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Distributed probability of slope failure in Thailand under climate change

Daisuke Komori[a], Prem Rangsiwanichpong[a,*], Naotatsu Inoue[b], Keisuke Ono[c], Satoshi Watanabe[d], So Kazama[e]

[a] Graduate School of Environmental Studies, Tohoku University, Sendai 980-8579, Japan
[b] JGC Corporation, Yokohama 220-6001, Japan
[c] CTi Engineering Co. Ltd., Tokyo 103-8430, Japan
[d] Graduate School of Engineering, University of Tokyo, Tokyo 113-8656, Japan
[e] Graduate School of Engineering, Tohoku University, Sendai 980-8579, Japan

A R T I C L E I N F O

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A B S T R A C T

Landslides are more widespread compared to any other geological hazards in Thailand. The steep slope and high elevation areas have more potential for landslide hazards. However, weather extremes, particularly extreme rainfall, play a major role in the occurrence of landslides in Thailand. The objective of the present study is to analyze the changes in the probability of landslide occurrences in Thailand due to climate change. For this purpose, probabilistic landslide hazard maps for extreme rainfall values for 5-, 10-, 50-, and 100-year return periods are developed for historical and future climatic conditions, derived from 10 global climate models (GCMs) under two representative concentration pathway (RCP) scenarios, namely, RCP 4.5 and RCP 8.5. The results reveal that the 5-year return period extreme rainfall amount will reach 200 mm/month in the eastern and southern provinces for RCP 4.5 and the northwestern, eastern, and southern provinces for RCP 8.5. The increase in extreme rainfall will cause a sharp increase in the landslide probability in Thailand, except in low altitude regions. The probability of 100-year return period landslide will increase by 90% in 40% and 80% of the areas in Thailand under RCP 4.5 and RCP 8.5, respectively. It is expected that the landslide hazard maps developed in this study will help policy makers take necessary measures to mitigate increasing landslide events due to climate change.

1. Introduction

Landslide research requires the use of soil and geological data, which are not fully available in developing countries due to lack of information concerning the location of and risks posed by landslides in mountainous regions. Landslides can cause significant damage to residents and can lead to economic losses in these countries. Therefore, it is important to assess future landslide risk distribution using quantitative analysis and to designate regions that require reinforcement measures to prevent landslides. Various methods of predicting the vulnerability to rainfall-induced landslides have been developed. Thus, analyzing landslide risks based on the geographic information system (GIS) and remote sensing techniques are necessary in the case of developing countries. In Thailand, a relative abundance of data have supported numerous landslide studies. Soralump (2010) prepared a landslide hazard map for Phuket Island using soil conditions and rainfall information obtained from site surveys. Jotisankasa and Vathananukij (2008) investigated geological features and soils in various districts of

* Corresponding author.
E-mail addresses: daisuke.komori.e8@tohoku.ac.jp (D. Komori), prem.rangsiwaichpong.q8@dc.tohoku.ac.jp (P. Rangsiwanichpong), inoue.naotatsu@jgc.com (N. Inoue), ksk-ono@ctie.co.jp (K. Ono), stswata@sogo.t.u-tokyo.ac.jp (S. Watanabe), so.kazama.d3@tohoku.ac.jp (S. Kazama).

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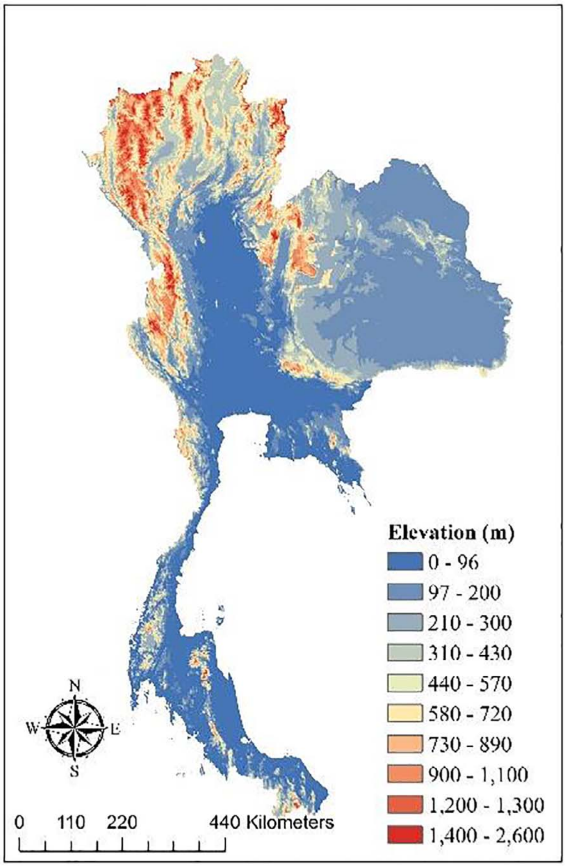

Fig. 1. Elevation of Thailand.

Thailand and assessed local landslide risks qualitatively. Both studies clearly demonstrated that slope failure and landslide damage are becoming more common in Thailand. The Land Development Department (LDD) of Thailand initiated the preparation of a landslide risk map in response to recurring landslide events occurring in recent years, and in 2006, they published a map presenting high, moderate, and low risk areas according to geographic conditions. However, the assessment generated no rainfall information or data in which landslides events in Thailand have occurred as a result of heavy rainfall, especially in the northern and southern regions of Thailand, where land has been eroded by significant water flows from the mountains that have descended to low elevation areas at the base of the mountains. Several researchers have found that rainfall is a key factor that shapes landslide events (Iida, 2004; Fan et al., 2016). However, few studies have analyzed the probability of landslide hazards under conditions of climate change in Thailand. Therefore, the analysis of landslide hazard probability under climate change conditions constitutes an important challenge for this country. Various methods for predicting the vulnerability to rainfall-induced landslides have been developed. The most common and reliable method used in the field of geotechnical engineering is slope stability analysis, which involves the use of a physical model based on in situ geotechnical parameters; however, this method can only be applied to smaller study areas (Wu and Sidle, 1995). Numerous researchers have attempted to make landslide predictions using GIS and regional models (He and Beighley, 2008; Pradhan and Lee, 2009; Wu et al., 2011). Additionally, some studies have used statistical methods to predict landslide probability levels (Komac, 2004; Lee et al., 2008; Goetz et al., 2015). However, the knowledge of rainfall distributions is needed to produce hydraulic gradient estimations. Therefore, the application of these methods requires the various forms of information, especially for economically developing countries that typically present low levels of rainfall observation density. In reference to Thailand, Yumuang (2006) studied landslide and debris flows in Phetchabun Province using GIS and remote sensing techniques. Kawagoe et al. (2010) assessed landslide hazards in Japan via a multiple logistic regression analysis. Ono et al. (2014) assessed rainfall-induced shallow landslides occurring in the Phetchabun and Krabi provinces of Thailand using a shallow landslide instability prediction model (SLIP). Furthermore, Inoue et al. (2014) attempted to project the probability of landslide occurrences in Thailand using a landslide probability model under multiple global climate models (GCMs). The objective of the present study is to analyze the probability of landslide hazard occurrences under climate scenarios for Thailand. We estimated the extreme daily rainfall level from (APHRODITE) to create a spatially distributed extreme rainfall map. The future distribution of extreme rainfall events can be analyzed from 10 types of GCMs under RCP scenarios, and the probability of landslide hazard occurrences across Thailand attributable to future climatic change can be estimated using the probability landslide model.

Table 1
Specification of each GCM.

Model	Institution	Abbreviation
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	mir5
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory	ge2m
CanESM2	Canadian Centre for Climate Modelling and Analysis	cae2
CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organisation in collaboration with the Queensland Climate Change Centre of Excellence	cs36
INM-CM4	Institute for Numerical Mathematics	inc4
CNRM-CM5	Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	cnc5
IPSL	Institut Pierre-Simon Laplace	ip5l
BCC	Beijing Climate Center, China Meteorological Administration	bc1m
MRI	Meteorological Research Institute	mrc3
NCC	Norwegian Climate Centre	noem

2. Study area and landslide history

Thailand is located at the centre of peninsular Southeast Asia. The country's topography can be divided into 5 physical regions that include the central valley, the highlands of the north and northwest, the northeastern and southeastern coasts, and the peninsula. Approximately 20% of Thailand is covered by a mountainous plateau area (Fig. 1). The average slope of this area exceeds 30%. Thailand's climate is classified as a tropical savanna with especially strong local downpours that frequently cause landslides occurring during the rainy season. For example, prolonged heavy rains occurring across Thailand's entire southern peninsula in Nakorn Sri Thammarat province on November 20–23, 1988 caused 373 injuries and 230 deaths. In 2001, a landslide occurred in the Wang Chin district of Phare province as a result of continuous heavy rainfall occurring in this region, causing 40 deaths (Teerarungsigul et al., 2015). In the same year, a significant landslide event occurred on March 11, 2001 in the village of Nam Ko in Phetchabun province. The area is located in central Thailand and is characterized by mountains and steep slopes. Heavy rainfall occurring during such events has had a return period of more than 50 years. The debris flows killed 136 people and economic losses cost approximately 100 million THB. Furthermore, several provinces of northern Thailand (Uttaradit, Sukhothai, Phrae, Lampang and Nan) were affected by the landslide. Landslide events occurring in these provinces in 2006 involved serious flash floods that caused 87 deaths. More recently, a significant landslide event occurred on Khao Panom Mountain at the end of March of 2011, as the area is characterized by the steep slopes of a dense tropical forest. The event caused considerable damage because villages are located in the area. Average annual rainfall levels in the Khao Panom area normally exceed 1500 mm. The climate in this area is tropical, and most rainfall here occurs between April and November. During this event, a heavy storm hit the area, and three subwatersheds suffered from landslides and debris flows. The return period of this storm event is estimated to exceed 50 years of the daily rainfall. Damages resulting from this event affected more than 800,000 people, and 13 people were killed (Department of Mineral Resources, 2012).

3. Data collection analysis

In this study, 1 km × 1 km U.S. Geological Survey (USGS) elevation data were used to calculate the relief energy and hydraulic gradient. The relief energy was calculated from the difference between the maximum and minimum elevation in each grid. The hydraulic gradient was estimated by infiltration analysis using the slope angle as determined by the largest elevation difference between adjacent grids. Furthermore, U.S. Department of Agriculture (USDA) data were used as soil data. We set required parameters by classifying soil into three types: sand, slit and clay. In addition, Asian precipitation highly resolved observational data integration towards evaluation of water resources (APHRODITE) $0.25^\circ \times 0.25^\circ$ resolution decimal degree precipitation data for 1987 to 2006 were used as climate data. The resolution of these precipitation data is still too coarse to analyze the probability of slope failure. Therefore, we used linear interpolation to downscale the precipitation data to 0.05 × 0.05 decimal degrees. Furthermore, we estimated the extreme daily rainfall level from APHRODITE to create a spatially distributed extreme rainfall map. The future distribution of extreme rainfall events can be analyzed from 10 types of GCMs under RCP scenarios, and the probability of landslide hazard occurrences across Thailand attributable to future climatic change can be estimated using the probability landslide model. We used two RCP scenarios to analyze future climate conditions. The first, RCP 8.5, is the scenario under which the greenhouse gas concentration and radiative forcing levels increase the most. The second, RCP 4.5, is a moderate scenario derived from 10 GCMs including GFDL-ESM2M, CNRM-CM5, CanESM2, CSIRO-Mk3.6.0, NorESM1-M, BCC-CSM1.1 M, IPSL-CM5A-LR, INM-CM4, MRI-cGCM3 and MIROC5 at a grid resolution of $0.5^\circ \times 0.5^\circ$. Details regarding each GCM are shown in Table 1.

4. Methodology

4.1. Infiltration analysis

We conducted an unsaturated infiltration analysis based on Richard's equation (Richards, 1931) to obtain the hydraulic gradient. The hydraulic gradient is a vector gradient between two or more hydraulic head measurements over the length of the flow path. Richard's equation represents the movement of water through unsaturated soil. The steps of infiltration analysis are written as Eqs. (1) to (7).

$$\frac{\partial\theta}{\partial t} = -\left(\frac{\partial V_x}{\partial x} + \frac{\partial V_y}{\partial y}\right) \quad (1)$$

$$V_x = -K_x\frac{\partial h}{\partial x} \quad (2)$$

$$V_y = -K_y\frac{\partial h}{\partial y} \quad (3)$$

$$h = p - L_x\sin\alpha - L_y\cos\alpha \quad (4)$$

$$C\frac{\partial p}{\partial t} = \frac{\partial}{\partial x}(K_x\frac{\partial p}{\partial x} - K_x\sin\alpha) + \beta\frac{\partial}{\partial y}(K_y\frac{\partial p}{\partial y} - K_y\sin\alpha) \quad (5)$$

$$K_y = K_{sy}\left(\frac{\theta-\theta_r}{\theta_s-\theta_r}\right)^{\beta}, K_x = K_{sx}\left(\frac{\theta-\theta_r}{\theta_s-\theta_r}\right)^{\beta} \quad (6)$$

$$\theta = (\theta_r-\theta_s)\left(\frac{p'}{p_0} + 1\right)\exp\left(-\frac{p'}{p_0}\right) + \theta_r \quad (7)$$

where θ is the water volume content, t is the time interval, V is the velocity, x is the horizontal direction, and y is the vertical direction. The parameter is the soil characteristic value, K is the hydraulic conductivity, and K_s is the unsaturated hydraulic conductivity. Eqs. (2) and (3) provide flow velocities in the horizontal and vertical directions. The total head hydraulic gradient can be calculated from the elevation head and from the sum of the hydraulic pressure head (P), as shown in Eq. (4). In 1931, Richard estimated a two-dimensional hydraulic head (h) from the relationship between the unsaturated hydraulic conductivity and the pressure head with water volume content(θ), as shown in Eqs. (5)–(7). Thus, C is the specific moisture capacity, θ_r is the residual water volume content, and θ_s is the water volume content of the saturation stage. The parameter p_0 is the hydraulic pressure head for the initial condition and p' is the hydraulic pressure for the saturated condition. The C value can be calculated from the gradient of soil moisture characteristic curves (Gosh, 1980; Ahuja et al., 1985; Kawakami, 2003).

4.2. Extreme daily rainfall

To estimate future climate projections, we applied the return period of extreme daily rainfall data of the GCM by the generalized extreme value (GEV) and the probability weighted moment (PWM) for a distribution function. The GEV method is widely used for assessing extreme rainfall patterns around the world (Martins and Stedinger 2000; Villasenor 2013; Chikobvu and Chifurira, 2015). The results shown that GEV is the one of best distributions for analyzing rainfall data of this research (Fig. 2). We analyzed two sets of return periods: 5- and 50-year return periods. However, the resolution from the GCM is still too coarse for use in landslide

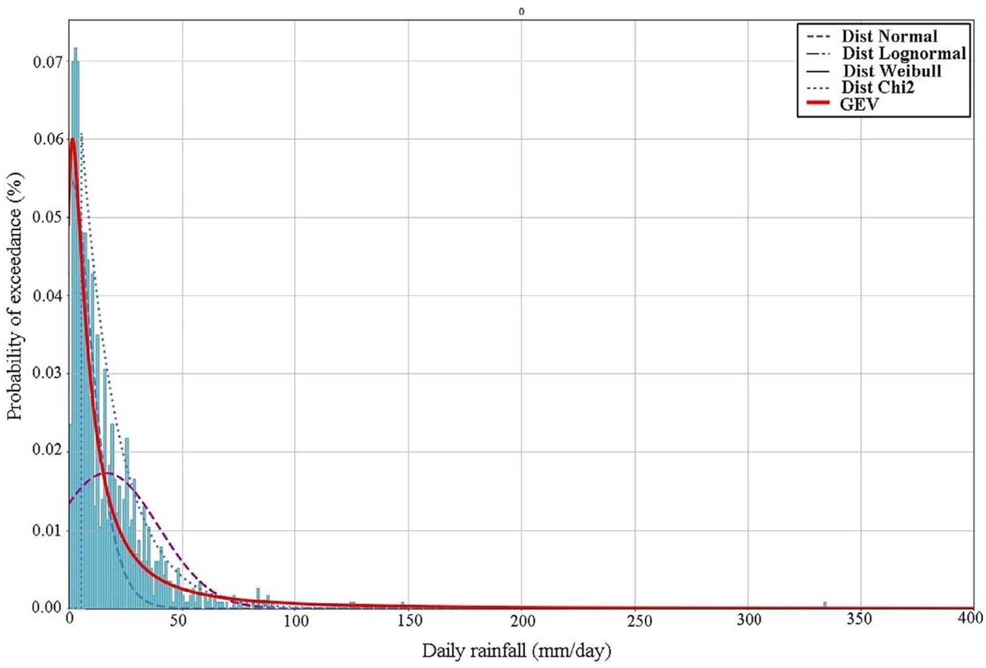

Fig. 2. Comparisons of the probability distribution functions for Ayutthaya station.

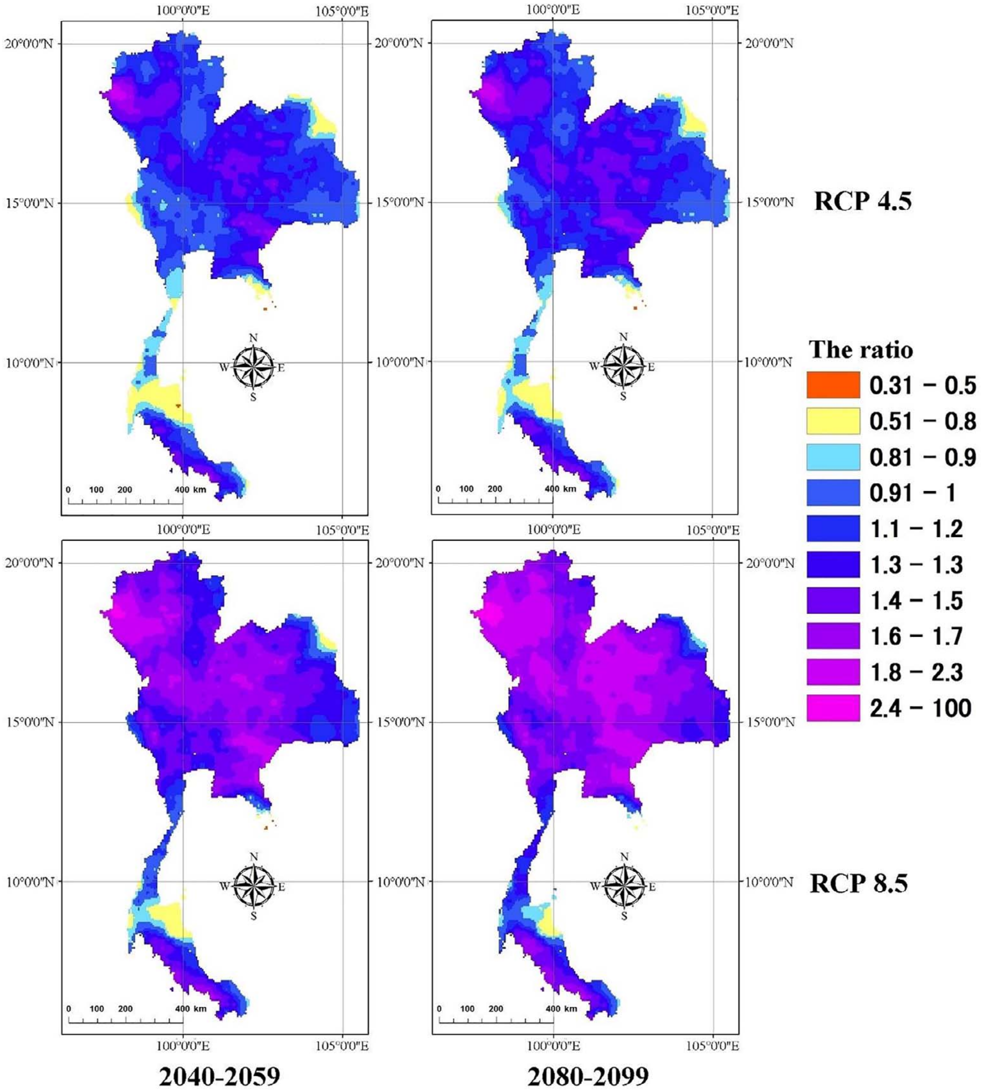

Fig. 3. The ratio between the present rainfall and the average of extreme rainfall by 10 GCMs for a return period.

assessments. Therefore, we downscaled the grid data of the climate model to analyze from 0.5° × 0.5° to 0.05° × 0.05° using a statistical downscaling method. The statistical downscaling method was developed to link the spatial gap between the GCM grid scale and local scale grid (Iizumi et al., 2008). In this research, we followed the method for downscaling the GCM data by Ono et al. (2011).

$$M_0 = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{8}$$

$$M_1 = \frac{1}{n(n-1)}\sum_{i=1}^{n-1} x_i(n-i) \tag{9}$$

$$M_2 = \frac{1}{n(n-1)(n-2)}\sum_{i=1}^{n-2} x_i(n-i)(n-i-1) \tag{10}$$

where

n is the number of data,
x_i is the value of lower rank in the data,
i is the rank, and
M is the probability weight moment.

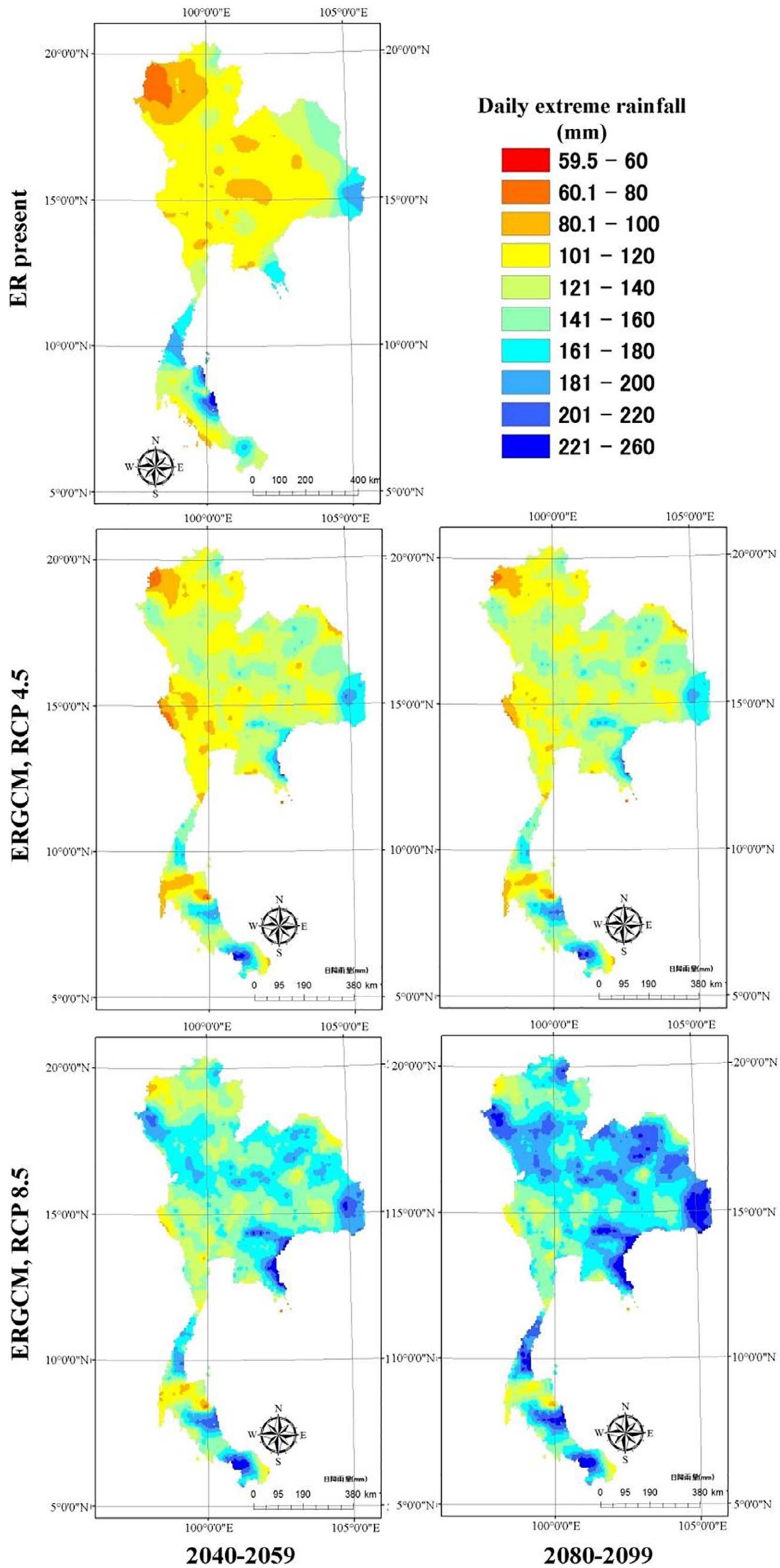

Fig. 4. Extreme rainfall with the present climate and the ensemble average of extreme rainfall from the GCM data for a 5 year return period under RCP 4.5 and 8.5.

Table 2
Comparison results of landslide hazard probabilities with a 50-year return period and the history of large landslide occurrence in Thailand.

Places	Dates	Killed	Injured	Missing	Probability (%)
Phipun District, Nakorn Si Thammarat Province	22 Nov 1988	230	–	–	98
Lansaka District, Nakorn Si Thammarat Province	22 Nov 1988	12	–	–	99
Khao Kochakoot Sub-district, Chantaburi Province	30 Jul 1999	–	–	–	88
Wangchin District, Prae Province	4 May 2001	43	–	4	79
Tambol Namkor, Lomsat District, Phetchabun Province	11 Aug 2001	136	109	4	92
Tambol Maeteenand Yangpieng, Omokoi District, Chiengmai Province	20 May 2004	1	–	–	81
Maeramart District, Tak Province	20 May 2004	5	391	–	76
Tarntho District, Yala Province	12 Dec 2004	2	–	–	83
Bunnangstar District, Yala Province	20 Dec 2005	–	–	–	84
Laplae, Tha Pla and Muang District, Uttaradit Procince	22 May 2006	71	–	32	78
Muang District, Phrae Province	22 May 2006	5	–	–	89
Fang District, Chiengmai Province	8 Oct 2006	8	–	–	97
Thongpapoom District, Karnchanaburi Province	9 Aug 2007	–	3	–	94

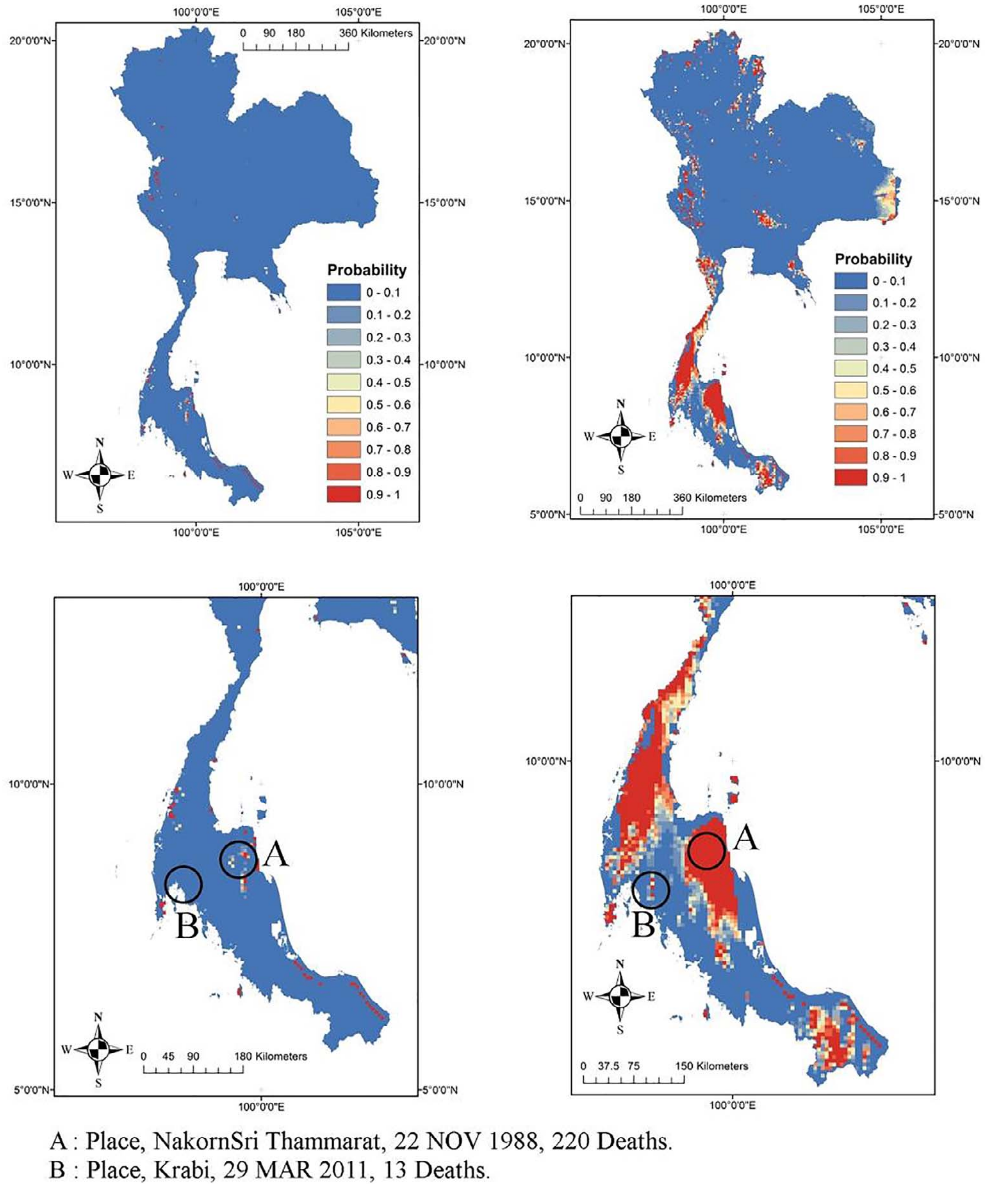

Fig. 5. Past landslide disaster in Thailand and the spatial distribution the probability of landslides estimated using extreme rainfall for return periods of 5 (Left) and 50 years (Right).

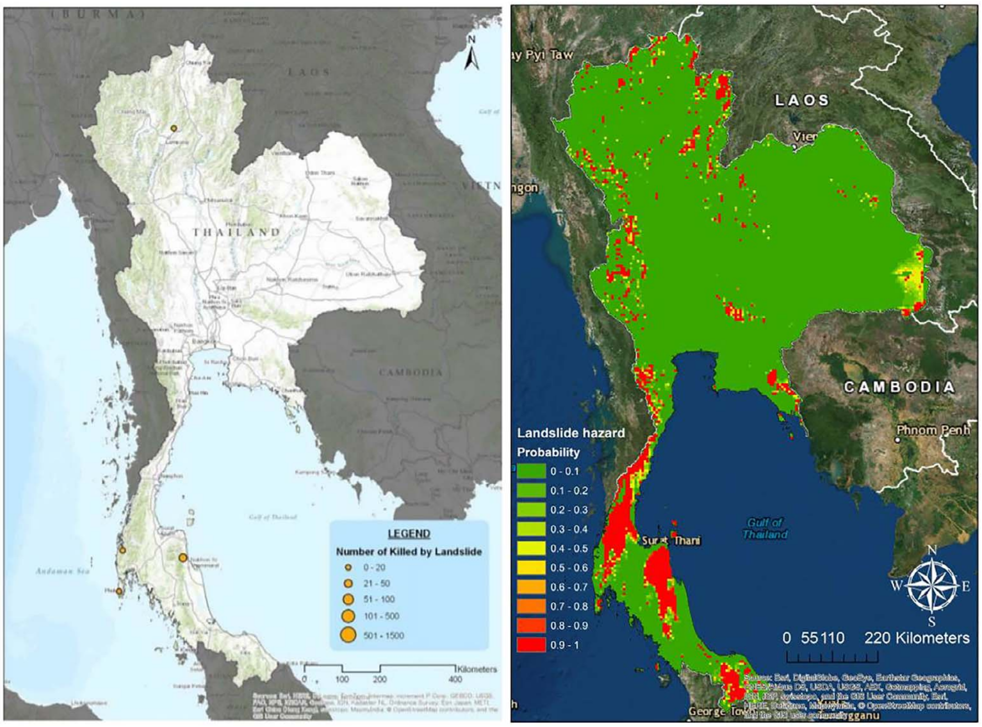

Fig. 6. Historical maps of landslide events from a Country report, 2015 (left), and Landslide hazard map (right).

5. Landslide probability assessment

In this research, we estimated landslide probability with a spatial analysis under climate conditions. Therefore, we estimated the landslide probability levels across Thailand by a multiple logistic regression method developed by Kawagoe et al. (2010). In 2014, Inoue et al. applied the coefficient value of the probability model for analyzing landslide hazards in Thailand, which is the same study compared with our research. Therefore, we can apply the coefficient of probability to this research. The equation for calculating the probability is written as Eq. (11).

$$p = \frac{1}{1 + \exp[-(-17.494 + 1179.25 \times \text{hyd} + 0.0097 \times \text{relief})]} \tag{11}$$

where p is the landslide probability (%), hyd is the hydraulic gradient (m/m), and relief is the relief energy level (m).

6. Results and discussions

6.1. Daily extreme rainfall and future climatic conditions

We assessed the extreme rainfall to predict the future probability of landslide occurrences for two climate periods using 10 GCMs under the RCP 4.5 and 8.5 scenarios. We analyzed rainfall for intermediate and future scenarios within a 5-year return period. Fig. 3 shows the ratio between the present rainfall levels and the extreme rainfall average by 10 GCMs for a return period of 5 years. The results show that the ratio of extreme rainfall in Thailand increases by more than 50% for the RCP 8.5 scenario. On the other hand, extreme rainfall in the same southern area for both scenarios decreased by approximately 30%. In addition, Fig. 4 shows extreme rainfall levels under present climate conditions and the collective average of the extreme rainfall levels from GCM data for a 5-year return period under RCP 4.5 and 8.5 scenarios. The results show that extreme rainfall patterns over a 5-year return period for RCP 4.5 are predicted to exceed 200 mm in the eastern and southern regions. For RCP 8.5, the average rainfall level increases in most regions of Thailand under the intermediate and future climate scenarios.

6.2. Validation landslide probability model

The landslide hazards in Thailand were analyzed using the probability of the landslide model for 5-, 10-, 50-, and 100-years return periods. We compared the landslide hazard probability results with the 50-year return period and the history of large landslide occurrences in Thailand (Table 2). The probability of landslide occurrences by our simulation corresponds to the country's history of landslides. For example, we compared the results of 5- and 50-year return periods with the landslide events that occurred in the

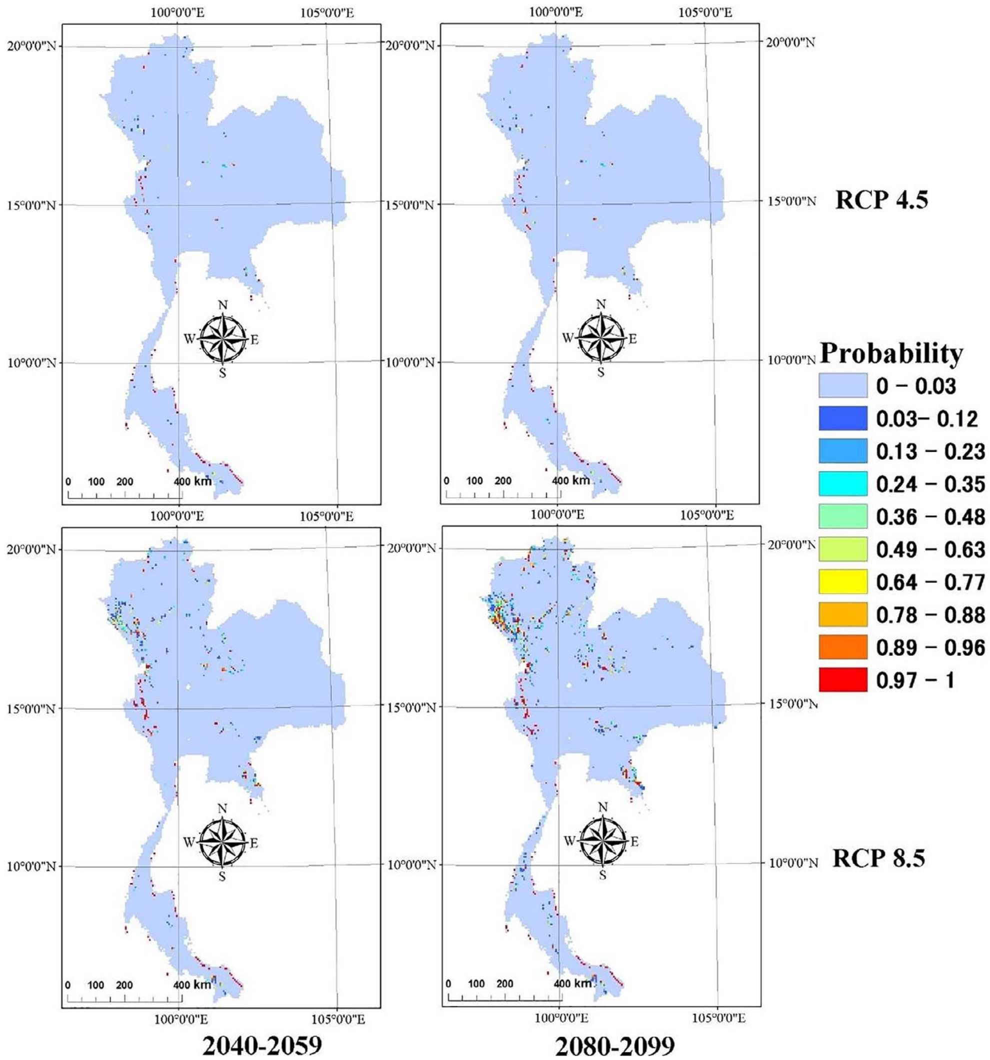

Fig. 7. The probability of landslides for a return period of 5 years under RCP 4.5 and 8.5 scenarios.

provinces of Nakorn Sri Thammarat and Krabi. The landslide that occurred at Nakorn Sri Thammarat in 1988 killed more than 200 people, and it ensued with rainfall return period of more than 300 years (Vongvisethsomjai, 1989). The result of landslide prediction shows that the probability of this event occurring over a 5-year return period is approximately 23%, and the probability occurring over a 50-year return period increases to 96%. Furthermore, high-risk areas were identified in Krabi province, where landslide event occurrence exceeds 50% over a 50-year return period (Fig. 5). In addition, the landslide hazard map was validated by a historical map of landslide events in Thailand (Country Report, 2015), as shown in Fig. 6. The results from landslide probability map correspond to the landslide events. These results confirm that the probability of the landslide model can predict long-term landslide event occurrence in Thailand.

6.3. Probability of landslide hazard occurrence under future climate conditions

6.3.1. RCP 4.5

The probability of landslide hazard occurrences under future climate conditions was calculated according to RCP 4.5 based on average extreme daily rainfall levels with return periods of 5, 50 and 100 years from 10 GCMs (Figs. 7–9). The results show that the probability of a landslide occurrence over a 5-year return period increases and is related to present and future climate conditions, especially in the northern region of Thailand. The future probability of a landslide occurrence estimated from extreme daily rainfall with a return period 50 years shows that landslide prone areas under intermediate and future climatic conditions will become more susceptible in the northern and southern regions, i.e., areas presenting a probability of 80% or above under present climate conditions. Furthermore, landslide probability levels of 20% to 90% appear in the eastern region. The area presenting probability levels exceeding 50% grows from the southeastern coast to the central area in correspondence with the expansion of high probability areas

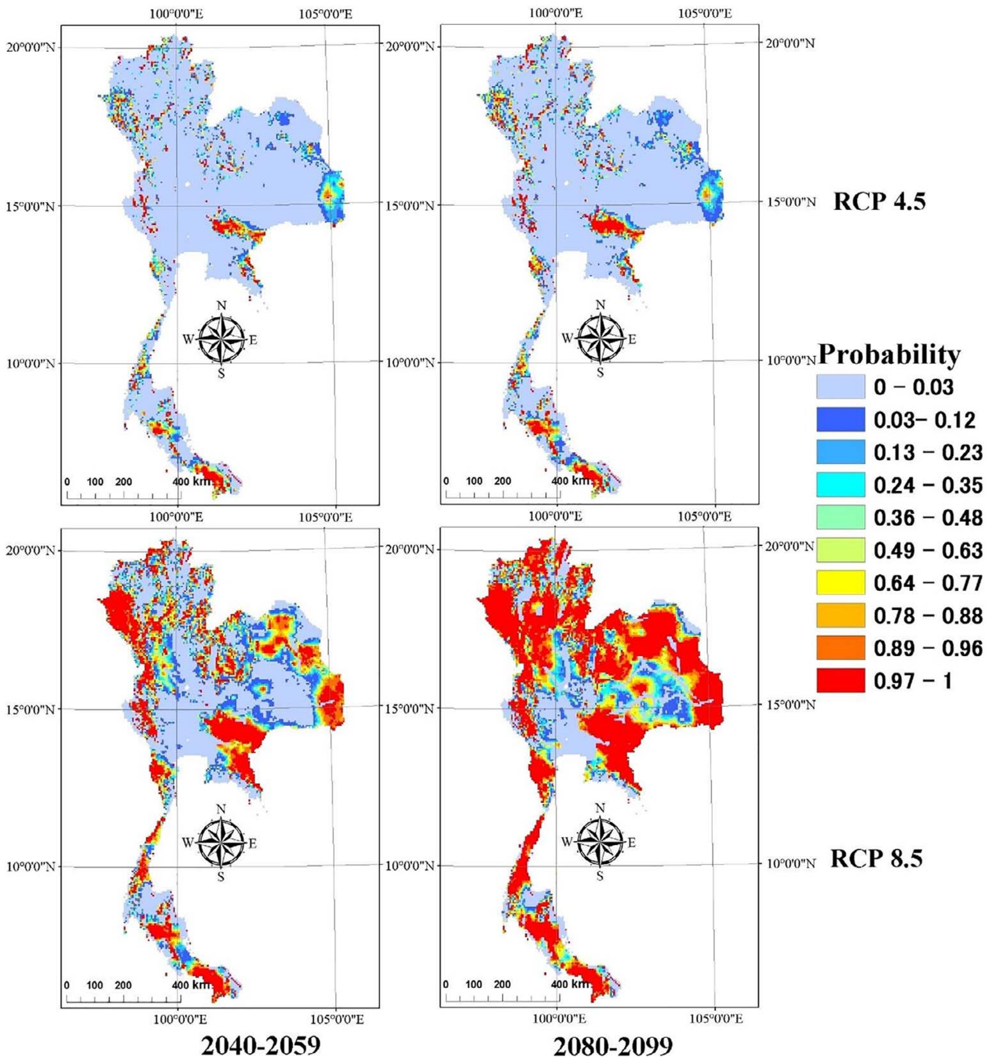

Fig. 8. The probability of landslides for a return period of 50 years under RCP 4.5 and 8.5 scenarios.

under both intermediate and future climate conditions (Fig. 8). Moreover, the probability of a landslide occurrence over a return period of 100 years exceeds 90% and is increasing in this area. Areas presenting high levels of landslide probability are predicted to account for 40% of Thailand's landmass under future climate conditions (Fig. 9).

6.3.2. RCP 8.5

The landslide probability results for a 5-year return period under RCP 8.5 show that a landslide-prone area will grow from 35% to 90% in the northern region under intermediate and future climate conditions relative to the present climate. In the southern region, the landslide-prone area will increase from 50% to 90% (Figs. 7 and 8). This increase in landslide-prone areas is substantially more pronounced than that shown for future climatic conditions under RCP 4.5. For a return period of 50 years, we found an increase in grids with a probability of landslide occurrence of more than 80%. This increase is even more prominent under future climate conditions, which show a probability of landslide occurrence of more than 90% in areas covering more than 50% of Thailand's landmass. However, in the areas surrounding Bangkok, landslide probability levels remain low. In addition, our comparison between the return periods of 100 and 50 years shows that the increase in landslide-prone areas of more than 90% over a return period of 100 years is higher than that reached under a return period of 50 years (Fig. 9). Moreover, a landslide probability level of 90% or higher is predicted over a return period of 100 years across most of the country, except for in low elevation regions and cities, including Bangkok.

7. Conclusions

This study estimated the probability of landslide occurrences in Thailand with changes in climatic conditions using the probability

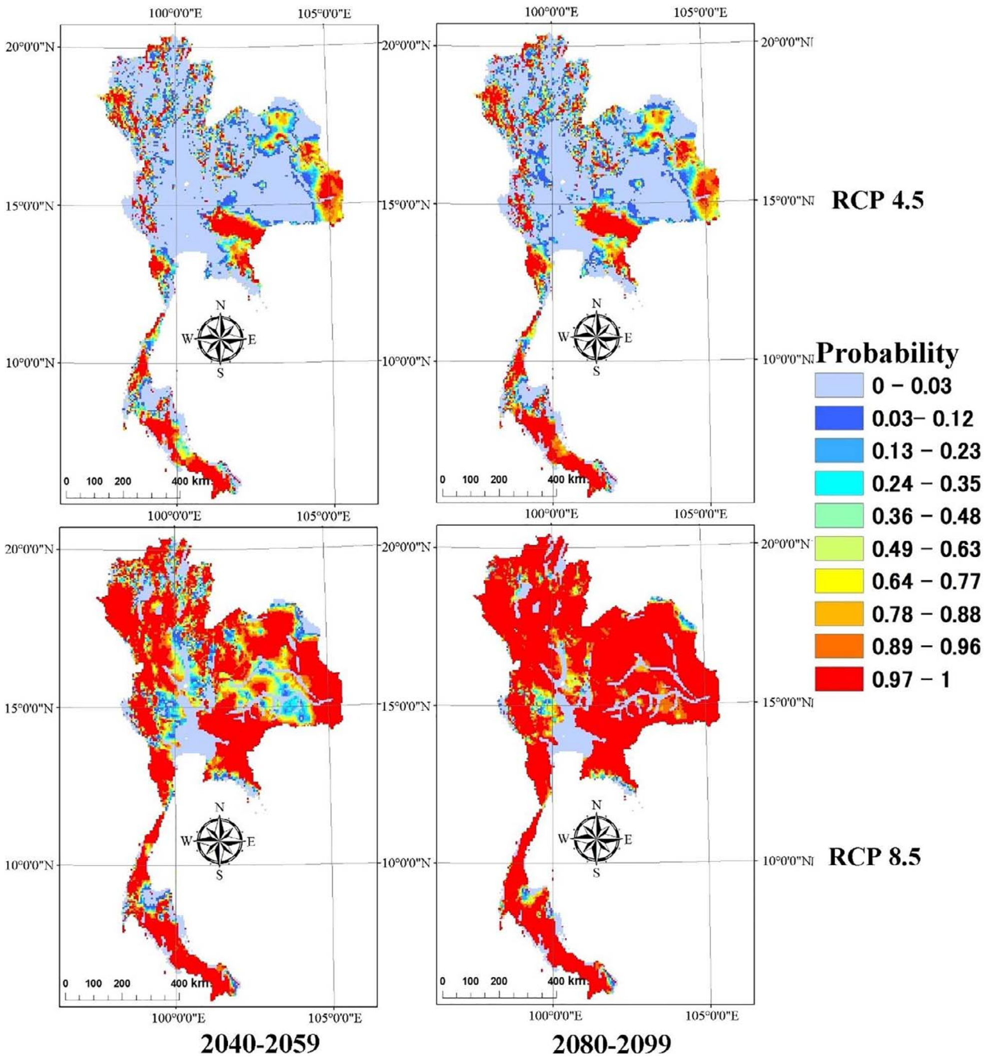

Fig. 9. The probability of landslides for a return period of 100 years under RCP 4.5 and 8.5 scenarios.

of a slope failure model with daily extreme rainfall. We analyzed the impact of climatic conditions on the probability of landslide occurrences in the future under the RCP 4.5 and RCP 8.5 scenarios. The probability of landslide occurrence is dependent on topographic and geological effects, hydraulic gradients and relief energy levels. Our results indicate that the probabilities of the landside model can estimate landslide disaster hazards corresponding to the history of landslide disasters in Thailand. Furthermore, our climate model's scenarios estimate that the probability of landslide occurrence will increase in the future. Future climatic patterns under the RCP 8.5 scenario over a return period of 100 years show that areas presenting landslide hazard probability levels of more than 90% will expand to 80% of the entire area. Therefore, the results of our study present new challenges regarding the protection and mitigation of landslides under climate variability in Thailand. Moreover, probability analyses of landslides based on daily extreme rainfall levels will be of use for developing countermeasures regarding landslide disasters in regions for which observed rainfall data are unavailable.

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