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Article

A New Assessment of Drought Risks on Economic and Social Sectors in Sukhothai Province, Thailand

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Abstract. This research introduces a novel approach to assess multiple drought risks through the development of a comprehensive Drought Risk Index (CRI). This index is developed by multiplying a newly formulated Multiple Drought Hazard Index (MDHI) with a Combined Vulnerability Index (CVI) and a Combined Exposure Index (CEI). The MDHI accounts for the impacts of meteorological, hydrological, and agricultural droughts, while the CVI and CEI encompass combined economic and social dimensions. The computed drought risk maps delineate various risk levels across the Sukhothai Province from 2007 to 2020. Given data limitations, the observed drought damages in the area are utilized to estimate vulnerability. The economic analysis predominantly focuses on agricultural losses, whereas the social analysis examines the impacts on affected populations, households, particularly females, children, those in poverty, and the aging population. Economic exposure is assessed based on the values of agricultural products while social exposure is based on population density, households and vulnerable social contents. Analysis of drought risk maps spanning 2007 to 2020 reveals a consistent escalation in drought-affected areas, transitioning from absence of drought to severe occurrences over the decades. Evaluating direct impacts in monetary terms and the number of affected population and households provides valuable insights into the historical and present-day ramifications of droughts. This study pioneers a novel methodology for drought risk assessment, aiming to adapt and mitigate potential future drought impacts.

Keywords: Drought risk assessment, multiple hazard, vulnerability, exposure, socio-economic impacts, Sukhothai Province.

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1. Introduction

Drought is a major natural disaster that affects water resources for human and environmental needs [1]. It occurs when precipitation is shortage and/or surface and groundwater are limited. Many countries face severe droughts, especially in South-East Asia, where over 70% of the region experienced extreme droughts in 2015-2016 and 2018-2020 after the 1997-1998 El Niño. These droughts exposed about 325 and 210 million people to moderate and high drought risk levels [2]. In Thailand, drought impacts various economic sectors, mainly agriculture. The estimated damage cost was 1.7 billion baht in 13 provinces during 2015-2016 [3]. In 2020, crop production losses reached 26 billion baht or US dollars 840 million (1Baht=0.028US dollars), and off-season rice production declined by 40% [4]. About 32,000 hectares of crops and orchards were damaged by the worst drought in 40 years [5]. Paddy fields, which cover 18% of the country area [6], are the most vulnerable. Rice is a vital export product for Thailand, along with tapioca, rubber, and canned pineapple [7]. However, drought analysis requires more than meteorological conditions (precipitation and temperature). Soil, surface, and groundwater storage also affect crops and humans. Soil moisture in the root zone relates to crop stress [8] or agricultural drought [9], which worsens with low precipitation. A long dry period can cause water shortage in streamflow, reservoir, and groundwater, leading to hydrological drought [10-11].

Different drought types require various indicators or indices to measure their severity, location, and duration [12]. The Standard Precipitation Index (SPI) is a global drought monitor that uses precipitation data to characterize meteorological drought [13]. It shows the period and intensity of precipitation deficit. For hydrological drought, surface and subsurface water resources are often measured by the Standardized Runoff Index (SRI), Standardized Streamflow Index, and Standardized Groundwater Index (SGI) from runoff and groundwater level data [14-18]. Remote sensing is used to analyze vegetation health and soil moisture on land surface by the Normalized Difference Vegetation Index (NDVI) [19-21]. The Normalized Difference Moisture Index (NDMI) indicates the status of soil water content and vegetation health for agricultural drought [22]. Socioeconomic drought is commonly assessed by surface water supply for household and agriculture using the Water Supply Index (SWSI) [23-24]. According to WMO and GWP [12], no single indicator can present all drought types due to different hydro-meteorological conditions in each country and region. The best way to determine drought indicator is using a multiple or composite index that covers all drought types. The multiple drought index has been developed in recent decades. For example, a previous study developed Multiple Drought Index (CDI) from the link between SPI and Streamflow Drought Index (SDI) in a sub-basin of Han River, Korea [25-26]. Ali [26] assessed a new multivariate multiple drought index for the Blue Nile River Basin from SRI, SPI, standardized soil moisture index (SSI), and standardized evapotranspiration index (SETI) for meteorological, hydrological, and agricultural droughts, respectively. A new multiple drought hazard index (MDHI) is developed in this study, taking into account the standardized precipitation index (SPI) for meteorological droughts, the standardized runoff index (SRI) for surface hydrological droughts, the standardized groundwater index (SGI) for subsurface hydrological droughts, and the normalized difference moisture index (NDMI) for agricultural droughts.

Drought risk assessment usually analyzes past and present climate data to relate to previous drought situations [27]. In Thailand, drought affects many aspects of economic and social sectors. However, no research has assessed the agricultural damages and the affected people in monetary terms for the past and present periods. The affected people and households, especially children, elderly, and poor, need to be considered to present the overall drought impacts [28]. Understanding drought hazard, vulnerability, and exposure is the key to drought risk assessment, which can identify the potential critical areas and damages from drought events.

The main objective of this study is to assess the risk conditions on socio-economic sectors in Sukhothai Province, Thailand, utilizing a new approach in estimating of hazard, vulnerability, and exposure. The direct impact on the economic sector was quantified in monetary terms, while social impacts were analyzed mainly based on the number of affected people and housing units. However, the quantification of social impacts in monetary terms poses challenges due to the intricate nature of social systems, the prolonged and enduring effects of drought, and the incorporation of non-market values into the assessment. This study emphasizes the significance of integrating both economic and social factors in the assessment of drought risk in the past till present.

2. Study Area

The Sukhothai Province is located in the lower northern region of Thailand with approximately 440 kilometers from Bangkok. It has a land cover (approximately 6,596.09 square kilometers or 4,122,557 rai). The upper part is connected to the Phrae and Uttaradit Provinces, the lower part is connected to the Phitsanulok and Kamphaeng Phet Provinces, and the eastern and western parts are connected to the Phitsanulok-Uttaradit, and Tak-Lampang Provinces, respectively. The administration divides the province area into 9 districts, namely Mueang Sukhothai, Khiri Mat, Ban Dan Lan Hoi, Kong Krailat, Si Samrong, Sawankhalok, Thung Saliam, Si Satchanalai, and Si Nakhon Districts as shown in Fig. 1(a). There are 86 sub-districts and 843 villages in the province. The locations of meteorological, hydrological and groundwater stations are shown in Fig. 1(b).

In Fig. 1(c), the agricultural land is about 3,913.76 km^2 or 59.33% of total area; forest land is located at the upper part of area and 2,087.46 km^2 or 31.64% of total area;

habitable land, water body and miscellaneous land area are about 351.12, 180.43, 63.32 km² or 5.32, 2.74 and 0.97% of total area, respectively. Paddy field is large proportion in agricultural area (approximately 2,237.79 km² or 57.18% of agricultural area). Field crops are sugarcane, cassava, maize, etc. Fruit farm land and perennial crop e.g., mango, orange, rubber tree and oil palm cover about 1,184.45 and 463.59 km² or 30.26 and 11.85% of the agricultural area. The other agricultural area (integrated farm/diversified farm, horticulture, shifting cultivation, pasture and farm house and aquaculture land) is about 27.93 km² or 0.71% of agricultural area. The Sukhothai Province has a tropical climate which divides into 3 seasons: summer (March-April), rainy (May-October) and winter (October-February). The average annual rainfall is 1,225.3 mm and average temperature is about 27.2 degrees Celsius.

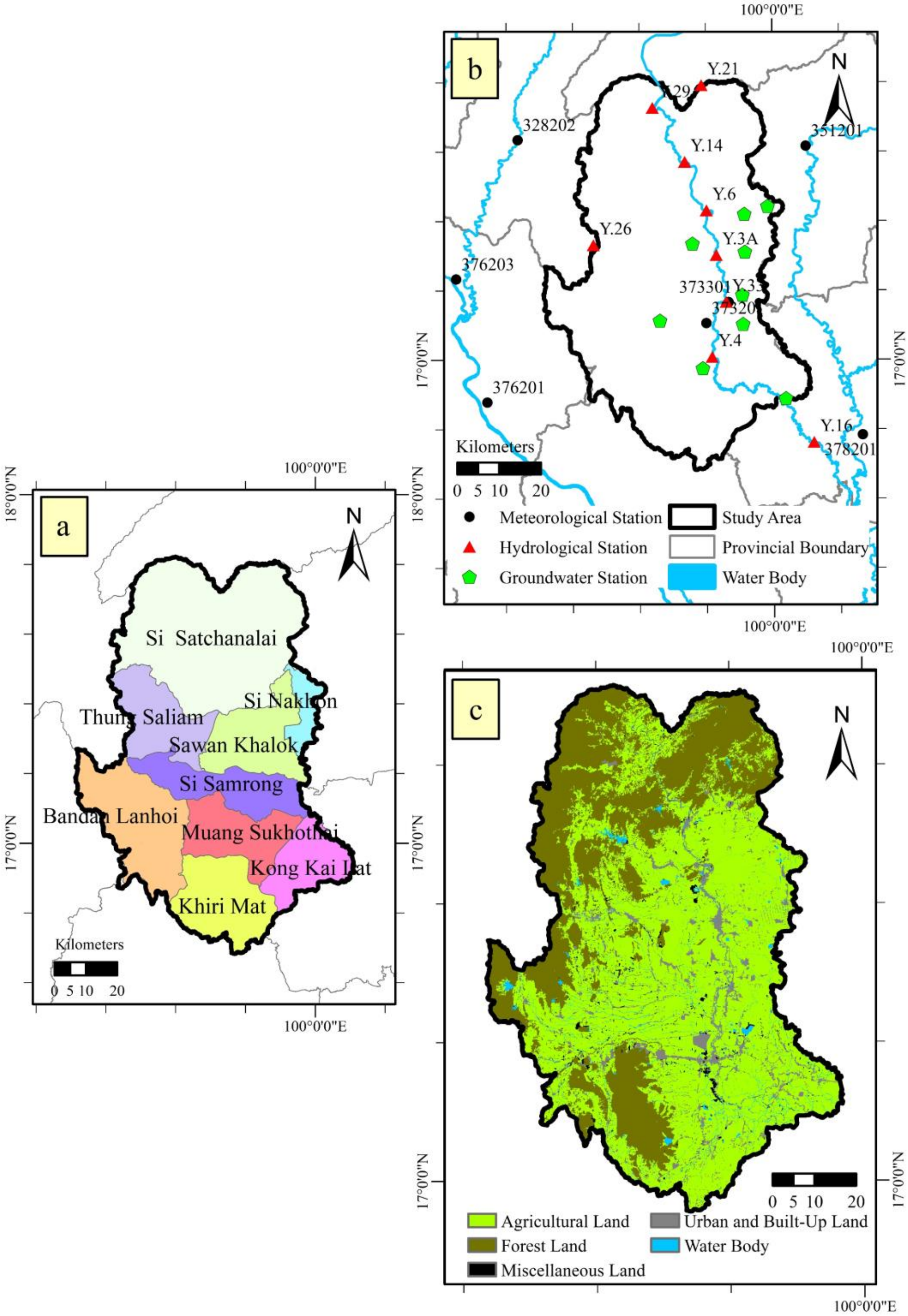

Fig. 1. (a) Sukhothai Province and its districts, (b) Locations of meteorological, hydrological and groundwater stations, and (c) Land use map in 2016.

3. Methodology

The overall methodology involves assessing drought hazards and risks in agricultural areas of Sukhothai Province as shown in Fig. 2. The research framework comprises three paths: Path A for drought hazard identification, Path B for vulnerability and exposure identification, and Path C for drought risk estimation.

Path A involves the development of a multiple drought hazard indices through the Multiple Drought Hazard Index (MDHI). The workflow in Path A extends from Block A.1 to Block A.4, as shown in Fig. 2. The index can represent three categories of droughts: meteorological, hydrological, and agricultural. The meteorological drought from Thai Meteorological Department (TMD) is characterized by the SPI, serving as a drought indicator. The SRI and SGI are derived from monthly runoff and groundwater level data from Royal Irrigation Department (RID) and Department of Groundwater Resources (DGR) in the study area, while the NDMI is obtained from satellite imageries from Landsat 5, 7, and 8 (https://earthexplorer.usgs.gov/). An approach employs the Analytic Hierarchy Process (AHP) technique to estimate weighting factors for each drought index (SPI, SRI, SGI, and NDMI). Then all drought indices and weighting factors are combined to form the multiple drought hazard indicator MDHI.

The workflow in Path B extends from Block B.1 to Block B.2. In Block B.1, the vulnerability is examined from physical characteristics, encompassing economic and social sectors. In the economic sector, the vulnerability index ($VI_{economic}$) is determined from the observed agricultural production losses and the drought duration-hazard-damage curves. The vulnerability index (VI_{social}) of the social sector is determined in relation to the observed drought hazard-damage curve. In Block B.2, the economic sector analysis focuses on agricultural damages, utilizing maps of crop income to define the exposure index ($EI_{economic}$). For the social sector, maps of vulnerable groups such as population and households, females, children under 5 years old, poverty, and aging population are used to determine the exposure index (EI_{social}).

The workflow in Path C extends from Block C.1 to Block C.2, utilizing input data from Paths A and B. The drought risk assessment investigates the estimation of the Drought Risk Index (CRI) from the function of hazard, vulnerability, and exposure. The study presents the past and current drought impacts in monetary terms in the economy sector and in numbers of affected people and housing units in social sector. The results of both drought hazard and risk maps will be compared with observed drought maps using statistical parameters.

3.1. Hazard

To assess drought hazard, this study investigates the different causes and parameters of agricultural, meteorological, and hydrological drought types. The multiple drought hazard index (MDHI) is developed by summing the weighted SPI for meteorological drought, the SRI and SGI for surface and subsurface hydrological drought, and the NDMI for agricultural drought. The respective weighting factors of SPI, SRI, SGI and NDMI are derived from the AHP technique The paddy field (rice) can withstand a rainfall shortage of about one month, while field crops (cassava, sugarcane, and corn) can withstand a rainfall shortage of about 3 months. For fruit crops, they can withstand a rainfall shortage of about 6 months. This guides us to use the timescales of 1, 3, and 6-months for paddy, field crop, and fruit/perennial crops, respectively.

The MDHI is calculated as the sum of the product of the weighting factor (W_i) and the hazard index (HI_i) for the three drought types: meteorological, hydrological, and agricultural as following:

$$MDHI = W_{SPI} \times HI_{SPI} + W_{SRI} \times HI_{SRI} + W_{SGI} \times HI_{SGI} + W_{NDMI} \times HI_{NDMI} \quad (1)$$

where MDHI is Multiple Drought Hazard Index, the sum of the weights $W_{SPI} + W_{SRI} + W_{SGI} + W_{NDMI} = 1$, W_i is the weighting factor from AHP, HI_i is the hazard index shown in Table 1.

Table 1. Drought hazard components.

No	Index	Drought Hazard Classification	Drought Hazard Level	HI_i	W_i
1	NDMI [22]	$NDMI \geq 0$	Canopy Cover	0	0.565
		$0 > NDMI \geq -0.20$	Mid-Low Canopy Cover, High Water Stress or Low Canopy Cover, Low Water Stress	0.20	
		$-0.20 > NDMI \geq -0.40$	Low Canopy Cover, Dry or Very Low Canopy Cover, Wet	0.40	
		$-0.40 > NDMI \geq -0.60$	Very Low Canopy Cover	0.60	
		$-0.60 > NDMI \geq -0.80$	Almost Absent Canopy Cover	0.80	
		$SRI < -0.80$	Bare Soil	1.00	
2	SRI [14]	$SRI \geq 0$	No Drought	0	0.262
		$0 > SRI \geq -1.0$	Mild Drought	0.25	
		$-1.0 > SRI \geq -1.5$	Moderate Drought	0.50	
		$-1.5 > SRI \geq -2$	Severe Drought	0.75	
		$SRI < -2$	Extreme Drought	1.00	
3	SGI [17]	$SGI \geq 0$	No Drought	0	0.118
		$0 > SGI \geq -1.0$	Mild Drought	0.25	
		$-1.0 > SGI \geq -1.5$	Moderate Drought	0.50	
		$-1.5 > SGI \geq -2$	Severe Drought	0.75	
		$SGI < -2$	Extreme Drought	1.00	
4	SPI [13]	$SPI \geq 0$	No Drought	0	0.055
		$0 > SPI \geq -1.0$	Mild Drought	0.25	
		$-1.0 > SPI \geq -1.5$	Moderate Drought	0.50	
		$-1.5 > SPI \geq -2$	Severe Drought	0.75	
		$SPI < -2$	Extreme Drought	1.00	
5	MDHI*	$MDHI \leq 0$	No Hazard		
		$0 < MDHI \leq 0.20$	Very Low Hazard		
		$0.20 < MDHI \leq 0.40$	Low Hazard		
		$0.40 < MDHI \leq 0.60$	Medium Hazard		
		$0.60 < MDHI \leq 0.80$	High Hazard		
		$0.80 < MDHI \leq 1.00$	Very High Hazard		

* MDHI is classified according to data provided by Land Development Department (LDD) and Department of Disaster Prevention and Mitigation (DDPM).

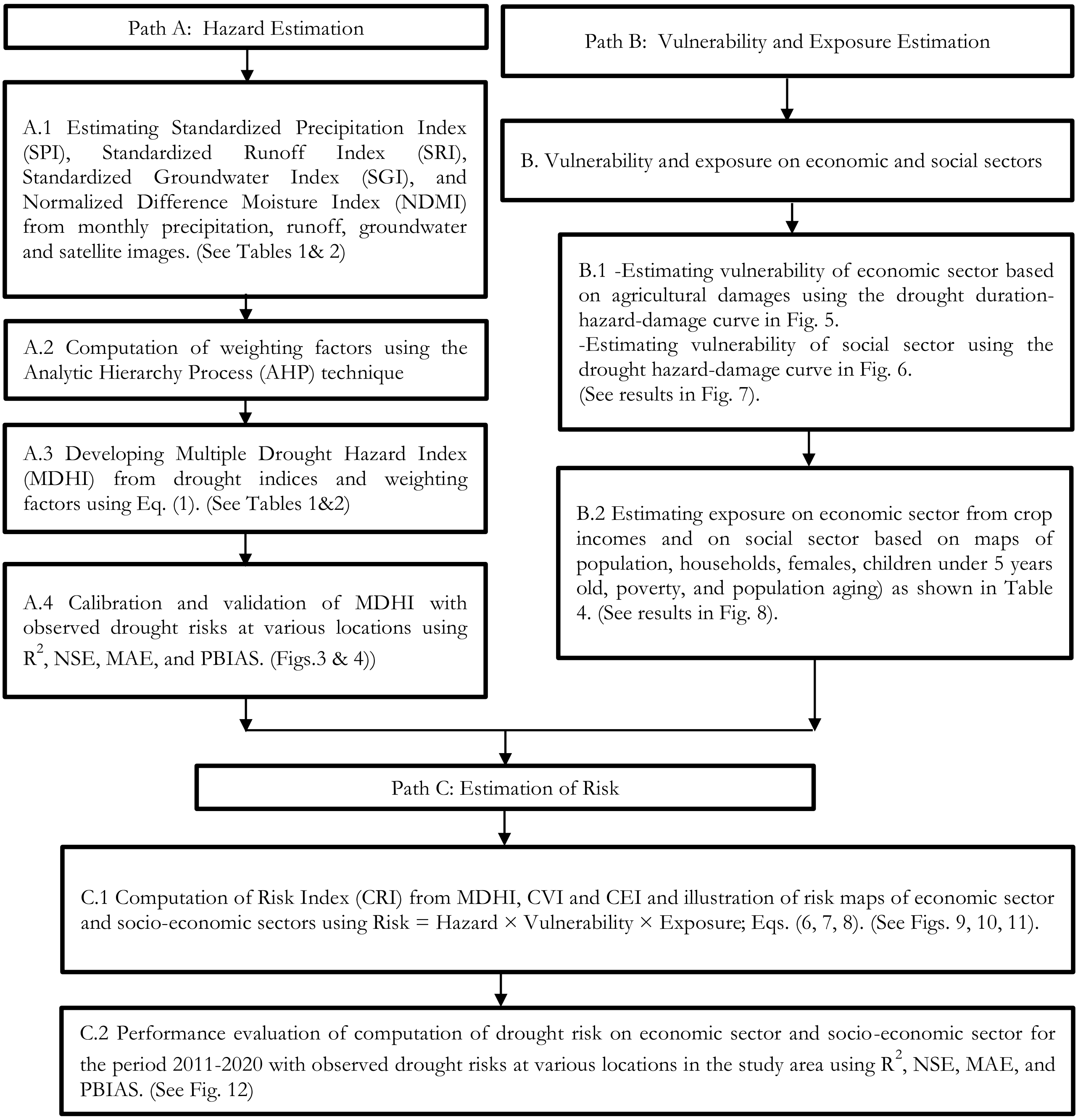

Fig. 2. Methodology and computational procedure for the drought hazard, vulnerability, exposure and risk on economic and social sectors in Sukhothai Province.

After developing the multiple drought hazard, it is classified into six hazard levels. These are: no (MDHI≤0), very low hazard (0<MDHI≤0.20), low hazard (0.20<MDHI≤0.40), medium hazard (0.40<MDHI≤0.60), high hazard (0.60<MDHI≤0.80), and very high hazard (0.80<MDHI≤1.00), as shown in Table 1.

This classification is based on repeated drought maps from 2006-2015 and 2012-2021 provided by the Land Development Department (LDD) (http://irw101.ldd.go.th/index.php), and drought-frequency maps at various locations from 2011-2020 provided by the Department of Disaster Prevention and Mitigation (DDPM) (https://portal.disaster.go.th/).

To measure the performance of the hazard simulation, four performance indicators were used: the coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), Mean Absolute Error (MAE), and Percent Bias (PBIAS). These indicators were used to verify the correlation between observed and computed hazard maps. The data observed consists of drought frequency maps, which were collected from DDPM. These maps include 827 surveying points gathered between 2012 and 2014, and 586 surveying points collected from 2015 to 2020. This data was used for calibration and validation purposes.

3.2. Vulnerability

Vulnerability is the condition of susceptibility to drought hazard of economic, social and environmental sectors [29]. In this study, the vulnerability is basically divided into two sectors: economic and social. The economic impact, which constitutes a large proportion of drought impacts, is the crop damage. Due to large variations of vulnerability over the large study area (6,596 km^2) from one location to another location, and lack of sufficient data, the vulnerability is estimated indirectly from the observed damages in the study area. The Vulnerability Index ($VI_{economic}$) is determined from the observed crop damage in relation to, drought duration and drought hazard, [30-32]. The Vulnerability Index (VI_{social}) of social sector is determined from the observed social impact or damage in relation to the drought hazard The Combined Vulnerability Index (CVI) for socio-economic sectors was analyzed from VI values of economic and social sectors as shown in Eq. (2).

$$CVI = W_{economic} \times VI_{economic} + W_{social} \times VI_{social} \tag{2}$$

where Combined Vulnerability Index is CVI value of economic and social sectors, $W_{economic} + W_{social} = 1$, W_i is the weighting factor from AHP.

3.3. Exposure

The exposure is estimated from the conditions of the economic and social sectors. The exposure to droughts can be classified into two sectors: economic and social. The economic sector pertains to the agricultural part, which incurs a significant percentage of damages and losses in Sukhothai Province. The agricultural land comprises various crops including rice, cassava, maize, pineapple, sugar cane, orange, mango, and coconut. This sector is defined based on crop yield and market prices of rice, cassava, maize, and sugarcane using the following Eq. (3):

$$\text{Crop Income} = \text{Crop Yield x Crop Price} \tag{3}$$

where Crop Yield is the crop productivity in unite (kilogram per rai), Crop Price is the commodity prices of each crop in unite (Baht per kilogram), Crop Income is the total financial return from each crop, measured in units (Baht per rai).

On the other hand, the social aspect focuses on vulnerable groups. These include the number of people, households, females, children under 5 years old, poverty, and population aging. These groups represent new challenges in the context of global social issues.

The Combined Exposure Index (CEI) for economic and social sectors was derived by analyzing the Exposure Index (EI) values of both economic and social sectors, as shown in Eq. (4)

$$CEI = W_{economic} \times EI_{economic} + W_{social} \times EI_{social} \tag{4}$$

where Combined Exposure Index is CEI value of economic and social sectors, $W_{economic} + W_{social} = 1$, W_i is the weighting factor from AHP.

Moreover, vulnerability within the social sector, utilized to define CEI, was analyzed through major vulnerability groups: the population and households. The computation of the exposure index on social sector was assessed from EI values of population and household with weighting factors.

$$EI_{social} = W_{population} \times EI_{population} + W_{household} \times EI_{household} \tag{5}$$

where $W_{population} + W_{household} = 1$, W_i is the weighting factor from AHP.

3.4. Risk

The Sendai Framework [33] broadly defines drought risk as the potential loss of life, injury, or destruction or damage to assets that could occur to a system, society, or community over a specific period of time. This is determined probabilistically as a function of drought hazard, exposure, and vulnerability. In the general approach to drought risk assessment, the indices of exposure and vulnerability are multiplied by the hazard, index which is assessed from the physical characteristics of the droughts [29]. Following the Sendai Framework and the World Bank, the drought risk formula is defined as shown in Eq. (6). The application in this study for economic sector and for social sector involves hazard, vulnerability, and exposure, represented by MDHI, VI, and EI respectively, as shown in Eq. (7).

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \times \text{Exposure} \tag{6}$$

$$RI = MDHI \times VI \times EI \tag{7}$$

where MDHI is Multiple Drought Hazard Index, VI is Vulnerability Index, EI is Exposure Index, and RI is Risk Index.

For combined economic and social sectors, the Combined Drought Risk (CRI) is computed from the product of MDHI, CVI, and CEI respectively, as shown in Eq. (8).

$$CRI = MDHI \times CVI \times CEI \tag{8}$$

The results of risk assessment are presented in terms of potential direct impacts based on biophysical-agro economic models, quantified economically or monetarily, through the crop yield and price data [34].

4. Results

4.1. Hazard

4.1.1. Standardized precipitation index (SPI)

The SPI technique was estimated using monthly time series data on precipitation. SPI1, SPI3, and SPI6 were utilized to assess damage to agricultural areas [7]. Monthly precipitation data from meteorological stations were gathered and analyzed to calculate SPI1, SPI3, and SPI6 from 1950 to 2021. Table 2 presents the average SPI values from all meteorological stations, including three timescales of drought events: 1, 3, and 6 months. These are divided into four-time steps: 2005s (2005-2009), 2010s (2010-2014), 2015s (2015-2019), and 2020s (2020-2021). The SPI1 values for 2005s and 2010s were positive, indicating wet conditions. Negative values were observed in 2015s and 2020s for stations 373201 and 380201. For SPI3, stations 328202, 373201, 373301, 378201, and 380201 showed negative values in 2015s and 2020s, while stations 376201 and 376203 exhibited positive SPI3 values. Most SPI6 values in 2015s and 2020s were negative, indicating dry or drought conditions.

4.1.2. Standardized runoff index (SRI)

Monthly runoff data was utilized to compute SRI values using the SPI technique. This involved analyzing the monthly runoff data from a gamma distribution to form a probability density function. Approximately nine hydrological stations at Yom River and its sub-rivers in Sukhothai Province were used to calculate the SRI value, as shown in Table 2. The majority of average SRI1, SRI3, and SRI6 values were positive in the 2005s and 2010s, indicating wet conditions. In the 2015s and 2020s, more than half of the hydrological stations recorded negative values, with a twofold increase from the 2015s to the 2020s. All stations presented a trend of SRI values changing from positive to negative, or from wet to dry conditions. This change to negative values in SPI6 during the 2020s was particularly noticeable. However, station Y.26 was closed in December 2017.

4.1.3. Standardized groundwater index (SGI)

The SGI was calculated by analyzing the monthly groundwater level data measured from groundwater wells in Sukhothai Province. Approximately nine groundwater wells, namely 5307C023, 5307D024, 5307F023, 5407A028, 5407D027, GWA137, GWA139, GWA141, and MB969, were used to calculate the SGI value for 1, 3, and 6 month timescales. For Table 2, the groundwater level data for stations 5307C023, 5307D024, 5307F023, 5407A028, and 5407D027 began in January 2014, and the SGI values range from January 2014 to December 2021. Most groundwater stations exhibit a similar trend, transitioning from positive to negative values, with a clear shift to dry conditions in the 2020s. However, the SGI value for GWA137 showed negative values in both the 2005s and 2020s

Table 2. The average SPI, SRI and SGI values with different timescales (1, 3 and 6 months) in 2005s (2005-2009), 2010s (2010-2014), 2015s (2015-2019) and 2020s (2020-2021).

No	Drought Timescale	1-Month				3-Month				6-Month			
	Code	2005s	2010s	2015s	2020s	2005s	2010s	2015s	2020s	2005s	2010s	2015s	2020s
	Standardized Precipitation Index (SPI)												
1	328202	0.14	0.20	0.15	0.10	-0.03	0.13	0.04	-0.02	0.02	0.10	-0.01	-0.03
2	373201	0.13	0.26	-0.10	-0.13	0.02	0.28	-0.30	-0.32	0.13	0.36	-0.49	-0.42
3	373301	0.16	0.19	0.01	0.04	-0.02	0.12	-0.17	-0.08	-0.05	0.12	-0.29	-0.08
4	376201	0.16	0.29	0.16	0.26	0.08	0.21	0.07	0.26	0.17	0.18	-0.09	0.34
5	376203	0.28	0.14	0.13	0.19	0.23	0.01	0.03	0.18	0.34	-0.07	-0.10	0.18
6	378201	0.24	0.26	0.04	0.01	0.17	0.28	-0.16	-0.13	0.21	0.30	-0.30	-0.28
7	380201	0.14	0.30	0.03	-0.03	0.05	0.33	-0.10	-0.20	0.10	0.39	-0.20	-0.38
	Standardized Runoff Index (SRI)												
1	Y.3A	0.45	0.12	-0.78	-1.43	0.54	0.22	-0.85	-1.64	0.70	0.36	-0.79	-1.89
2	Y.4	0.72	0.87	0.08	-0.12	0.89	0.99	0.03	-0.22	1.01	1.04	0.02	-0.27
3	Y.6	0.81	0.46	-0.19	-1.41	0.91	0.66	-0.13	-1.59	0.89	0.84	-0.12	-1.64
4	Y.14	0.62	0.73	-0.23	-1.09	0.68	0.80	-0.27	-1.10	0.75	0.89	-0.29	-1.02
5	Y.16	0.43	0.32	-0.34	-0.85	0.50	0.35	-0.51	-1.12	0.61	0.42	-0.61	-1.42
6	Y.21	0.78	0.62	0.21	0.15	0.76	0.62	-0.02	-0.07	0.70	0.63	-0.22	-0.29
7	Y.26	0.72	0.53	-0.31	-	0.74	0.51	-0.58	-	0.75	0.54	-0.72	-
8	Y.29	1.21	0.95	0.81	0.81	1.29	0.62	0.42	0.38	1.24	0.32	0.00	-0.02
9	Y.33	0.61	0.17	-0.33	-0.90	0.67	0.23	-0.39	-1.12	0.74	0.42	-0.40	-1.31
	Standardized Groundwater Index (SGI)												
1	5307C023	-	0.63	0.02	-1.36	-	0.65	0.04	-1.39	-	0.67	0.07	-1.43
2	5307D024	-	0.61	0.06	-1.41	-	0.62	0.08	-1.45	-	0.64	0.12	-1.49
3	5307F023	-	0.97	-0.18	-1.56	-	1.01	-0.19	-1.55	-	1.06	-0.19	-1.50
4	5407A028	-	0.24	0.33	-1.00	-	0.21	0.35	-1.03	-	0.21	0.35	-1.02
5	5407D027	-	1.16	0.24	-1.25	-	1.23	0.30	-1.35	-	1.26	0.38	-1.40
6	GWA137	-0.84	0.80	0.27	-1.51	-0.92	0.79	0.28	-1.48	-1.00	0.74	0.29	-1.41
7	GWA139	1.17	0.32	-0.42	-1.58	1.19	0.35	-0.41	-1.62	1.22	0.40	-0.39	-1.68
8	GWA141	1.17	0.31	-0.42	-1.57	1.22	0.32	-0.40	-1.60	1.28	0.33	-0.38	-1.62

4.1.4. Multiple drought hazard index (MDHI)

The MDHI is calculated by summing the product of the weighting factor (W_i) and the hazard index (HI_i) for three types of droughts, as shown in Eq. (1). The weighting factors, derived from the AHP technique, were computed in a previous section and are as follows: $W_{NDMI} = 0.565$, $W_{SRI} = 0.262$, $W_{SGI} = 0.118$, and $W_{SPI} = 0.055$. These factors were analyzed from a questionnaire survey with 500 samples. From the survey, NDMI (agricultural drought) was found to have the greatest impact on

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agricultural areas, particularly non-irrigated paddy fields, compared to SRI and SGI (hydrological drought), and SPI (meteorological drought). SPI is considered less important than both SRI and SGI which directly reflect surface water and groundwater resources for both in agricultural and community sectors during water scarcity situations

A sensitivity analysis is carried out to determine the effects of the four weighting factors of NDMI, SRI, SGI, and SPI by changing each of them one by one by ±10% keeping the other three weighting factors unchanged. In this analysis, the weighting factor of NDMI is varied by ±10%. The results as shown in the following Table 3 indicate that when the mean of MDHI determined by AHP, is changed by+10% and -10%, MDHI is changed from 2.71 to 2.64 and 2.75 (or in percentages -2.58% and +1.48%) respectively. Accordingly, the standard deviation SD of MDHI of 0.49, it is changed to 0.43 and 0.48 (or -12.24% and -2.04%) respectively. For the weight change of SRI by +10% and -10%: the results show a change of the mean of MDHI by AHP from 2.71 to 2.54 and 2.80 (or -6.27% and +3.32%) respectively; while the standard deviation is changed from 0.49 to 0.40 and 0.50 (or -18.37% and +2.04%) respectively. For SGI, the mean of MDHI of 2.71 by AHP is changed to 2.65 and 2.76 (or -2.21% and +1.85%) respectively; while the standard deviation of 0.49 is changed to 0.43 and 0.48 (or -12.24% and -2.04%). For SPI, the mean of MDHI of 2.71 is changed to 2.69 and 2.71 (or -0.74% and 0.00%); and the standard deviation changes from 0.49 to 0.45 and 0.46 (or -8.16% and -6.12%) respectively." The sensitivity analysis shows that the effects of ±10 % variations of the individual weighting factors of NDMI, SRI, SGI, and SPI do not have significant effects on the MDHI in the study area."

Table 3. Results of the sensitivity analysis of ±10% variation in the weights of NDMI, SRI, SGI and SPI indices.

Variation	% Changing in weight	Mean	SD	% Change w.r.t. AHP Mean	% Change w.r.t. AHP SD
AHP (Base case)		2.71	0.49		
NDMI	+10	2.75	0.43	1.48	-12.24
	-10	2.64	0.48	-2.58	-2.04
SRI	+10	2.54	0.50	-6.27	2.04
	-10	2.80	0.40	3.32	-18.37
SGI	+10	2.65	0.48	-2.21	-2.04
	-10	2.76	0.43	1.85	-12.24
SPI	+10	2.71	0.45	0.00	-8.16
	-10	2.69	0.46	-0.74	-6.12

The MDHI is divided into six hazard levels: no, very low, low, medium, high, and very high, as recommended by the LDD of Thailand. Due to lack of data on hazard levels, the computed multiple drought hazard maps are compared to the observed numbers of drought events at various locations from 2012-2014 (for calibration) and 2015-2020 (for validation), as shown in Fig. 3.

In calibration, the observed surveying points indicated that 12, 213, and 602 samples experienced once, 2, and 3 events per 3 years, respectively. The model performance was found to be satisfactory, with $R^2 = 0.78$, NSE = 0.76, MAE = 0.06, and PBIAS = -3.1%. For validation, the observed surveying points showed that 291, 244, 39, and 12 samples experienced one, two, three, and four events per six years, respectively. The model's performance was again satisfactory, with $R^2 = 0.77$, NSE = 0.76, MAE = 0.11, and PBIAS = 0.2%. The comparison revealed a very satisfactory or very good agreement between the computed and observed numbers of drought events at all 781 and 520 locations for calibration and validation, respectively. All statistics indicate that the computed hazard maps strongly agree with the definition of drought hazard in Sukhothai Province.

The computed drought hazard maps during 2007-2020 are shown in Fig. 4. The current hazard maps from November-2019 to March-2020 which covered paddy field land, field crop land, orchard and perennial crop lands of 2,059, 1,241, 306 and 224 km², respectively. The high hazard areas were in Si Satchanalai District in the upper parts of the study area and another hazard areas are Thung Saliam, Sawankhalok and Ban Dan Lan Hoi Districts in the middle parts of the study area.

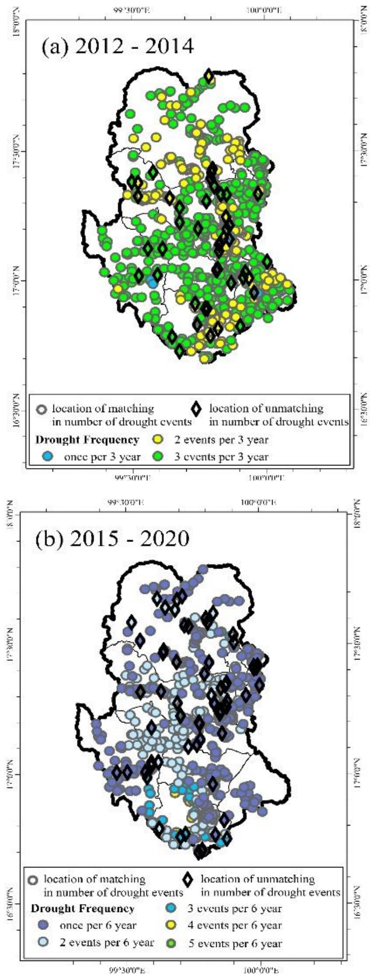

Fig. 3. The computed and observed numbers of drought events in the study area: (a) calibration from 2012 to 2014, and (b) validation from 2015 to 2020 with indications of matching and unmatching agreement.

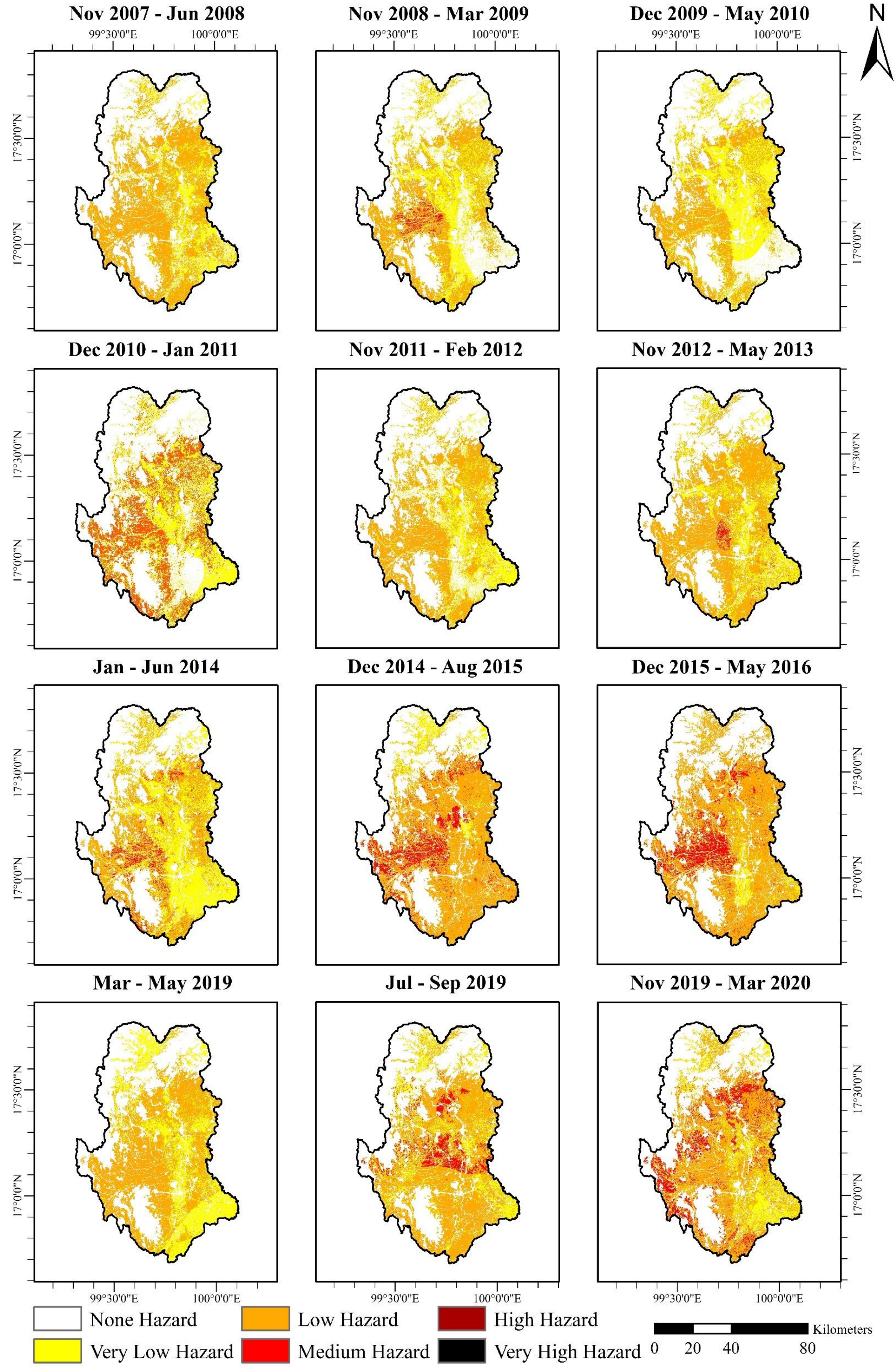

Fig. 4. Computed drought hazard maps from Multiple Drought Hazard Index (MDHI) during 2007-2020.

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4.2. Vulnerability Index

Vulnerability primarily refers to the likelihood of individuals or groups being affected by natural disaster damages and losses, considering social, physical, economic, and infrastructural aspects [35-38]. The quantification of vulnerability is based on potential damages, and it is linked to social and agricultural product damages.

The hazard assessment in this study is categorized into six levels: no hazard, very low, low, medium, high, and very high. In terms of drought damages, the drought duration-hazard-damage curve (Fig. 5) was developed based on an analysis of questionnaire surveys that examined crop damages due to drought conditions. The survey results indicated that the impact of drought varies with duration: rice is affected after 1 month; Maize, Black and Green Mung Bean after 2 months; Black and Red Sesame, Soybean, Durian after 3 months; Marian Plum, Mango, Sapodilla, Tangerine after 4 months; Banana, Longkong after 5 months; and Cassava, Sugarcane, Acacia after 7 months.

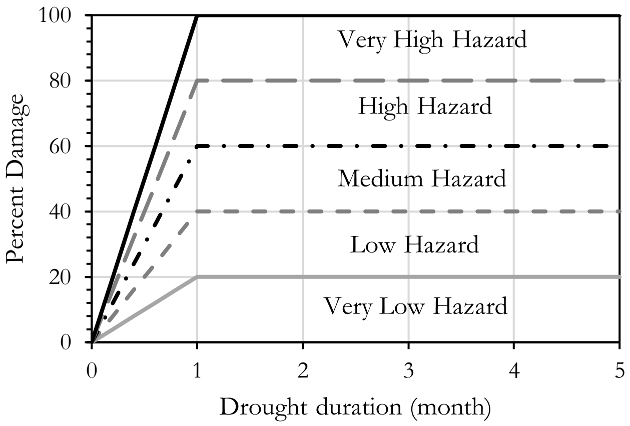

Fig. 5. Drought duration-hazard-damage curve for rice.

The magnitude of crop damage depends on the vulnerability (VI); due to limited data, it is assumed that their relationship is linearly proportion. As shown in Fig. 5 for rice which can stand droughts of not more than one month, a zero percent of crop damage is set equivalent to VI = 0. The 1- 20 and 21-40 percent of crop damages for very low and low hazards are set equivalent to VI = 0.2 and 0.4, respectively. For the medium and high hazards, corresponding to 41-60 and 61-80 percent of crop damages, the damages are set to VI = 0.6 and 0.8, respectively. Lastly, for a very high hazard which corresponds to 81-100 percent of crop damages, it sets to VI of 1.0.

For the social sector, the observed relationship between hazard level and percent damage of affected population from no hazard to very high hazard levels, is shown in Fig. 6. The relationship was established based on observed drought hazard and number of affected populations from 2007 to 2016. This was achieved by categorizing hazards into low (1-12 months), medium (13-24 months), and high (over 24 months) durations, and then the percentage of affected population relative to the total population [39] was estimated. The same relationship is applied to household units as each household unit has approximately on average a constant number of occupants.

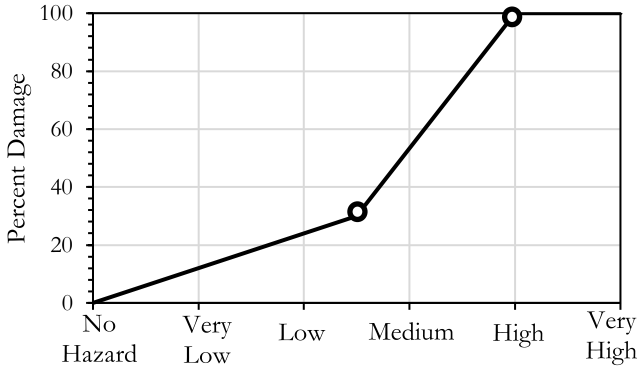

Fig. 6. Drought hazard-damage curve for social sector.

For no hazard, the VI would be zero, indicating zero percent of affected people (no vulnerability). The very low and low hazard levels have VI values of 0.20 and 0.40 respectively, representing 1-12% and 13-24% of affected people. Medium and high hazards correspond to VI values of 0.60 and 0.80, indicating 25-53% and 54-100% of affected people. Finally, a very high hazard level can correspond to a VI of 1.00, indicating 100% of affected people. The affected housing units are found to vary proportionally with the residing population at about 2.84 people per a housing unit.

The vulnerability maps of economic and social sectors on November, 2019 are shown in Fig. 7(a) and (b). In Fig. 7(a), the map covers the most area with very high vulnerability level, particularly in the paddy field regions in the middle and lower parts of Sukhothai Province. Areas with low and medium vulnerable levels are in Sawankhalok and Si Samrong Districts in the middle parts of the study area. Figure 7(b) shows highly vulnerable areas primarily located in Si Satchanalai District in the upper parts of the study area, with Thung Saliam, Sawankhalok, and Ban Dan Lan Hoi Districts in the middle areas of the study zone. The very low vulnerability area is shown in Mueang Sukhothai and Kong Krailat Districts.

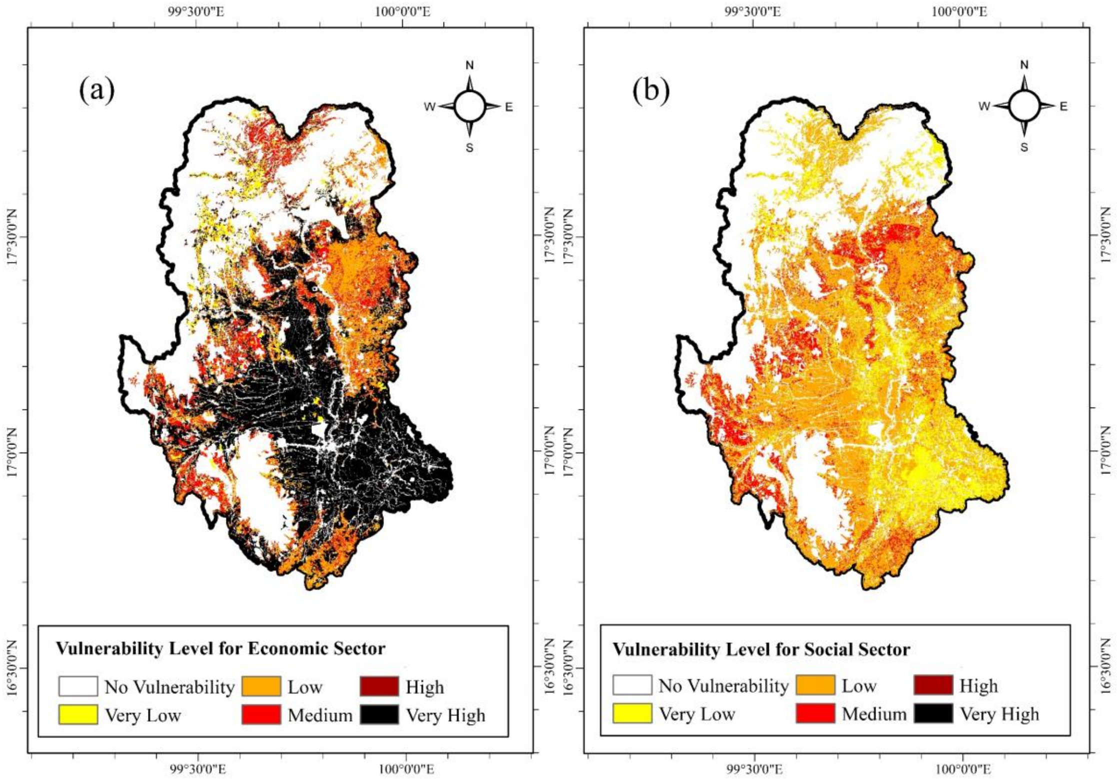

Fig. 7. The vulnerability maps of (a) economic and (b) social sectors on November, 2019.

4.3. Exposure Index

Exposure is typically assessed by evaluating the quantities of surrounding people, infrastructure, housing, production capacities, and other human assets situated in areas prone to hazards [29, 33]. In this study, exposure index (EI) is divided into two sectors: economic and social sectors. For the economic sector, agricultural products significantly influence the economy of Sukhothai Province. In this study, the primary inputs for assessing compensation based on crop damages from droughts are crop yield and price data. Both types of data were collected by the Office of Agricultural Economics (OAE) of Sukhothai Province from 2009 to 2022 (https://www.oae.go.th/), expressed in terms of kilograms per rai (kg/rai) and Baht per kilogram (Baht/kg) in which 1 rai = 0.0016 km^2 and 1 Baht = 0.028US dollars. Agricultural production in Sukhothai Province is divided into 77 crop types, including abandoned paddy fields, active paddy fields, abandoned field crops, mixed field crops, corn, sugarcane, cassava, pineapple, etc. Agricultural maps from 2013, 2016, 2018, and 2021 were collected by LDD. The combination of crop yield and price data facilitates the calculation of crop income in terms of units (Baht/rai), as shown in Eq. (3), and is employed to analyze the Exposure Index (EI) as shown in Table 4. The paddy fields were categorized based on EI values of 0.00, 0.20, 0.40, 0.60, and 0.80. These values correspond to different crop income ranges as shown in Table 4. For field crops and orchard/perennial lands, the EI values were estimated as shown in Table 4. These data are used to assess the compensation required to mitigate the impact on crops by DDPM when droughts occur. The exposure map of the economic sector for November 2019 indicates very low to very high levels of exposure across the agricultural areas, with Sawankhalok and Si Samrong Districts exhibiting very high exposure levels.

In the social sector, the number of people affected in drought-prone areas is a major factor in determining exposure. This study collected data on various demographic densities, including overall population, females, children under 5 years, people over 60 years, poverty people, households, and poverty households from Department of Provincial Administration (DOPA) (https://stat.bora.dopa.go.th/stat/statnew/statMenu/newStat/stat/). This data was used to show the social impact of drought, taking into account different population characteristics. This study proposes a categorization based on the number of people and housing units per km^2. For the overall population, exposure index is delineated as shown in Table 4. Similarly, for categories related to females and households, exposure levels are classified as shown in Table 4. For categories of children under 5 years, population aging, poverty households and poverty population, the EI is classified as shown in Table 4. These categorizations provide a comprehensive framework for assessing risk levels across different demographic groups and housing situations, contributing to a more nuanced understanding of exposure in the context of subdistrict-level planning and policy-making. The exposure map of the social sector, analyzed from a population density map for November 2019, is shown in Fig. 8(b), varying exposure levels across different areas. The Mueang

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Sukhothai and Mueang Kao subdistricts have very high exposure levels.

For socio-economic sectors, the Combined Vulnerability Index (CVI) is computed by Eq. (2) and Combined Exposure Index (CEI) is computed by Eq. (4). The weighting factors in Eqs. (2) and (4), determined by AHP technique, in which $W_{economic}$ = 0.75, and W_{social} = 0.25. These factors were derived from an analysis of the major impacts, which indicated a greater influence of the economic sector compared to the social sector.

In terms of the social sector for CEI, the exposure index (EI) values were computed from the population and households, identified as major vulnerable groups pivotal in assessing socio-economic vulnerability to drought, as demonstrated in Eq. (5). The weighting factors, determined through AHP technique, are specified as follows: $W_{population}$ = 0.50, and $W_{household}$ = 0.50. These weights reflect the equal significance of the population and household components within the social sector.

Table 4. Classification of drought exposure index (EI) and asset values or properties of economic and social sectors.

Exposure Level	Exposure Index (EI)	Economic Sector (Crop Income: Baht per rai)*			Social Sector (people/housing units per km^2)						
		Paddy Field	Field Crop	Orchard/ Perennial Land	Population	House hold	Female	Children under 5 years	Population Ageing	Poverty Population	Poverty Household
No Exposure*	0	0	0	0	0	0	0	0	0	0	0
Very low	0.20	1-1,113	1-1,148	1-1,690	1-1,000	1-500	1-500	1-100	1-100	1-100	1-100
Low	0.40	1,114-2,226	1,149-2,296	1,691-3,380	1,001-2,000	501-1,000	501-1,000	101-200	101-200	101-200	101-200
Medium	0.60	2,227-3,339	2,297-3,444	3,381-5,070	2,001-3,000	1,001-1,500	1,001-1,500	201-300	201-300	201-300	201-300
High	0.80	3,340-4,452	3,445-4,592	5,071-6,760	3,001-4,000	1,501-2,000	1,501-2,000	301-400	301-400	301-400	301-400
Very High	1.00	Over 4,453	Over 4,593	Over 6,761	Over 4,001	Over 2,001	Over 2,001	Over 401	Over 401	Over 401	Over 401

(Source: Modified financial compensation required rate following major emergencies or disasters of Thailand Government and cost of agricultural production). There is no exposure in non-agricultural areas.
* 1 rai = 0.0016 km^2 and 1 Baht = 0.028USD.

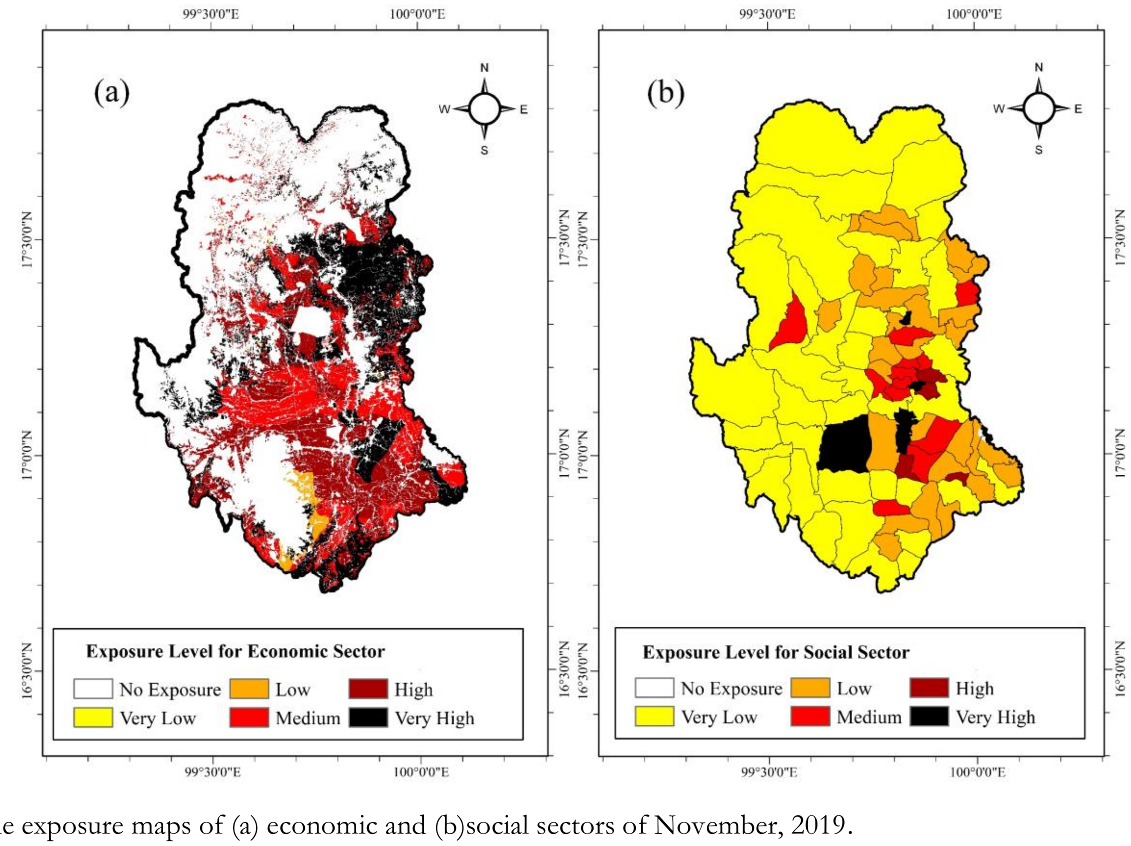

Fig. 8. The exposure maps of (a) economic and (b)social sectors of November, 2019.

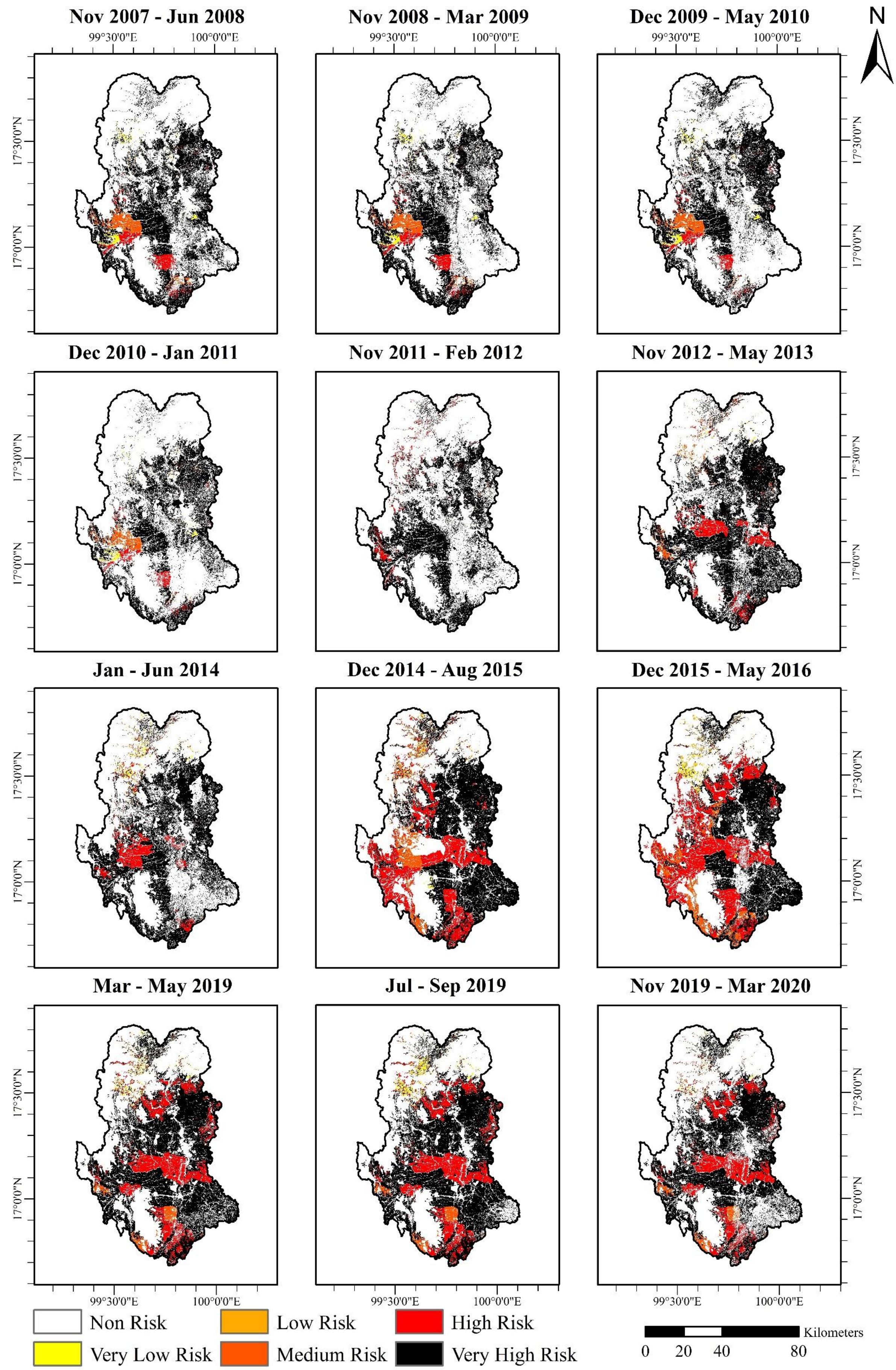

Fig. 9. Computed drought risk maps on economic sector during 2007-2020.

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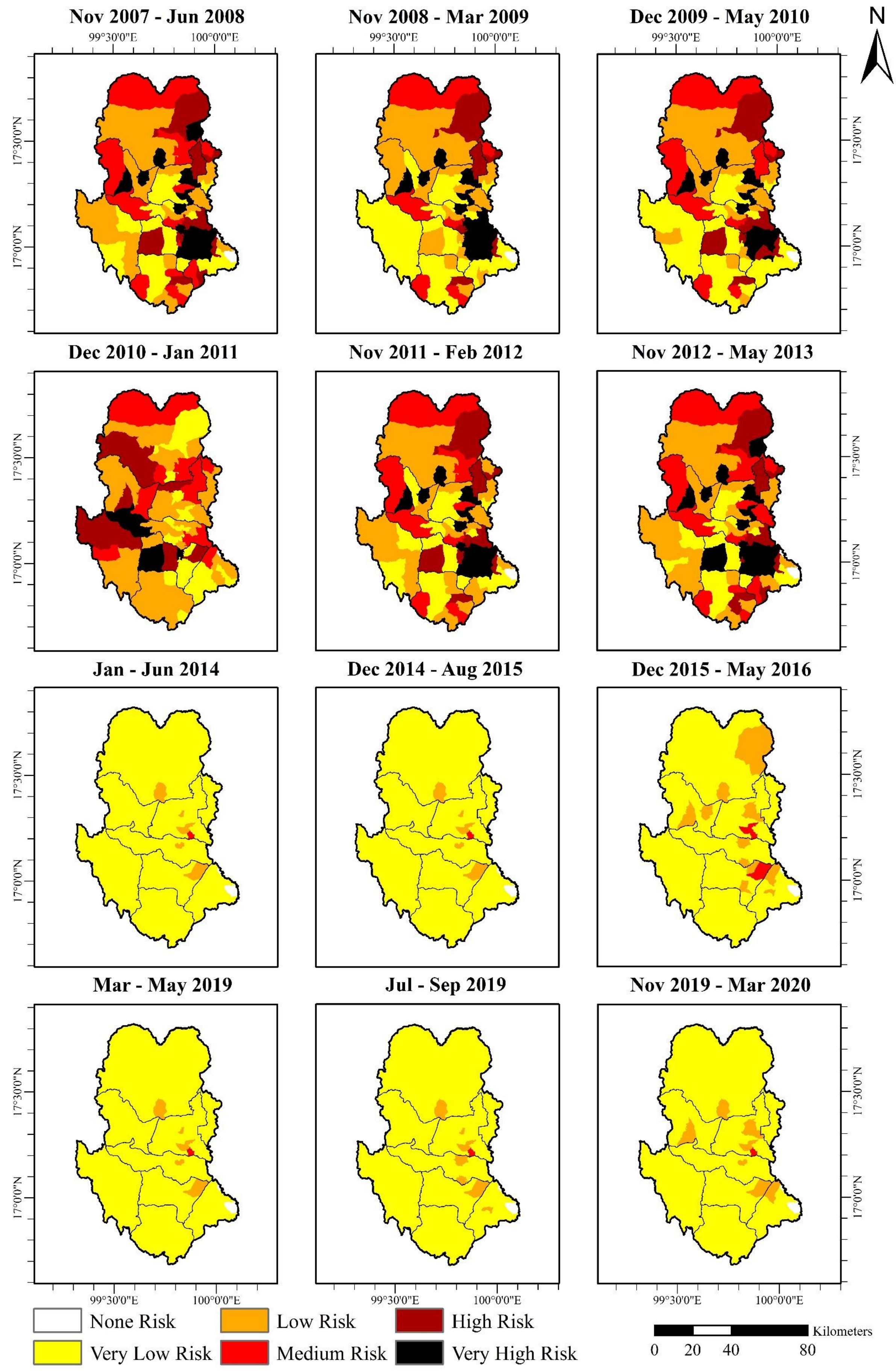

Fig. 10. Computed drought risk maps of affected people on social sector during 2007-2020.

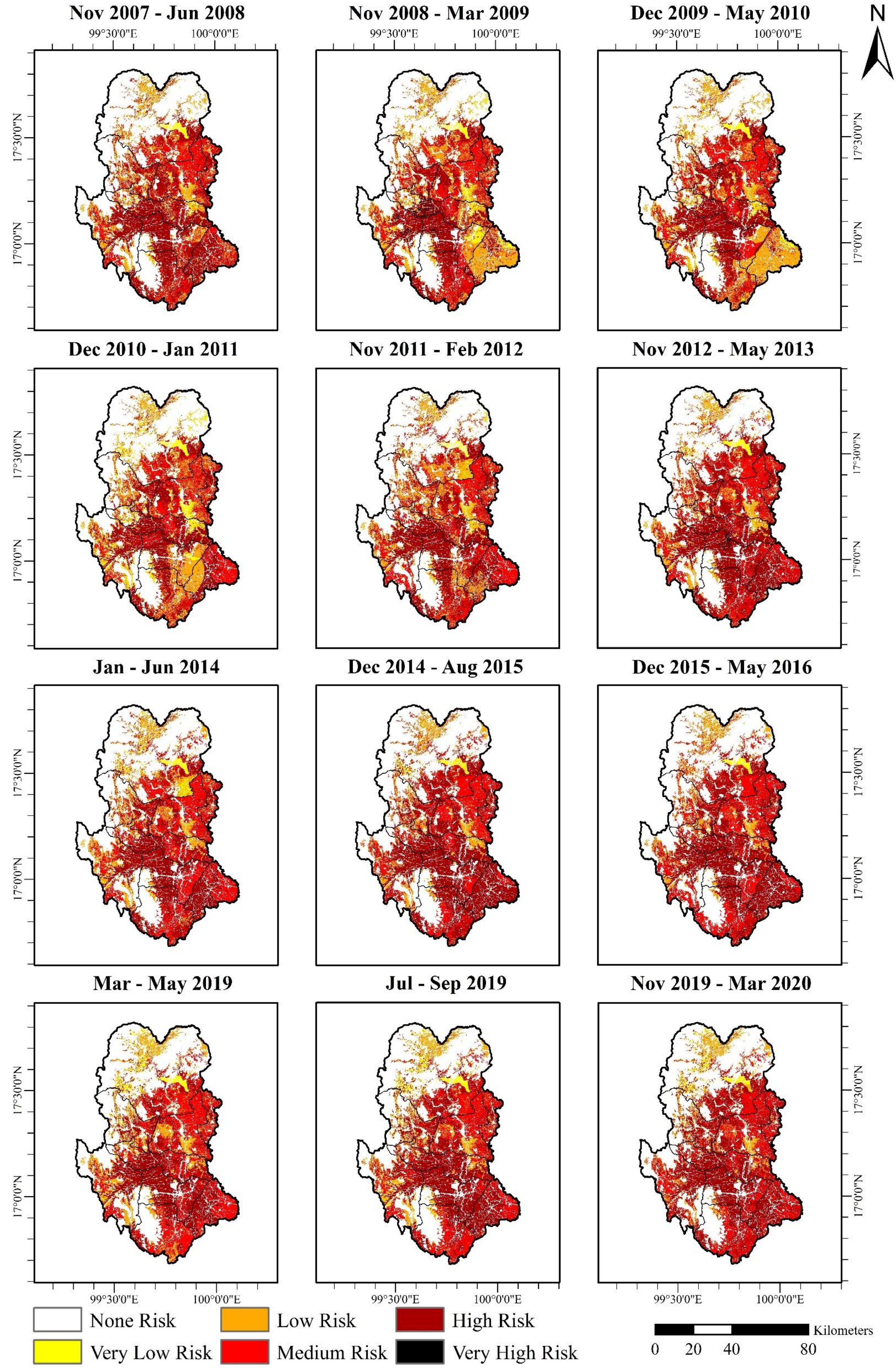

Fig. 11. Computed combined drought risk maps on economic sector and social sector during 2007-2020.

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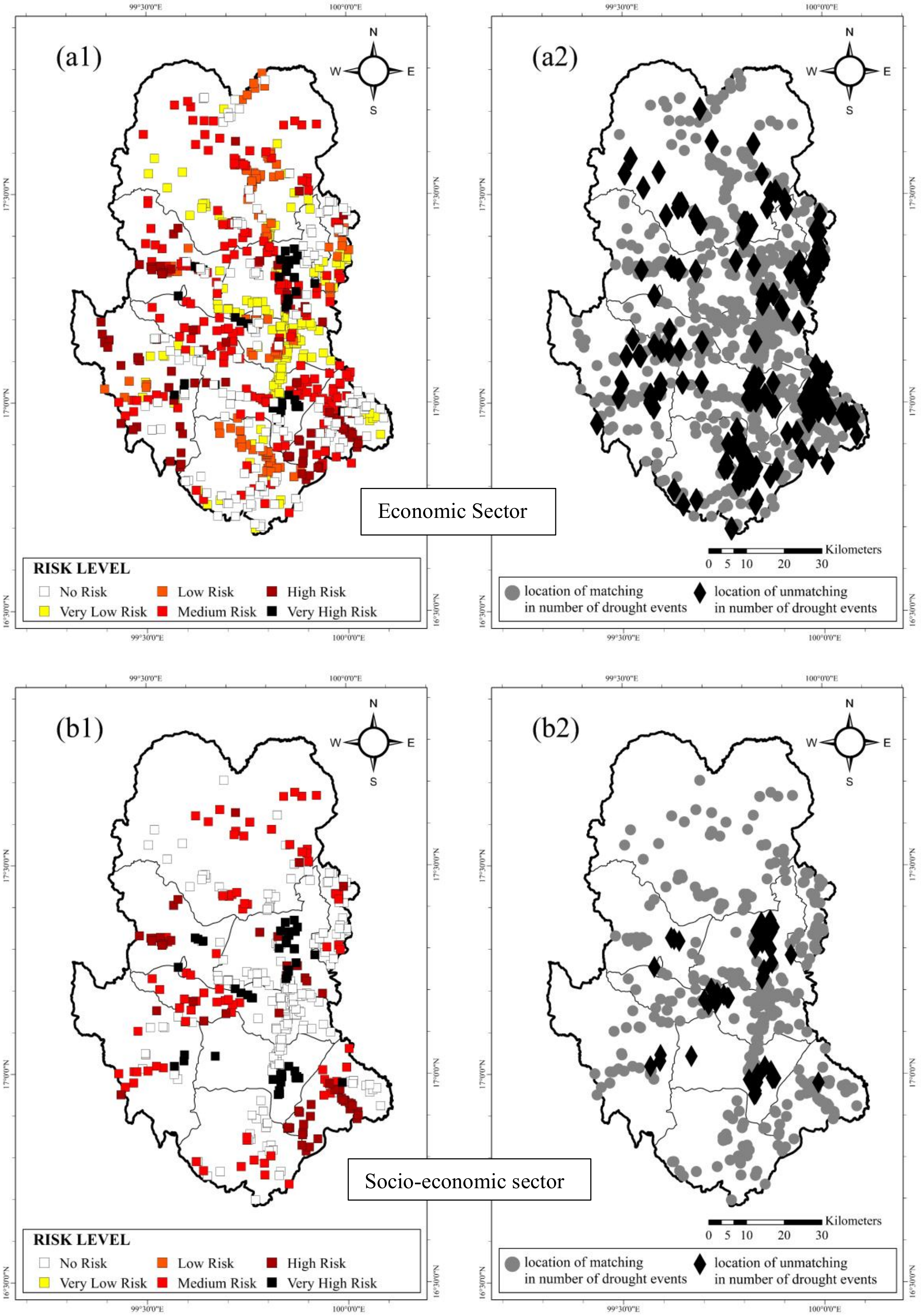

Fig. 12. (a1) Locations and observed risks of economic sector from 2011-2020; (a2) locations of matching and unmatching results of computed and observed risks; (b1) locations and observed risks of socio-economic sector and (b2) locations of matching and unmatching results of computed and observed risks.

4.4. Risk

Drought risk was probabilistically determined as a function of drought hazard, exposure, and vulnerability, according to Eqs.(6) and (7) [29, 33]. In this study, the hazard was quantified using MDHI according to Eq. (1). The vulnerability and exposure were derived from the Vulnerability Index (VI) and Exposure Index (EI) respectively, employing the drought duration-hazard-damage curve for the economic sector, which includes crop income considerations, and the drought hazard-damage curve for the social sector, where population and households are the key exposure factors.

The drought risk on economic and social sectors are divided into six levels: none (RI≤0), very low risk (0<RI≤0.20), low risk (0.20<RI≤0.40), medium risk (0.40<RI≤0.60), high risk (0.60<RI≤0.80), and very high risk (0.80<RI≤1.00).

Figures 9, 10 and 11 show the computed overall drought risk maps of 12 drought events on economic and social sectors from 2007 to 2020. The events are: November 2007 – June 2008 (event 1), November 2008 – March 2009 (event 2), December 2009 – May 2010 (event 3), December 2010 – January 2011 (event 4), November 2011 – February 2012 (event 5), November 2012 – May 2013 (event 6), January 2014 – June 2014 (event 7), December 2014 – August 2015 (event 8), December 2015 – May 2016 (event 9), April 2019 – June 2019 (event 10), July 2019 – September 2019 (event 11), and November 2019 – March 2020 (event 12). For economic sector, as shown in Fig. 9, the drought risk maps from 2007 to 2020 show the areas with no risk to very high risk of drought. For example, in Table 5, event 12 spanning from November 2019 to March 2020, encompasses the areas with very low drought risk (127 km^2), low (484 km^2), medium (1,248 km^2), and high (1,977 km^2) risk levels. The risk trend has increased from no risk to higher levels over time, with changing hazard status from none to very low, very low to low, low to medium, medium to high, and high to very high, respectively. In 2019-2020 or events 10-12, the risk level was similar from April 2019 to March 2020, covering the whole area with very low, low, medium, high, and very high-risk levels. This indicates that this area has faced a long-term drought risk. In term of social sector, the population, female, children, old people and household have similar trends that change from very low to high risk levels for 2007 to 2013. During November 2007-May 2013, the areas have very low, low and medium levels that also have very high risk at Mueang Kao, Pak Kwai, Thani and Ban Kluai sub-Districts at Mueang Sukhothai District and Taling Chan and Na Khun Krai sub-Districts at Si Samrong and Thung Saliam Districts, respectively.

In 2014 and onward, DDPM changed its policy and criteria in accounting for the numbers of affected people and households in the social sector. By comparing the available observed drought damages of event 8 (January 2014 –June 2014) and event 9 (December 2015 – May 2016) with the computed drought damages of the same two events shown in Table 5, it is found that the numbers of affected people and households under the new policy and criteria introduced in 2014 are only 15% of the computed numbers of affected people and households under the previous policy and criteria before 2014.

On the drought risk of social sector under the new policy and criteria introduced in 2014, it was found that the drought risk was much reduced to only 0.15 times of the drought risk calculated by Eq. (7) and the drought hazard-damage relationship in Fig. 6. As shown in Fig. 10, during November 2007 to March 2013, the social drought risk levels are mainly classified as very low level and low level except in the sub-districts nearby Yom River and Kong Krailat District. From January 2014 to March 2020 under the new policy, the social drought risk level was reported to decrease mostly from low to very low drought risk level almost everywhere. Hence much less compensation on the affected people and households was reported from 2014 onward.

The statistical parameters used for risk assessment showed that the computed data were highly acceptable and accurate. The observed data in economic sector from DDPM collected from 2011 to 2020, comprised 866 points are shown in Fig. 12(a1 and a2). The coefficient of determination (R^2) value was 0.75, indicating a very good performance; the Nash-Sutcliffe Efficiency (NSE) was 0.73, indicating a good performance; Mean Absolute Error (MAE) was 0.32; and Percent Bias (PBIAS) was 2.80%, indicating a very good accuracy. The comparison shows a very good agreement between the computed and observed numbers of drought events at 670 locations. The verification of the observed and computed data on the social sector employed the percentage difference technique. The observed data were divided into two groups: affected population and household from 2007 to 2016 or events 1-9. The results showed that the computed affected people and households for events 2, 3, 5, 6, 8, and 9 were similar to the observed data, with less than 10% discrepancy. However, observed data of economic damages for past decades are unavailable. The model performance shows high accuracy for both the economic and social sectors.

For the socio-economic sectors, the validation of the drought risk map was conducted using observed data obtained from DDPM during 2011 to 2020, comprising 413 data points, as depicted in Fig. 12(b1 and b2). The resulting statistical indicators revealed a robust performance with R^2 value of 0.87, signifying a high level of accuracy; NSE value of 0.86, indicating good performance; MAE of 0.13; and PBIAS of 9.50%, reflecting very good accuracy. This comparison demonstrates a highly satisfactory agreement between the computed and observed numbers of drought events at 361 locations.

The major effect of a drought event is the reduction of water availability and quality for agricultural areas, which led to losses in crop productivity in drought-prone areas. The results show that the computed direct damages were up to a maximum of 10,545 million Baht in event 5 (November 2011 to February 2012) and a minimum of 8,107 million Baht in event 10 (April 2019 to June 2019) as shown in Table 5.

For the social sector, the drought risk on population, female, children, people over 60 years, and household are shown in Table 5. Event 6, which occurred from November 2012 to May 2013, had the highest value and its impact was similar to observed data. Specifically, the drought affected to approximately 223,660 to 245,975 people and 74,552 to 81,753 housing units. Furthermore, the droughts impacted around 155,818 females, 23,516 children, and 43,517 individuals aged 60 years and above. Similarly, Event 9, which spanned from December 2015 to May 2016, also had a comparable impact in terms of observed and computed data, affecting approximately 51,705 to 51,679 people and 19,335 to 20,766 housing units. This event affected about 25,937 females, 3,652 children, and 7,870 individuals aged 60 years and above.

Table 5. The computed damages on economic and social sectors of drought events during 2007-2020.

Events	Economic Sector		Social Sector						
	Risk Area (km^2)	Damages (Million Baht)	Population (persons)	Household (homes)	Female (persons)	Children under 5 years (persons)	Population Aging (persons)	Poverty Population (persons)	Poverty Household (homes)
1	2,623	10,298	233,865	73,204	148,299	22,271	41,398		
2	2,230	8,979	193,027*	60,574*	123,180	18,110	34,930		
3	2,290	9,246	185,528*	57,965*	118,019	17,244	33,221		
4	2,327	9,255	145,875	44,871	59,707	14,101	23,033		
5	2,441	10,545	211,797*	63,824*	91,342	20,052	37,542		
6	2,803	9,475	245,975*	81,753*	155,818	23,516	43,517		
7+	2,692	8,232	34,299	13,605	17,450	2,601	5,045		
8	2,739	8,317	37,170*	14,658*	18,682	2,753	5,483		
9	2,800	8,231	51,679*	20,766*	25,937	3,652	7,870		
10	2,535	8,107	34,749	14,266	17,544	2,330	5,619	2,793	2,232
11	2,583	8,438	40,423	16,523	20,391	2,748	6,529	3,307	2,645
12	2,672	8,788	41,814	17,127	21,188	2,778	6,814	3,358	2,691

* Observed data are available, computed values are less than 10% discrepancy compared to observed data
+ From event 7 and onward, DDPM changes its criteria in accounting affected population, households and other social components

5. Discussions

Comparative analysis: No study that has ever been made on drought risk assessment in Sukhothai Province. By referring to previous studies in other river basins in Thailand, Mekong region and worldwide.

In this study, the drought hazard maps computed for the period 2007-2020 show the historical trend of hazard areas transitioning from no hazard to very low, very low to low, low to medium, medium to high and, high to very high levels. This result is the same as the results of previous studies related to past and future trends of drought hazards in agricultural areas such in Upper Nan River Basin [4] and Wang River Basin [40] in northern Thailand, and in Upper Mun River Basin [41] and Songkhram River Basin [7], both the subbasins of the Mekong River Basin in northeastern Thailand [7].

The results of drought risk assessment in this study align with trends observed and computed in the subbasins of the Mekong River, e.g., Upper Mun River Basin, Thailand [41-43] and in the Songkhram River Basin, [7], where agricultural drought risk has similarly transitioned respectively from no risk to low, low to medium, and medium to high levels over time, in terms of agricultural and socio-economic impacts. This is also consistent with a broader pattern of increasing drought risks, leading to water shortages and conflicts on water allocation. European Commission: Joint Research Centre [44] presented World Drought Atlas which shows that drought is a global threat, and its risks are increasing every day. Without urgent actions and international cooperation, its cascading impacts may ripple across economies, financial systems, populations, and ecosystems, increasing the risk of triggering shocks and long-term effects. The World Drought Atlas provides policymakers and governments at multiple levels, drought impacts on various critical systems, worldwide and examples of drought risk management and adaptation.

Moreover, the study on global drought risk trends indicates an increase worldwide, from the past (1991–2014) to the future, including near-term (2021–2040), mid-term (2061–2080), and long-term (2081–2100) projections [45].

A risk assessment based on drought hazard, vulnerability, and exposure in the Sukhothai Province from 2007 to 2021 was made using the new multiple indices of drought hazard (MDHI), vulnerability (CVI) and exposure (CEI). The new multiple indices open a new approach in understanding on the overall impact of complicated drought phenomena leading to effective integrated drought management strategies.

The results of the multiple hazard index in this study indicated a similar trend in the values of SPI, SRI, and SGI, transitioning from positive (no drought) to negative (drought) through meteorological, hydrological, and groundwater observation stations. The SPI values, which represent slight dry conditions or near-normal levels, ranged from 0.34 to -0.42. These were compared with the SRI (ranging from 0.81 to -1.89) and SGI (ranging from -1.00 to -2.15) for all cases of 1, 3, and 6-month drought timescales during the 2020s (2020-2021) period. All these individual parameters clearly changed from positive (wet) to negative (dry or drought) conditions.

The MDHI results were calculated by summing the weighted SPI, SRI, SGI, and NDMI values. These weighting factors for all drought indicators were estimated using the AHP technique. The results showed that the weighting factors for W_{NDMI}, W_{SRI}, W_{SGI}, and W_{SPI} are 0.565, 0.262, 0.118, and 0.055, respectively. The areas with the highest hazard levels are situated in the Si Satchanalai District, which is in the upper part of the study area. Other areas of concern include the Thung Saliam, Sawankhalok, and Ban Dan Lan Hoi Districts, located in the middle parts of the study area. Approximately 2,059 km² of paddy field area, 1,241 km² of field crop area, 306 km² of orchard area, and 224 km² of perennial crop area faced varying levels of drought hazard from very low to high between November 2019 and March 2020.

The drought hazard maps computed for the period 2007-2020 show the increasing trend of drought hazard levels from no hazard to low, low to medium, and medium to high levels. This increasing trend is in line with the results of other previous studies on the trends of drought hazards for agricultural areas in Upper Nan River Basin [4] and Wang River Basin [40] in the northern region of Thailand and in Songkhram River Basin, a subbasin of the Mekong River in the northeastern region of Thailand [7].

Validation of risk indices: The discrepancies between the observed and computed numbers of drought events in the Sukhothai Province are shown in Fig. 12. The discrepancies are found at some locations sparsely distributed over the study area and do not mainly represent the overall performance of drought risk assessment of the whole study area. Though these discrepancies are visible at some locations, the policy recommendations on drought mitigation and adaptation are made for the whole study area according to the majority of the observed and computed numbers of drought events. These policy recommendations are given at large on improving water management, changing of crop varieties and crop patterns in the study area.

For agricultural economic sector, the results in Table 5 revealed that the highest impact on economic sector amounted to approximately 10,545 million Baht and a maximum affected area of 2,441 km² in event 5, which occurred from November 2011 to February 2012. In the social sector, the drought risk was assessed on different demographics including the general population, females, children, people and households. The results showed that in event 9, in which data were available from December 2015 to May 2016, a close agreement between the observed and computed impacts was obtained, i.e., 51,705 and 51,679 affected people; 19,335 and 20,766 and affected household units, respectively. Moreover, about 25,937 females, 3,652 children, and 7,870 people aged 60 years and above were affected. In event 12 from November 2019 to March 2020, the affected an area covered agricultural losses of 2,672 km2 and 8,788 million Baht, respectively. It also impacted approximately 41,814 persons and 17,127 households. The combined agricultural economic and socio-economic drought risk maps from 2007 to 2020 in Fig. 11 shows increases in risk in the direction from the northern part to the southern part of the province with higher risks in the southeast part of the study area.

On socio-economic losses, Edwards, et al (2018) [46] described the impacts of droughts on farmers and employees in agricultural sectors in Australia in 2007, such as reduced income, job instability and health impacts. While the agricultural sector was most directly affected. Same as found in this study, the drought risk assessment of the agricultural economic sector and social sector involves the interconnected impacts on both sectors. In Table 5, drought event 1 to event 6 were before the change in policy of DDPM in 2014. The drought event 7 to event 12 were after the change in DDPM policy from 2014 onward. The computed data in Table 5 show a trend of positive relationship of risk areas and monetary agricultural losses in the economic sector. In the social sector, the positive relationship of affected people and households including other people social characteristics such as sex, age and poverty is also found. These positive relationships were in line with the observed data in the events 2, 3, 5, 6, 8, and 9. For example, from drought event 9 (December 2015 to May 2016) to event 12 (November 2019 to March 2020), the evolving trends of agricultural economic impact of all drought events show a positive relationship in risk areas and agricultural monetary losses; while in the social sectors, a positive relationship in numbers of affected people and affected households does exist. Therefore, in all, this implies that there is a positive relationship between the impacts on the agricultural economic sector and the impacts on the socio-economic sector.

Linking recommendations to findings: The proposed methodology estimates the combined drought risk by considering various components of hazard, vulnerability, and exposure. This study focuses on mitigation and adaptation strategies specific to the study area (Sukhothai Province). It is well known that seventy percent of the Sukhothai Province area is mainly utilized for rice cultivation in which fifty percent of the provincial area is non-irrigated (rainfed) and twenty percent is irrigated. In the irrigated areas where water supply is available, water management strategies are possible for drought risk reduction. This water management includes increasing storage capacities of existing reservoirs and ponds, or constructing new reservoirs in the Mae Yom, Sukhothai, and Tho Thong Daeng operation and maintenance projects. Lining irrigation canals is also an effective measure in reducing seepage water losses along irrigation canals and hence reducing drought risks. By overlaying the risk maps (Fig. 9) over the irrigated areas for the 2007–2019 period, it is found that for paddy fields the recommended mitigation measures can potentially reduce drought-affected areas and monetary losses on average as much as 22% and 13.51%, respectively; field crops 8.38% and 2.26%; orchards and perennial crops1.28% and 0.18%. Additionally, for the 2007–2019 period, the utilization of alternative water resources, such as groundwater to supplement water demand, for field crops, can potentially reduce drought-affected areas and monetary losses by approximately 4.22% and 1.14% for irrigated areas, and 4.92% and 1.33% for non-irrigated areas. For orchards and perennial crops, drought-affected areas and monetary losses can be reduced by approximately 0.59% and 0.08% for irrigated areas, and 2.36% and 0.32% for non-irrigated areas.

In the non-irrigated areas, where water resources are limited and effective water management strategy is difficult, crop management should be exploited. Adopting drought-resistant varieties such as the Hom Siam rice [47-48] to replace the prevailing RD 85 rice mostly grown in the areas could provide a feasible solution in reducing drought problems. The Hom Siam rice is more superior than the RD 85 rice as it offers significant improvement in both yield and drought resilience. Under optimal growth conditions, the Hom Siam exhibits a yield increase of over 50%. Under drought conditions, Hom Siam features a root system that is 20% more extensive, with a higher proportion of deep roots. This unique root structure is critical for maintaining the plant's water status and contributes to sustained biomass production under water-limited conditions.

According to field surveys, in the non-irrigated areas, planting of Hom Siam drought-resilient rice to replace the prevailing RD 85 rice would potentially reduce current drought impacts and drought risks by about 50%. In the irrigated areas where water supply shortage is not critical, increasing reservoir storages or building new reservoirs would potentially reduce drought impacts as much as 22%. Due to its sustainability, replacing the prevailing RD 85 rice variety by Hom Siam rice is not required in the irrigated areas. These measures would help alleviate the impacts of droughts, which are particularly severe in the middle and lower parts of Sukhothai Province.

6. Conclusions

A risk assessment based on drought hazard, vulnerability, exposure in the Sukhothai Province from 2007 to 2021 was done using the new multiple indices of drought hazard (MDHI), vulnerability (CVI) and exposure (CEI). The new multiple indices open up a new approach in understanding the overall impact of complicated drought phenomena leading to effective integrated drought management strategies.

The study contributes a new method in drought risk assessment for agricultural and socio-economic sectors which can be used as a guide for actionable strategies for government, policymakers, planners and researchers. The proposed methodology estimates multiple or combined drought risk considering various components of hazard, vulnerability and exposure. This study provides mitigation and adaptation strategies in Sukhothai Province in reducing drought risks in irrigated and non-irrigated areas. These include 1) water resources management in irrigated areas by increasing water supply through increasing reservoir capacities, groundwater utilization as a supplementary resource, irrigation canal lining to reduce seepage and increasing water use efficiency; 2) crop management by modifying cropping patterns in non-irrigated areas by introducing drought-resistant crop varieties, particularly for rice to replace the existing crop varieties.

The results of this study on drought risk assessment are in line with the results of other previous studies which indicate a considerable increasing trend in agricultural drought risks from no risk to low, low to medium, and medium to high levels over time in the northern region and the northeastern region of Thailand (a part of the Mekong River Basin), [7, 41-43] and worldwide [44, 45]. These mitigation and adaptation measures would help alleviating the impacts of droughts, which are particularly severe in the middle and lower parts of the Sukhothai Province.

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