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Fuzzy AHP Integrated with GIS Analyses for Drought Risk Assessment: A Case Study from Upper Phetchaburi River Basin, Thailand

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Abstract: This study aimed to analyse and assess desertification risks in the Upper Phetchaburi River Basin. Upstream areas are especially crucial for aquatic ecosystems since the mid- and downstream areas are continuously being utilized for agricultural and community purposes. Many parts of the basin have been at moderate risk of drought. The fuzzy analytical hierarchy process (FAHP) is an effective and widely accepted model used to identify complicated environmental problems and disasters and prioritize factors in environmental studies. This study emphasized on four main factors influencing drought: Climate, physical factors, soil and land utilization factors. Each factor contains ten sub-criteria to identify severity levels and specific issues. The major areas of the basin were facing different risk levels: moderate (21%), high (5.79%) and severe (0.07%). Precipitation and slope gradient were the main factors affecting drought risks. The problematic areas were agricultural areas located in midstream and downstream areas. Therefore, spatial mitigations and possible ways forward should focus on increasing moisture contents—to reduce soil erosion and enhance soil fertility—and create restrictions to ensure appropriate land use. The mitigations must take into account spatially critical factors and must also include an integrated plan for the entire basin area.

Keywords: fuzzy AHP; drought; triangular fuzzy numbers; land use; drought risk

1. Introduction

Drought has attracted attention across basin areas in many parts of the world. Land degradation, drought and desertification are all consequences of human activities [1–5]. Erosion, agrochemical cropping, monoculture farming and changes in the fertility and drainage of soil are all causes of land degradation [4,6,7]. Human activities complicate [3,4,8] and increase the risk of drought [5,6,9] rendering its occurrence and severity more difficult to predict [9,10]. Therefore, obtaining data and conducting risk assessments in areas at risk of droughts are vital for planning for the future of land development, drought prevention and minimizing the adverse impacts from it.

Recent research has shown that mathematical models such as the drought hazardous and vulnerability index (DHVI) (e.g., [11–14]) are effective tools for assessing the risk of drought (e.g., [15–17]). However, the models often do not include all anthropogenic effects [18–20]. Among these tools, the fuzzy analytical hierarchy process (FAHP), a combination of analytical hierarchy process (AHP) and fuzzy theory [21,22], include anthropogenic factors. FAHP is effective for estimating the degree of importance, or weight, and is used for various purposes including site selection, evaluation, planning, decision making and forecasting (e.g., [23–27]). The FAHP approach was proposed by Chang [28] as a way of solving the limitations of AHP [24,29,30]. Even though FAHP is a highly complex process, it is more

applicable and effective than the conventional AHP when dealing with real world problems, especially for risk assessment and disaster predicting (e.g., [29,31–35]).

Both FAHP and AHP methods are extremely useful for prioritizing multiple-choice criteria and sorting them into a hierarchical structure. FAHP assesses the relative importance of each criterion and also generates an overall rank of alternatives or weight of factors. In the classic AHP method, the numerical values of linguistic variables are directly used for the evaluation of the criteria. If the environment where the decision-making process takes place is fuzzy, then fuzzy numbers will be used for the evaluation concerning some deviations of the decision makers. According to the literature, the AHP method is a decision support tool that is widely employed to solve complex decision problems or as a weight-estimating technique in many fields such as water resource management, environmental management, economic development and medicine and healthcare [1,27,28,36–38].

However, AHP has its limitations. Crisp values are required in order to use the AHP analysis. Therefore, its limitations lie in analyzing data sets with vagueness and uncertainty, or those containing complex factors, that are common in real world situations. Fuzzy set theory is widely applied for risk assessment in many research fields (e.g., [22,23,25,26]). The concept of fuzzy sets is a great generalization of the classical notion of a set. A fuzzy set model is a class of objects with a continuum of grades of membership that divides evaluation results into intervals [21]. The fuzzy set model has its function to locate the assessment results in the intervals which makes them more plausible. Therefore, the integration of fuzzy sets and AHP gives a much better and more exact representation of the relationship between criteria and alternatives [24,28,30–35,39]. The key to success of the FAHP method lies in correctly prescribing the domain of the fuzzy evaluation and reasonably constructing a fuzzy evaluation matrix. Therefore, subjective limitations are inevitable. Moreover, there has been research comparing the outcomes of AHP and FAHP. The results revealed that FAHP was less sensitive to the changes than AHP [40,41]. The FAHP process was used to express uncertainty and to obtain more accurate results than the AHP method [42].

FAHP is widely used among researchers to weigh selected risk factors and construct a fuzzy logic theory (e.g., [23–25,31,39–41]). Drought risk assessment is an intrinsically complex, multidimensional process which includes both uncertain quantitative and qualitative factors [38,39]. Therefore, FAHP is considered to be highly appropriate for assessing and predicting drought risks [24,31,39]. For example, Wijitkosum [39] applied AHP with the triangular fuzzy numbers (TFNs) method to analyze data obtained from the quantitative and qualitative criteria for assessing drought risk at Lam Ta Kong Watershed. Aher et al. [41] used FAHP to identify vulnerable areas located in sub-watersheds in the transition zone between the mountainous and the water scarcity regions of western India. Both studies exposed critical factors that affected drought risks in the watersheds. Policy makers were able to use this data to establish drought policy and management. Hosseini-Moghari et al. [31] considered FAHP as an effective tool for drought risk management for qualitative criteria that takes into account subjectivity and uncertainty and aids with synthesizing group judgments. Sadeghravesh et al. [42] prioritized five combating-desertification alternatives for central Iran via FAHP by reducing the uncertainty associated with group decision-making. Therefore, it is well established that FAHP is practical for predicting and identifying the vulnerability of the environment against hazardous disasters.

Also research has shown that FAHP is useful to assess the risks of floods (e.g., [40,43–45]), to create landslide susceptibility maps, to assess soil erosion (e.g., [32,46–48]) and functions as a decision-making tool for disaster and spatial management (e.g., [24,31,40,41,45]). Geographic information system (GIS) analysis and remote sensing (RS) for spatial analysis, are modern tools that play an important role in graphical visualization, dissemination of information and to facilitate interpretation of such spatial information [48–51]. For this reason, in many studies GIS and RS techniques have been applied along with mathematical models such as FAHP and have made significant contributions to area-based environmental analyses [39,52–55].

This study was conducted in the Upper Phetchaburi River Basin (UPRB) in the southeastern part of Thailand where drought has recently become a critical problem [56]. There are only a few studies

of such issues. The basin is classified as a tropical rain forest at higher elevations [57], particularly in the upstream area of Kaeng Krachan National Park, which is on the (tentative) list as a possible UNESCO Natural World Heritage site. The basin is on a drought-watch list because many areas are at moderate risk of desertification [58]. Therefore, it seems prudent to conduct risk analysis in the UPRB to provide useful data for proactive planning in order to develop preventive measures for potential drought-related problems. This study used FAHP to identify specific sites at risk of drought. FAHP was combined with remote sensing and GIS techniques. This research also provides useful general background knowledge for sustainable land use and development. The physical data are crucial for government planning agencies.

2. Materials and Methods

2.1. Study Area

The UPRB is a sub-basin of the Phetchaburi River Basin ($12^{\circ}25'26.91''$ N– $13^{\circ}14'38.326''$ N $99^{\circ}5'42.864''$ E– $100^{\circ}2'2.70''$ E) located in the southeastern part of Thailand. It covers an area of 3447.54 km², which is 62% of the Phetchaburi River Basin (Figure 1). The west is a high mountain range on the border between Thailand and Myanmar. An internal regional border between the Phetchaburi and Ratchaburi Provinces lies in the north of UPRB. Some areas of the basin are located in Kaeng Krachan National Park. The national park was declared as an The Association for Southeast Asian Nation (ASEAN) Heritage Park in 2003. The Kaeng Krachan Forest Complex (KKFC) was added to the list of potential UNESCO Natural World Heritage during the 35th Session of the World Heritage Committee, UNESCO, Paris, France on 19 December 2013.

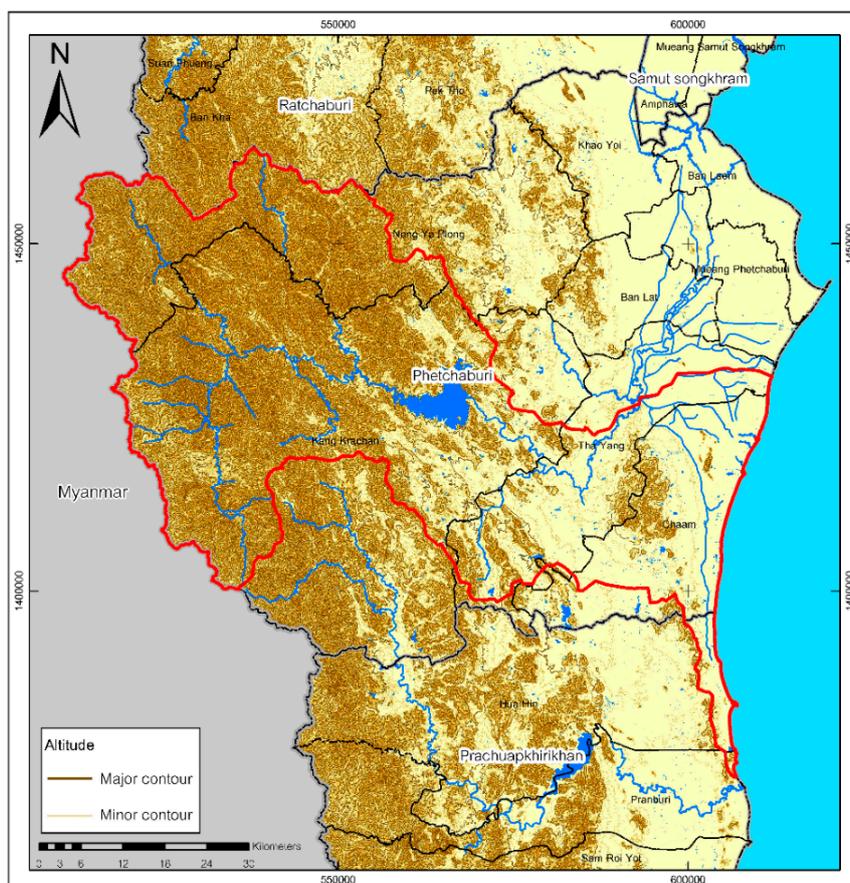


Figure 1. Upper Phetchaburi River Basin.

Of the total area, 67% of the basin is a downward slope from west to east with a gradient of more than 35%. The total area is 84% forested [57]. The plain area, useful for human settlement and farming, makes up about 14% of the total area. The average annual rainfall is 943.80 mm and average annual evaporation is 1624.0 mm, giving an annual specific yield of 7.84 L/s/km².

The Phetchaburi River is the main river in the basin. It originates from Kaeng Krachan National Park and supplies Kaeng Krachan and Phetchaburi Dams. The high range mountains (700 m above mean sea level, mamsl) have slopes greater than 35% in the upstream areas (upper Kaeng Krachan Dam) most of which are within the perimeter of a national tropical rain forest reserve. The topography of the central part of the basin is classified as a piedmont plateau, with undulating and rolling terrains at an elevation of 100 mamsl. Downstream are the lowland areas and the sea coast with an average elevation of 3 mamsl where the land is used for agriculture, community settlements and tourism.

2.2. Data Collecting and Evaluating the Drought Risk Factors

The risk of drought is subject to a combination of frequency, severity and its spatial extent, and the vulnerability of a population or activity [4–6,59–61] Meteorological factors, soil characteristics, water resources and human activities [5,6,39,60–63] must be investigated for each locality [4]. For this study the four main factors: Climatic, physical, soil and human activities; ten sub-criteria were used to identify and analyze the levels of drought risk.

Precipitation is the most important climatic factor. Rain data for this region has been collected over a 30-year period from seven agrometeorological stations in the UPRB area. Since the Upper Phetchaburi River Basin is partially located in Kaeng Krachan National Park, a rainforest that provides habitat for wild animals and is close to the Thai–Myanmar border. Moreover, the terrain is also mountainous with a gradient level of 75%–100% covering the west side of the basin. The geographical features made it difficult to establish more meteorological stations in the area within the national park premises. Therefore, the agrometeorological station was the only station available in the upstream area and six more agrometeorological stations were scattered in the midstream to downstream basin area. Precipitation data analysis from all meteorological stations revealed that the distribution of precipitation in the area is homogenous. Even though there is only one station in the area, the mountainous upstream area is similar in terms of heights and covered by thick forests. Therefore, precipitation rate is not much different in the area. Moreover, the precipitation data were analyzed with areal data using equal interval. The stability and consistency of the data were analyzed using the double mass curve model [5]. Therefore, the precipitation data obtained from the seven agrometeorological station are suitable as representatives of the area. The Penman–Monteith equation [64] calculates the reference evapotranspiration (ET₀) [65]. The aridity index (AI) relates the proportion of annual precipitation to the potential evapotranspiration [5]. The physical data of slope gradient and altitude are the key factors contributing to deep soil moisture that are related with vegetation and drought [39,66], were obtained from 1:50,000 maps of the study area. They were used to create digital elevation models (DEMs) that were in turn used to derive the slope and aspect.

Soil factors include texture, water drainage capacity, fertility and erosion, and are linked with drought and desertification. First, there is a relationship between soil texture, water drainage capacity and erosion resistance which sustains vegetation [67–73]. Soil fertility and soil moisture are an important factor to support planting and vegetation, including agricultural crops [66,74,75]. The soil erosion must develop more extensively [72]. Soil erosion adversely affects soil fertility [72,76]. It decreases soil depth and productivity [72] and reduces vegetation cover [5,6,73]. Erosion is also a major cause of land degradation [68,69] and desertification [5]. It can be assessed using the universal soil loss equation (USLE) with six factors. In Thailand, $R = 0.4669X - 12.1415$ has been used to estimate the erosion level for planning soil conservation [73,77], when R is rainfall and runoff erosivity (Mg/ha/year), X is an average annual rainfall (mm/year).

Land utilization includes land use and land cover as risk factors. Land use is defined by the way humans dominate the land to suit their needs. Changes in land coverage such as deforestation

may cause drought [4,70,78,79]. Since land cover is a significant index in drought risk, [4,5,78–80], land use should be analyzed in parallel with land cover (LULC). For this study, the ENVI software (Ver. 4.7, Harria Geospatial Solutions, Broomfield, CO, USA, 2009) processed satellite images from Landsat 7 (ETM) and linotype, a multispectral scanner. Image geo-referencing accuracy was initially cross-checked against a reference map.

2.3. Concept of Fuzzy Logic and Fuzzy Set Theory

Fuzzy logic was introduced by Zadeh [21] to handle ambiguous, vague and uncertain data [81,82]. The important principle of fuzzy sets is that its members are recognized as fuzzy membership functions which can be any real number in the interval [0,1] which are different from a crisp set. Each member is mapped in the set to a real number, 0 and 1, to indicate the degree of membership of that member. A fuzzy sets number which is a member 'F' can be represented in the equation below.

$$F = \{(x, \mu_F(x)), x \in R\} \tag{1}$$

where x is a real number and has value between $-\infty < x < +\infty$ and R is a universal set of the real number $\mu_F(x)$ and is a membership function. $\mu_F(x)$ represents a degree of membership between 0 to 1. The value 0 means that it is not a member of a set, and the value 1 means that is fully a member of a set. The values between 0 and 1 means that it partially belongs to the set. The meaning of each value of fuzzy sets number can be defined in different ways such using both terms for linguistic variables such as equal, moderate, considerable, moderate increase or using fuzzy numbers of the maximum of nine levels (Table 1).

Table 1. The definition of fuzzy numbers that is divided into nine levels.

Fuzzy Numbers	Linguistic Variable
$\tilde{1}$	Equally importance
$\tilde{3}$	Moderately importance
$\tilde{5}$	Strongly importance
$\tilde{7}$	Very strongly importance
$\tilde{9}$	Extremely importance
$\tilde{2}, \tilde{4}, \tilde{6}, \tilde{8}$	Intermediate values between adjacent scale values

Source: [83,84].

The fuzzy sets membership function can be used in a wide range of domains in which information is ambiguous, vague or uncertain such as in bioinformatics. Membership function is a technique to solve practical problems of fuzzy set operations. Membership function such as Triangular Fuzzy Numbers (TFNs) [85] is intuitive, computationally simple and useful for the data processing in a fuzzy environment [86–88]. TFN (Equation (2)) is applied to carry the values of criteria based on fuzzy logic to solve problems or make decisions [39,89].

$$\mu_F(x) = \begin{cases} 0 & x < l \\ \frac{x-l}{m-l} & l \leq x \leq m \\ \frac{u-x}{u-m} & m \leq x \leq u \\ 0 & x > u \end{cases} \tag{2}$$

The TFN of \tilde{y} is shown as the equation of $\tilde{y} = (l, m, u)$, when $l \leq m \leq u$. Where l is the lowest possible value, m is the middle possible value and u is the upper possible value in the decision maker's interval judgement. If $l = m = u$, the fuzzy number gets a crisp number. Each TFN is associated with a triangular membership function, which describes the TFN domain.

2.4. AHP and Fuzzy Comprehensive Evaluation Model

The Analytical Hierarchy Process (AHP), established by Saaty [90,91] is a flexible method to analyze multi-criteria problems. AHP is a modeling tool that builds a hierarchy for decision making by establishing priorities [22,29,92]. However, the AHP is limited when dealing with vague and uncertain data especially those similar to human cognition [24,30]. Therefore, the FAHP approach [93] was proposed as a tool for this study because it is useful in prioritizing and ranking criteria and sub-criteria of drought risk factors under fuzzy data [23,24,31,39].

Chang [28] proposed the FAHP approach as a model to analyze data with multiple criteria obtained from fuzzy environments [22,29,82,89]. The key to its success lies in accurately prescribing the domain of a fuzzy evaluation and constructing a reasonable fuzzy comparison matrix (FCM) [24,29,83]. Prioritization criteria or factors are accomplished by comparing the value of individual criteria in each hierarchy. By comparison, FAHP is accomplished by setting the level of significance for each criterion and fuzzy sets number which is divided into nine levels (Table 1). The fuzzy ratio scales are used to indicate the relative strength of the factors in the corresponding criteria, from which the fuzzy judgment matrix can be constructed [29,39,83,84]. The final scores of alternative values are also represented by fuzzy numbers.

The pairwise comparisons for criteria at each level of the hierarchy are constructed by TFNs. The fuzzy comparison matrix, $\tilde{A}(a_{ij})$ is calculated by Equation (3).

$$\tilde{A} = \begin{bmatrix} (1, 1, 1) & (l_{12}, m_{12}, u_{12}) & \dots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1, 1, 1) & \dots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & \dots & (1, 1, 1) \end{bmatrix} \tag{3}$$

where

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = \tilde{a}_{ij}^{-1}(1/u_{ji}, 1/m_{ji}, 1/l_{ji}) \text{ for } i, j = 1, \dots, n \text{ and } i \neq j. \tag{4}$$

$$\tilde{A}X = \tilde{\lambda}X \tag{5}$$

The results of the comparison of each pair of the criteria establish weights for each criterion corresponding to the eigenvector of each matrix. The principal eigenvector is the priority vector of a consistent matrix. The eigenvalue of the pairwise comparison matrix [90] represents the highest result from $\tilde{A}X = \tilde{\lambda}X$ (Equation (5)), where X is the corresponding eigenvector of the matrix \tilde{A} which is a $n \times n$ matrix containing (\tilde{a}_{ij}) and n is the size of the matrix. After that, a consistency rate (CR) of each matrix in comparison with the fuzzy was derived as shown in Equation (6), where a consistency index (CI) was obtained from Equation (7). The CR value is obtained by comparing the CI value with one of the following set of numbers in Table 2, each of which is an average random consistency index derived from a sample of randomly generated reciprocal matrices.

$$CR = CI/RI \tag{6}$$

$$CI = (\lambda_{max} - n)/(n - 1) \tag{7}$$

where λ_{max} is the largest eigenvalue of matrix \tilde{A} [90], representing the highest result from Equation (5), and n is the matrix size. The random index (RI) is the average CI of randomly generated pairwise comparison matrices of the same size as \tilde{A} with elements from the Saaty's scale. The RI of the matrices of order 1–15 can be seen in Table 2. The matrix \tilde{A} is considered to be sufficiently consistent if CR of a decision should not exceed 0.1 [39,82,84,89,94].

Table 2. Average random consistency indexes random index (RI) of the judgement matrix.

<i>n</i>	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Source: [39,90].

2.5. Analysis of Drought Risk in the UPRB Using FAHP

In FAHP model, a combination of AHP and fuzzy sets is used to weight the effective factors contributing to drought and to model drought risk. The most important drought risk factors were filtered out by AHP and a multi-level index system was constructed based on the relationship between the factors and the sub-criteria (attribute). Considering the actual situation in the UPRB area, the ten sub-criteria used as the index system were categorized into factors which were climatic, physical, soil and land utilization systems, as shown in Figure 2.

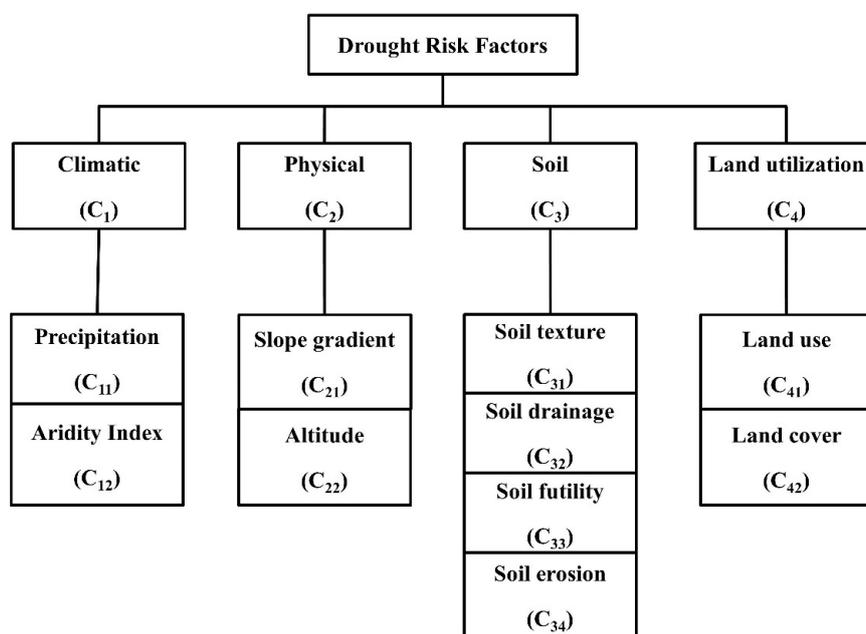


Figure 2. The hierarchy model of the drought risk evaluation of the Upper Phetchaburi River Basin (UPRB).

The essence of the process is decomposition of a complex problem into a hierarchy with a goal at the top of the hierarchy, criteria and sub-criteria at levels and sub-levels of the hierarchy. There are ten pairwise comparison matrices including: A climatic sub-criteria comparison matrix (C11 and C12), a physical sub-criteria comparison matrix (C21 and C22), a soil sub-criteria comparison matrix (C31, C32, C33, C34) and a land utilization sub-criteria comparison matrix (C41 and C42). The fuzzy triangular numbers along with linguistic variables (Table 1) were used to express the relative importance of criteria and sub-criteria in the five matrices.

The algorithms for the analysis using FAHP are as follows. The comparison of the fuzzy values was performed using fuzzy numbers (FNs) 1, 3, 5, 7 and 9 (Table 3). The determined relative weight of each drought factor was calculated using the pairwise comparison data between each pair of risk criterion in the same hierarchy. The judgment matrix was generated by comparing the index of the same level one by one. The fuzzy weight factor for each sub-criterion was calculated using a geometric mean technique. Ten pairwise comparison matrices were developed using Equations (2) and (3). The calculation using the TFNs was then performed. The ten sub-criteria system were calculated and structured according to the relationship between factors as shown in Table 3.

Table 3. Scale for the relative importance of variables used in the pairwise fuzzy comparison matrix (FCM).

Intensity of Importance	Fuzzy Number	Linguistic Variable	TFNs (<i>l, m, n</i>)	Reciprocal of Fuzzy Values ($1/u, 1/m, 1/l$)
1	1	Equally important	(1, 1, 2)	(0.33, 1.00, 1.00)
3	3	Weekly important	(2, 3, 4)	(0.20, 0.33, 1.00)
5	5	Strongly important	(4, 5, 6)	(0.14, 0.20, 0.33)
7	7	Very strongly important	(6, 7, 8)	(0.11, 0.14, 0.20)
9	9	Extremely more important	(8, 9, 9)	(0.09, 0.11, 0.14)
2, 4, 6, 8	9	The median of the above adjacent judgement	($x - 1, x, x + 1$; $x = 2, 4, 6, 8$)	($1/(x + 1), 1/x, 1/(x - 1)$; $x = 2, 4, 6, 8$)

Source: [39,83].

The defuzzification of weight was calculated using centroid average (CA) [95,96] which was the centroid of a triangular fuzzy number $\tilde{A} = (l, m, n)$. Defuzzification is the process of transforming a fuzzy output from the fuzzy inference system into a crisp output. The centroid defuzzification method defined the centroid coordinate of \tilde{A} in the horizontal axis as its defuzzified value [97,98]), where the output obtained is a crisp quantity. Finally, the consistency test to verify conformity of the calculation results was carried out. To calculate the CR, the eigenvalue (λ_{max}) of the pairwise comparison matrix was derived using Equations (6) and (7).

The drought risk factors and sub-criteria of the UPRB were analyzed using the FAHP model. The weighted sum from each layer was calculated in order to classify levels of drought risks. Following this process, the areas at risk were mapped using the ArcGIS software. The five different levels of drought were very high, high, moderate, low and very low.

3. Results and Discussion

3.1. Factors Affecting Drought Risk in the UPRB

The average annual precipitation in the basin is 943.50 mm. The precipitation data were analyzed with areal data using equal interval. The result indicated that the major part of the UPRB (64.0% by area) is between 842.95–982.16 mm, which was most of the area in the middle part of the basin and some area located in the eastern part at the border of the National Park. This level was considered as risky for drought. The AI of the area at risk was between 0.20 and 1.00 while the AI in most of the area (92.82%) was between 0.50 and 0.65, a value considered to be drought-affected [5].

In Keang Krachan National Park, which has a gradient 75%–100% and a high level of precipitation, the majority of the basin (67.07%) is a >35% forested slope. The rest of the area is covered by various soil textures: sandy loam (6.36%), sand (5.22%), clay (5.00%), powdery sand (2.13%), loam (6.17%) and saline soil (1.09%). Of the area in the central part of the basin, 22.45% has very low soil fertility and only 2.43% has high fertility. Good water drainage was measured in 17.97% of the area. The northeastern part had a low to very low water drainage capacity. The extent of soil particle transportation depends on the gradient of the area. It was estimated that 63.43% of the basin area had a low soil erosion rate and 1% is very high. Bare land is found in some parts of middle areas.

Land use statistics revealed that 84.85%, 2915.96 km², of the basin was scattered forest. Agriculture accounted for 279.76 km² (8.12%) and was situated mostly in the middle and the lower part of the basin downstream from the Kaeng Krachan Dam. The use of bulldozers for land clearing for farming was common (4.35%) in the central part of basin. Most of the residential buildings (1.43% of the basin) are located downstream.

The analysis of the priority of factors (Table 4, Figure 3) revealed that climatic factors had the highest relative weight followed by soil, land utilization and physical factors, respectively. Among the ten sub-criteria, the most significant factors were the precipitation level (a climatic factor) and slope gradient (a physical factor).

Table 4. Weight values of the drought risk factors assessed by fuzzy analytical hierarchy process (FAHP).

Factors/Criterion	Priority of Criterion	Sub-Criterion	Priority of Sub-Criterion	Final Priority of Sub-Criterion
C ₁	0.4425	C ₁₁	0.7461	0.3301493
		C ₁₂	0.2539	0.1123508
C ₂	0.0790	C ₂₁	0.7461	0.0589419
		C ₂₂	0.2539	0.0200581
C ₃	0.2916	C ₃₁	0.1363	0.0397451
		C ₃₂	0.3498	0.1020017
		C ₃₃	0.1211	0.0353128
		C ₃₄	0.3928	0.1145405
C ₄	0.1868	C ₄₁	0.5588	0.1043838
		C ₄₂	0.4412	0.0824162

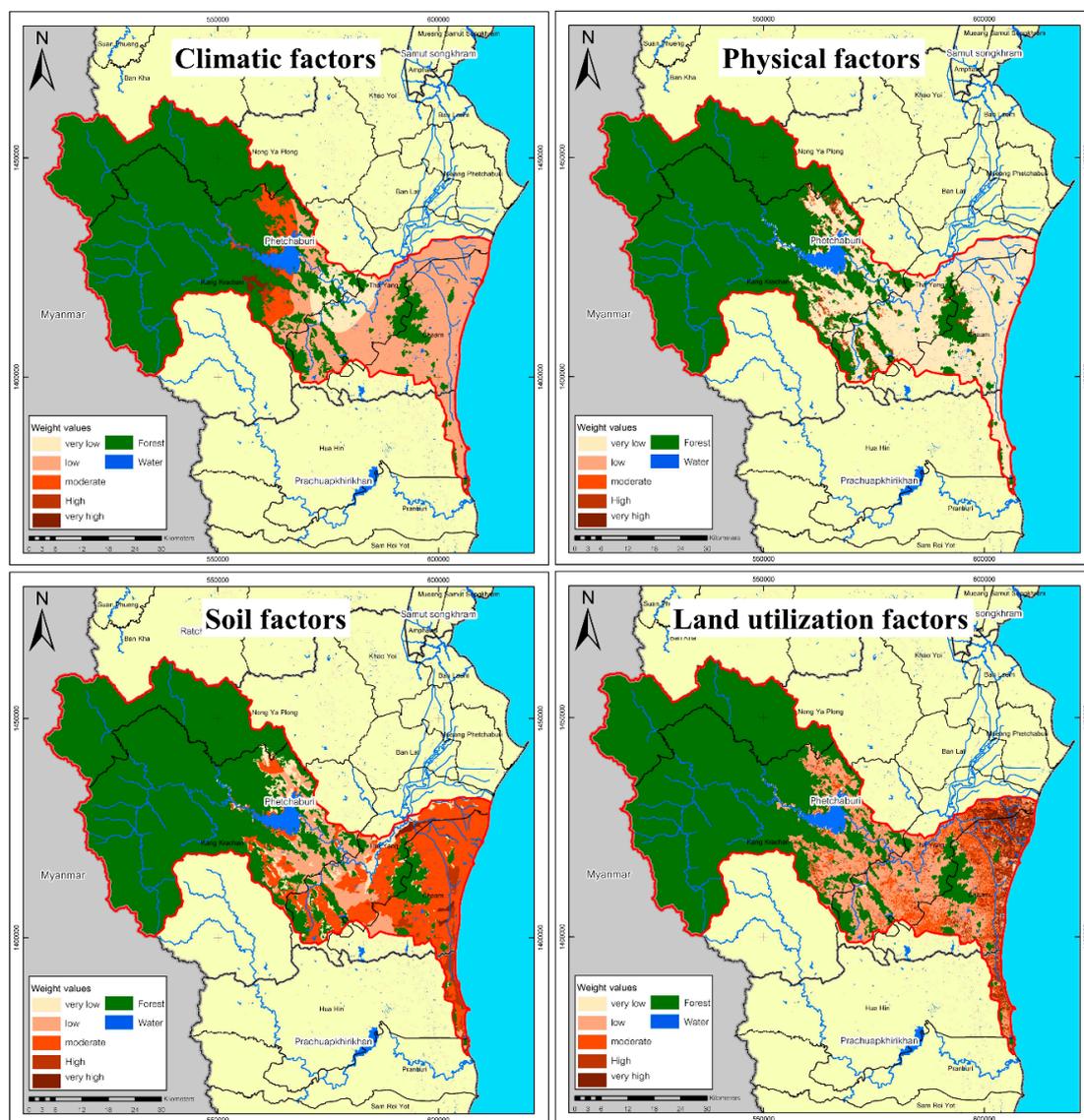


Figure 3. The weighted values of drought risk factor of UPRB.

The results of this study are different from those of Suvachananonda [56] who indicated that the slope gradient and soil drainage were more significantly related to drought in UPRB than rainfall. The

Areas at a moderate risk of drought are common throughout the basin, especially in the center and downstream. These areas had a low annual precipitation and high soil drainage. Although, the central part of the basin is mostly a level plain, human activities such as using bulldozers expose the topsoil and destroy the vegetation. Moreover, land use has changed from forests to agricultural and residential use on bare land. Such changes in land use typically lead to a decreased rainfall and increased annual runoff [80,99–101], making it vulnerable to erosion [69]. Furthermore, the soil had low fertility, which poses a higher risk of both drought [6,9,102,103] and desertification [4,5]. Areas at a high risk of drought were in parts of the middle of the basin, where the average precipitation was less than 900 cm³/year. Sandy loam has very low fertility but very good drainage and therefore a low water holding capacity, high erosion rate and high degradation [4,73,104], which in turn affects vegetation [6,67,71]. The rate of water loss is accelerated without vegetation [7,67]. The agricultural areas were mostly located in the plain, which had a low gradient level of 2%–5%, although some agriculture is carried out in an area with a steep gradient of 75%–100%. Most of the agriculture in the plain had high erosivity that may have resulted from the inappropriate land use. Therefore, the area was considered to be at a relatively high risk of drought.

Although the major drought risk factors in this area were climatic (precipitation) and physical (slope gradient), it is also necessary to consider the land use and changes in land use [4,73,102,105]. The majority of the study area was covered with forests, which, by and large, sustain soil resources, maintain humidity and reduce both the loss of water from the soil [7,66,102,106], and the rate of soil erosion [104,107,108], and hence the desertification risk [4,5]. This explains why drought does not usually occur upstream at the higher elevation.

The overall area of the basin was at a moderate drought risk level; previous studies showed that some areas were at risk of desertification [58]. Therefore, an appropriately planned development of the area is necessary to establish preventive measures for possible droughts. In particular, areas at high risk of drought defining land use and establishing human activities suitable for the capacity of the region.

4. Conclusions and Recommendations

The upstream area of the Upper Phetchaburi River Basin was deemed to be at a moderate risk of drought although some parts were at a high and a very high risk. Areas at risk were those in the plain areas that are used for agricultural and economic purposes as is also true of the downstream area where communities are located. Three groups according to their appropriate mitigations are recognized. The first group is in the upper areas of Kaeng Krachan National Park that follow mitigations enforced by Department of National Parks, Wildlife and Plant Conservation. Forest areas are crucial for moist content and precipitation rate.

The other two are mid-stream and downstream. Relevant public sectors should initiate mitigations and conservation plans to ensure that changes in land use are appropriate to prevent drought and desertification. Agricultural areas in the downstream areas suffered from a risk of high erosion. Therefore, farming with machines that leaves the topsoil exposed should be prohibited. Cover vegetation and planting for soil amelioration should be encouraged. Vetivers, for example, have a very effective root system that holds on tightly to the soil and retains moisture. Moreover, the use of agrochemical pesticides and monocropping should be restricted while crop rotation and organic farming should be encouraged. Organic soil amelioration materials from sources such as biochar should be used. Biochar is effective at reducing rate, retaining moisture and therefore increases the quality and quantity of yields.

Building small and medium sized reservoirs or cheek dams in several areas is an effective way to increase moisture content both in the soil and in the atmosphere. The reservoirs store and make water resources available for both agriculture and human and animal consumption. Preserving the forest areas midstream and downstream also contributes to the hydrology of the area.

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