which indicates capacity of people to cope with drought impacts; (iii) 'The adult literacy rate': this indicator is based on the assumption that poorly educated population have low capacity of finding alternative employment, adaptation tools and seek support from the government and other social entities, thereby being vulnerable to drought; and (iv) 'The percentage of monthly average income per capita based on agriculture, forestry and fishery', which directly reflects dependence of people on agricultural-related economic activities and thereby shows their vulnerability to drought. Summary of indicators and data sources used for calculating DHI, DEI, and DVI is presented in Table 1.

Other indicators widely used in drought vulnerability assessment could also be appropriate; however, data were not readily available. For example, 'access to safe drinking water' could be an appropriate indicator, yet only data on 'urban population provided with clean water' is available from Vietnam statistics yearbooks. In addition, while 'rural population' appears as a suitable indicator for assessing drought vulnerability, confidence in reliability of this indicator is low given the fact that rural population is undergoing through rapid rural-urban transition process (Saksena et al. 2014). 'GDP per capita' was not selected because it does not directly reflect the economic capacity particularly in agricultural sector as it takes into consideration different sources of income rather than merely from agricultural production activity.

3.2. Data manipulation and mapping

To calculate DHI, data for SPI, VHI, and SSM was extracted for the study area using ArcGIS tool. This spatial data was classified and mapped to demonstrate monthly drought progression and then transformed into statistical data at the administrative level using Zonal statistics tool of ArcGIS (Kim et al. 2021; ESRI n.d.-b). The average statistical value of SPI, VHI, and SSM for each province in the dry season was used to calculate DHI for each province.

As most of the selected indicators have different measurement units and scale, data was standardized considering maximum and minimum values of each determinant across administrative regions and transforming the data into a range between 0

and 1. For indicators with a positive correlation to the overall vulnerability, standardized indicator values were calculated using equation (1). Equation (2) was used to calculate standardized values of indicators with negative correlation to the overall vulnerability (SPI, VHI, SSM, and literacy rate).

$$z_i = \frac{x_i - x_{min}}{x_{max} - x_{min}}, \tag{1}$$

$$z_i = 1 - \frac{x_i - x_{min}}{x_{max} - x_{min}}, \tag{2}$$

where z_i – normalized indicator value, x_i – indicator value for province i, x_{min} and x_{max} – respective minimum and maximum values across all provinces (Naumann et al. 2014).

Once the data for each indicator was standardized, the hazard, exposure and vulnerability indices (DHI, DEI, and DVI) were calculated using equations (3), (4) and (5), respectively.

$$DHI = \frac{1}{n} \sum_{i=1}^{n} z_i, \tag{3}$$

where DHI is the drought hazard index, n is the number of hazard indicators, and z_i refers to the standardized hazard indicators.

$$DEI = \frac{1}{n} \sum_{i=1}^{n} z_i, \tag{4}$$

where DEI is the drought exposure index, n is the number of exposure indicators, and z_i refers to the standardized exposure indicators.

$$DVI = \frac{1}{n} \sum_{i=1}^{n} z_i, \tag{5}$$

where DVI is the drought vulnerability index, n is the number of vulnerability indicators, and z_i refers to the standardized vulnerability indicators.

Finally, DRI was calculated using equation (6) (Le VT et al. 2019; Sun et al. 2020):

$$DRI = (DHI + DEI + DVI)/3, \tag{6}$$

where DHI, DEI and DVI are the hazard, exposure and vulnerability indices, respectively.

GIS was used to produce maps of drought hazard, exposure, vulnerability and risk. To produce map layers of DHI, DEI, DVI, and DRI for each province, the data was classified using ArcGIS's natural break classification method (Nasrollahi et al. 2018; ESRI n.d.-a). The Natural Breaks classification method, developed by George Frederick Jenks in 1967, is an attempt to classify data in the most accurate way. The classification scheme arranges values into classes by iteratively comparing sums of the
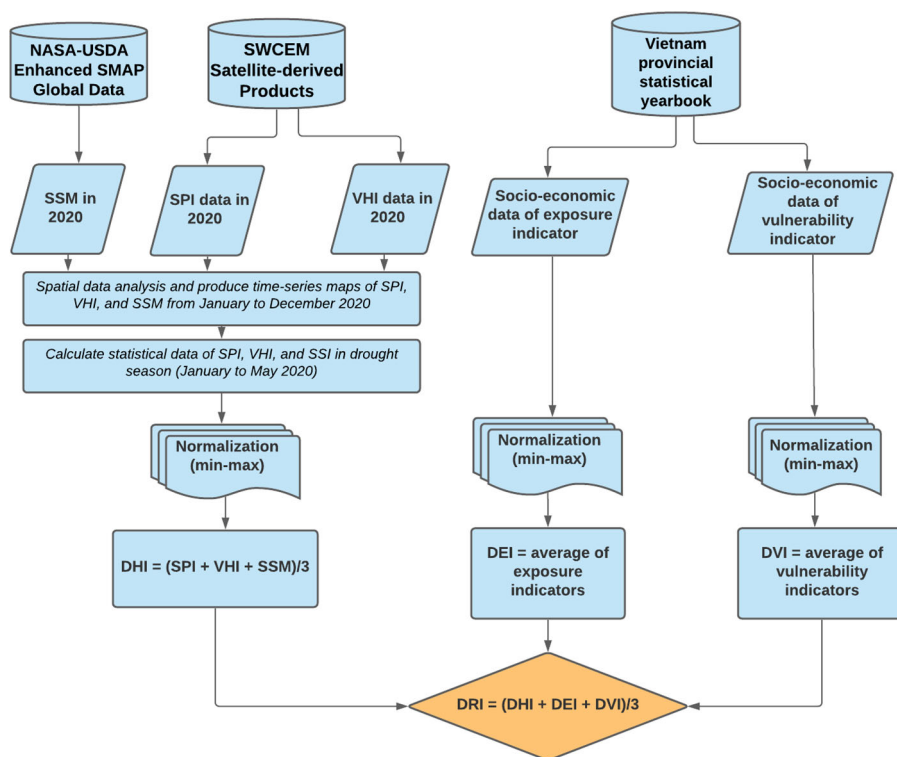
Figure 2. The methodology flow chart.

squared difference between observed values within each class and class means. This classification method is broadly used by cartographers to represent spatial data with less than 07 breaks or classifications (Baz et al. 2009; Chen et al. 2013). In this research, four classes were established for each type of index: mild, moderate, severe, and extreme level. The flow chart of method is presented in the Figure 2.

4. Results

4.1. Case study for the 2020 drought

As a proof-of-concept for the developed approach to drought risk assessment, a case study of drought in Vietnam in 2020 was selected. This year is chosen because of two main reasons. First, the most updated rainfall data was released in full by (SWCEM)/ (WMO) in 2020. We believe that the drought risk in one-year 2020 can demonstrate our method of drought risk composite index which considers three components: hazard, exposure, and vulnerability. The year 2020 is also the time period when Vietnam suffered from extreme drought condition (Khoa 2020; Quoc 2020; UNESCAP 2020), not long after 2015–2016 disastrous drought period in Vietnam (UNDP 2016).

Remotely-sensed SPI, VHI, and SSM data for the year 2020 was classified and calculated using ArcGIS to evaluate drought risk over the study area. An evolution for drough conditions as indicated by SPI, VHI, and SSM maps from January to December 2020 is shown in Figures 3–5, respectively.
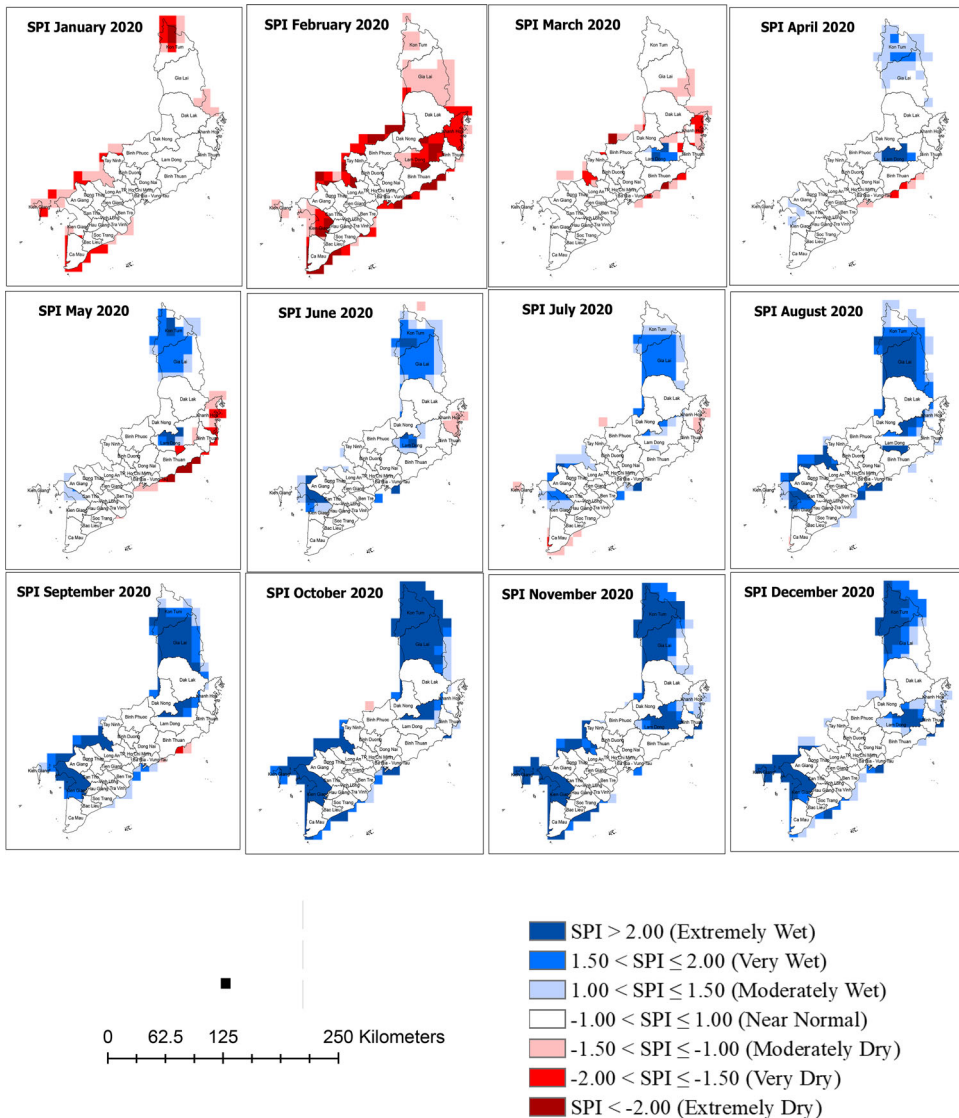
Figure 3. Maps of SPI from January to December 2020.

SPI data analysis indicated that drought conditions occurred in the study area from January to May with average monthly SPI values over the study area ranging from −3.7 to −0.16; severe or extreme drought were observed in most provinces in February (Figure 3). Drought conditions indicated by SPI are in agreement with the rainfall seasonality in the study area which experiences wet conditions during the East Asian monsoon (Vu TM et al. 2018). Depending on the region, onset of the rainy season differs; however, typically the rainy season begins in April-May and ends in November-December (WB 2020).

SSM derived from NASA-Enhanced USDA's SMAP Global Data also indicate drought in January to May in the study area (Figure 5), which shows a very good agreement with the SPI result and the practical seasonality of drought pattern
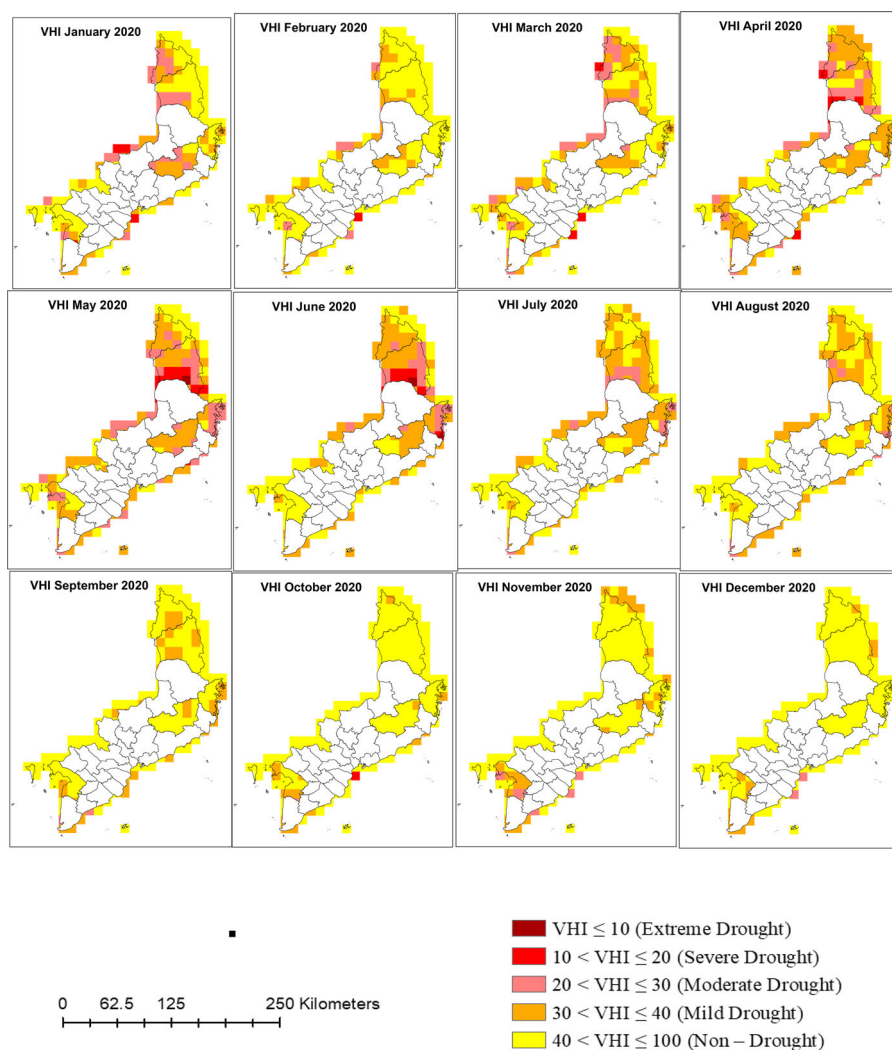
Figure 4. Maps of VHI from January to December 2020.

(MONRE 2020; WB 2020). It was observed from SSM monthly maps that March was the driest month among 12 months in 2020.

Analysing monthly VHI maps, it was found that drought conditions occurred from April to July with May being the driest month with a VHI mean value of about 35 (Figure 4). There is three-month time lag between agricultural drought (as represented by VHI) and meteorological drought (as represented by SPI), which can be explained as the time for vegetation to respond to drought (Wang et al. 2014; Ryu et al. 2019). Further research is required to assertain the correlation between SPI and VHI in indicating drought conditions; however, it is not within the scope of this study.

The results of case study for drought in 2020 demonstrate that SPI and VHI derived from SWCEM as well as SSM derived from NASA-Enhanced USDA's SMAP Global Data perform well for assessing drought hazard in the study area. The drought
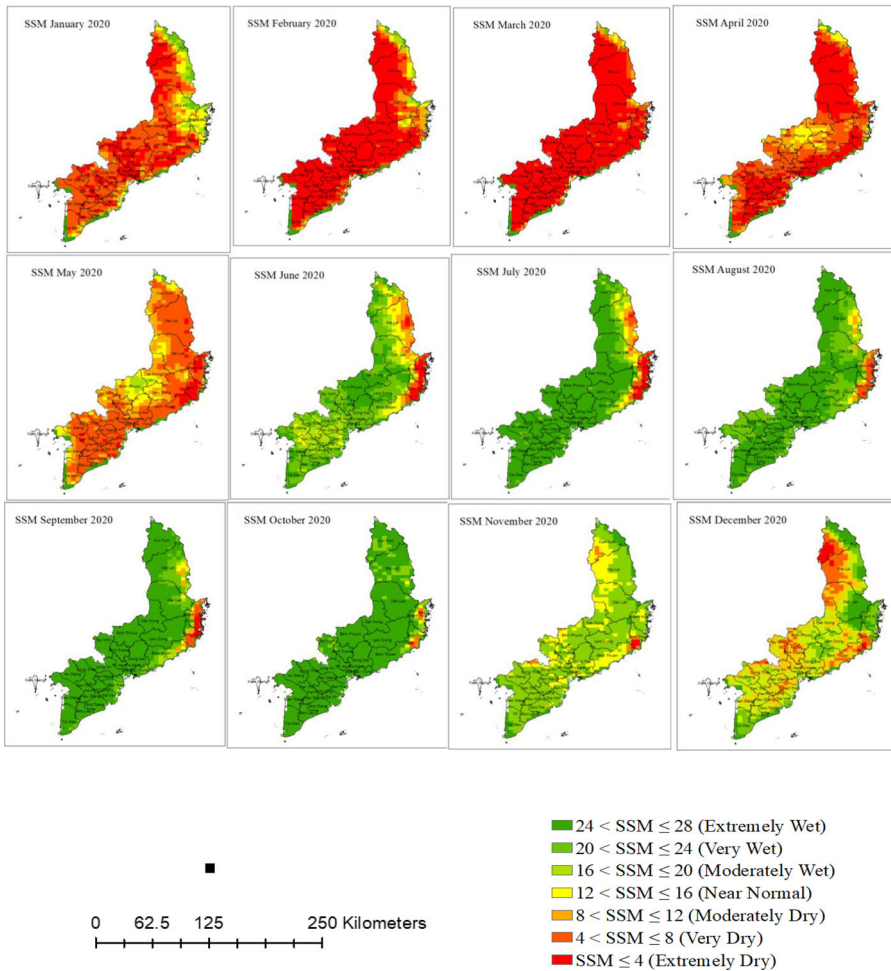
Figure 5. Maps of SSM from January to December 2020.

period is identified from January to May based on the results of drought pattern analysis of SPI and SSM indicators and it is also supported by the literature (MONRE 2020; Stojanovic et al. 2020; WB 2020).

4.2. Drought risk

Ranking of drought risk for administrative provinces in the study area is essential for prioritization in drought risk management given the fact that Vietnam has limited resources for adaptation and response. The mapping results for drought hazard, exposure, vulnerability, and the combined drought risk index are presented in Figure 6.

4.2.1. Drought hazard
For comparison and ranking among administrative provinces, average statistical data of SPI, VHI, and SSM values during drought conditions identified from
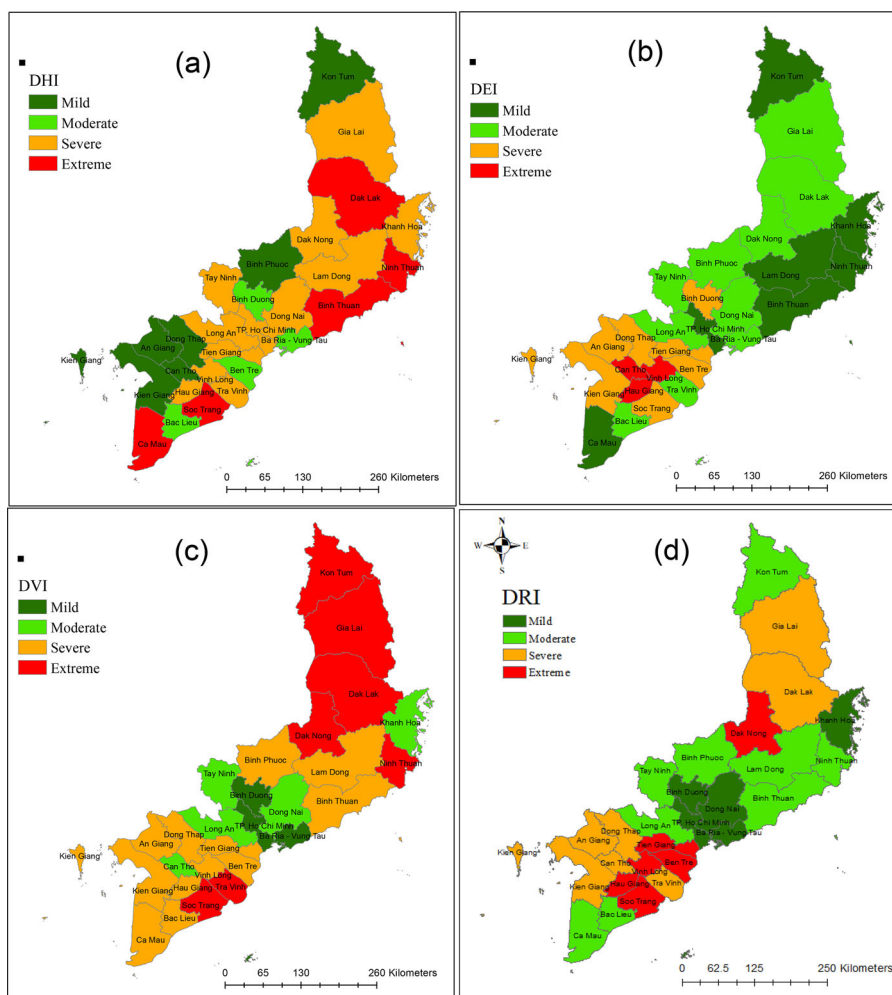
Figure 6. Maps of (a) DHI; (b) DEI; (c) DVI, and (d) DRI.

January to May, were calculated to produce DHI. Under the assumption that SPI, VHI, and SSM are equally important contributors, the DHI was computed as the arithmetic mean with equal weighting of these three indices after being standardised using min-max function. The results were then classified into four levels: mild, moderate, severe, and extreme drought hazard by natural breaks classification method. The DHI map (Figure 6a) shows that a large part of the study area suffered from drought condition, in which the top-ranking provinces include Binh Thuan, Ca Mau, Dak Lak, Ninh Thuan and Soc Trang. Indeed, Binh Thuan was also declared as a hot spot in the past drought event in 2016 (UNESCAP 2020). Although this South Central Coast province is affected by East Asian monsoon from May to October, its topographic condition with Truong Son range has limited the precipitation amount and make it prone to extremely dry condition (Tran et al. 2017; Hien et al. 2019).

4.2.2. Drought exposure

The DEI was calculated based on statistical data of exposure assessment indicators including percentage of agricultural land area and agricultural population density. Averaging with equal weighting was used and then the DEI was classified into four levels: mild, moderate, severe, and extreme exposure. Drought exposure map shown in Figure 6b demonstrates that the Mekong Delta region, except Ca Mau, has higher exposure to drought compared to other regions; and in this region, the most exposed provinces are Vinh Long, Hau Giang, and Can Tho. The higher index values can be attributed to high proportion of agricultural population and assets in this region. In Hau Giang, for example, there is 83.7% agricultural land over total land use area, and its agricultural population density is also the highest in the study area (121 persons/km^2). In general, provinces which are more associated with agricultural activities shown through high percentage of agricultural land and density of population working in agricultural production sectors are more exposed to drought risk.

4.2.3. Drought vulnerability

Drought vulnerability in this study is referred to socio-economic conditions of the population including agriculture value added, agriculture-sourced monthly income of population, poverty rate, and literate rate (see Table 1 for details). Similar to DEI, DVI was also classified into four levels: mild, moderate, severe, and extreme vulnerability. The map of drought vulnerability index shown in Figure 6c indicates that mountainous provinces in Central Highlands are most vulnerable to drought. This region has high poverty rate and heavy dependency on agriculture for income. In addition, some provinces in the Mekong Delta region including Soc Trang and Tra Vinh also have less adaptation capacity to drought due to poor socio-economic condition. By contrast, least vulnerable provinces are located in the South East region, including Dong Nai, Ba Ria-Vung Tau, Binh Duong and Ho Chi Minh city. These are most economically developed provinces where economic activities are dependent on the industrial and service sectors. Additional correlation analysis was conducted to show the contribution of the selected indicators to the overall DRI. The results show that among four vulnerability indicators, agriculture sourced income had the greatest contribution (0.87) while literate rate and agriculture value added indicators came second (0.83) and third (0.81), respectively. The indicator with least contribution was poverty rate (0.65). This suggests that developed areas with less reliance on agricultural activities and higher education level are less vulnerable to drought risk.

4.2.4. Drought risk

The DRI map shown in Figure 6d provides overall ranking of drought risk across the provinces, which integrates three assessment components of hazard, exposure, and vulnerability. This map allows to identify provinces most at drought risk. Among the administrative regions, provinces in the lower Mekong Delta region which have severe DRI are Vinh Long, Hau Giang, Soc Trang, Tien Giang, and Ben Tre. The high values of DRI are related to high exposure and vulnerability of these provinces to drought (Figure 6b and c). In addition, when proposing national plan for drought mitigation strategy, Central Highland provinces such as Dak Nong, Gia Lai, and Dak

Lak should be paid attention as they have high drought risk. The DRI map also demonstrates that the region with least drought risk is the South East where provinces are less exposed, less vulnerable, and less likely to suffer from drought hazard (Figure 6a–d). Further information can be found in Appendix (online Supplementary material) (DHI, Table A1; DEI, Table A2; DVI, Table A3; DRI, Table A4).

5. Discussion and conclusion

The expected outcome from this study aims to support drought mitigation and adaptation strategies by policy makers and technical officials, especially in the agriculture sector, to identify high drought risk areas in Vietnam. This can be achieved through the following specific objectives: (i) to propose appropriate set of indicators, data sources, and quantification method for drought risk assessment; and (ii) to create drought risk maps for Vietnam.

According to the World Bank's definition of drought risk and its three elements including hazard, exposure, and vulnerability, drought hazard refers to the physical aspects of drought events and it can be characterized in terms of their severity and frequency (WB 2019). Drought exposure, on the other hand, refers to existing elements such as the entities, assets, infrastructure, and people in an area in which drought hazards may occur. Among the three elements, vulnerability is the broadest concept and involves both biophysical and socio-economic dimensions (Tánago et al. 2016). Biophysical aspects of vulnerability refer to environment conditions such as topography, soil characteristics, river network, and vegetation cover that make the area more vulnerable to drought (Shahid and Behrawan 2008; Alamdarloo et al. 2021; Kim et al. 2021); whereas, socio-economic vulnerability convey the characteristics of a social group that makes it susceptible to suffering the consequences of drought (Cheng and Tao 2010; Naumann et al. 2014; Carrão et al. 2016). For this reason, the socially vulnerable are believed to be more affected by disaster events, and this social vulnerability is often linked with a lack of capacity to cope with disaster stress (Nguyen et al. 2019).

This study presents, for the first time, a comprehensive drought risk analysis as proof of concept for Vietnam by incorporating the hazard and socio-economic conditions of the regions, and use of space-based SPI, VHI, and SSM for drought hazard assessment. The findings confirm the importance of socio-economic aspects in addition to physical hazard in drought risk assessment. The proposed composite DRI overcomes the limitations of the drought assessment methods currently undertaken in Vietnam which focus predominantly on drought hazard monitoring. In fact, limited information of drought hazard would result in inappropriate and inadequate mitigation measures. For example, our findings show that the Mekong Delta has the largest area with high DRI as the region depends heavily on agriculture and has poor socio-economic conditions, even though the Mekong Delta region is not on the top list of DHI. Therefore, drought response strategy should be prioritized for this region.

It is also emphasized that each drought risk component (DHI, DEI and DVI) is as important as the final combined DRI. Indeed, component drought risk layers allow investigation of overall DRI and characteristics of each province under drought impact,

such as the probability of drought hazard occurrence, the level of exposure, and the adaptation capacity. This can help drought managers to propose suitable approach for drought response depending on circumstances in each province or region. For example, although Binh Thuan and Ca Mau have moderate level of drought exposure and drought vulnerability, DHI shows that these provinces are most likely to suffer from drought. Therefore, an appropriate response could be investing in early warning service and proposing flexible plan for crop planting season. Meanwhile, provinces in the Mekong Delta region with heavy dependence on agriculture may consider shifting its economic structure toward industrial development thereby lowering its reliance on agricultural production due to high potential drought risk.

Composite index of drought risk is increasingly recognized as a powerful tool in drought risk management as it often seems easier for the public to interpret composite indicators rather than to identify common trends across many separate indicators. However, a composite indicator could potentially give misleading policy messages because it may cause policymakers to draw simplistic policy conclusions (Svoboda and Fuchs 2016). To reduce this risk, when applying the results of DRI, it is important to acknowledge an associated assumption made during the process (Baptista 2014). In case of this proof-of-concept study, the selection of indicators was relatively subjective with aim to focus on drought risk assessment for agricultural sector. In addition, when taking the region-averaged value, it is assumed that every part in the same provinces is equally affected by drought. However, in practice, each province may have further administrative division such as districts and communes that may have different levels of impact from drought events.

In summary, drought risk assessment incorporating hazard, exposure and vulnerability components was conducted for 27 provinces from four administrative areas in Vietnam: South Central Coast, Central Highlands, South East, and Mekong River Delta. Satellite data of SPI, VHI, and SSM for 2020 was used for drought hazard assessment. Meanwhile statistical data of land use and socio-economic characteristics for exposure and vulnerability assessment was obtained from statistical yearbooks for 2019. Maps of drought hazard, exposure, vulnerability, and the combined drought risk map were produced in GIS. The results showed that the highest at-risk provinces were in the Mekong Delta region which is the agricultural production centre of Vietnam. By contrast, the South East region was less impacted by drought compared to other regions. The assessment results can be used to identify the areas of higher drought risk and provide prioritized actions of adaptation through crop selection, irrigation plan, and tillage practice. SPI and VHI data derived from WMO SWCEM products and SSM derived from NASA-Enhanced USDA's SMAP Global Soil Moisture Data were used to improve spatial coverage and the accuracy of the drought hazard assessment. This case study examined a severe drought event in selected provinces of Vietnam for one year (2020); future research could extend this proof-of-concept methodology to assess drought risk for the entire country and on a longer time period. Drought risk analysis at district or community level would be useful for developing more specific and detailed regional plan for drought risk management.

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Disclosure statement

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Data availability

Datasets related to this article can be found at:

- https://ftp.cpc.ncep.noaa.gov/precip/PORT/SEMDP/. . . . . , an open-source online data repository hosted by WMO Space-based Weather and Climate Extremes Monitoring Demonstration Project (WMO n.d.).
- https://developers.google.com/earth-engine/datasets/catalog/. . . . . , an open-source online data for NASA-USDA Enhanced SMAP Global Soil Moisture Data (Earth Engine Data Catalog [date unknown]).
- https://www.gso.gov.vn/en/statistical-data/. . . . . , an open-source online data repository hosted by the General Statistics Office of Vietnam (GSO n.d.).
- Provincial Statistical yearbook of each province in the study area is obtained from each respective provincial statistical website.

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