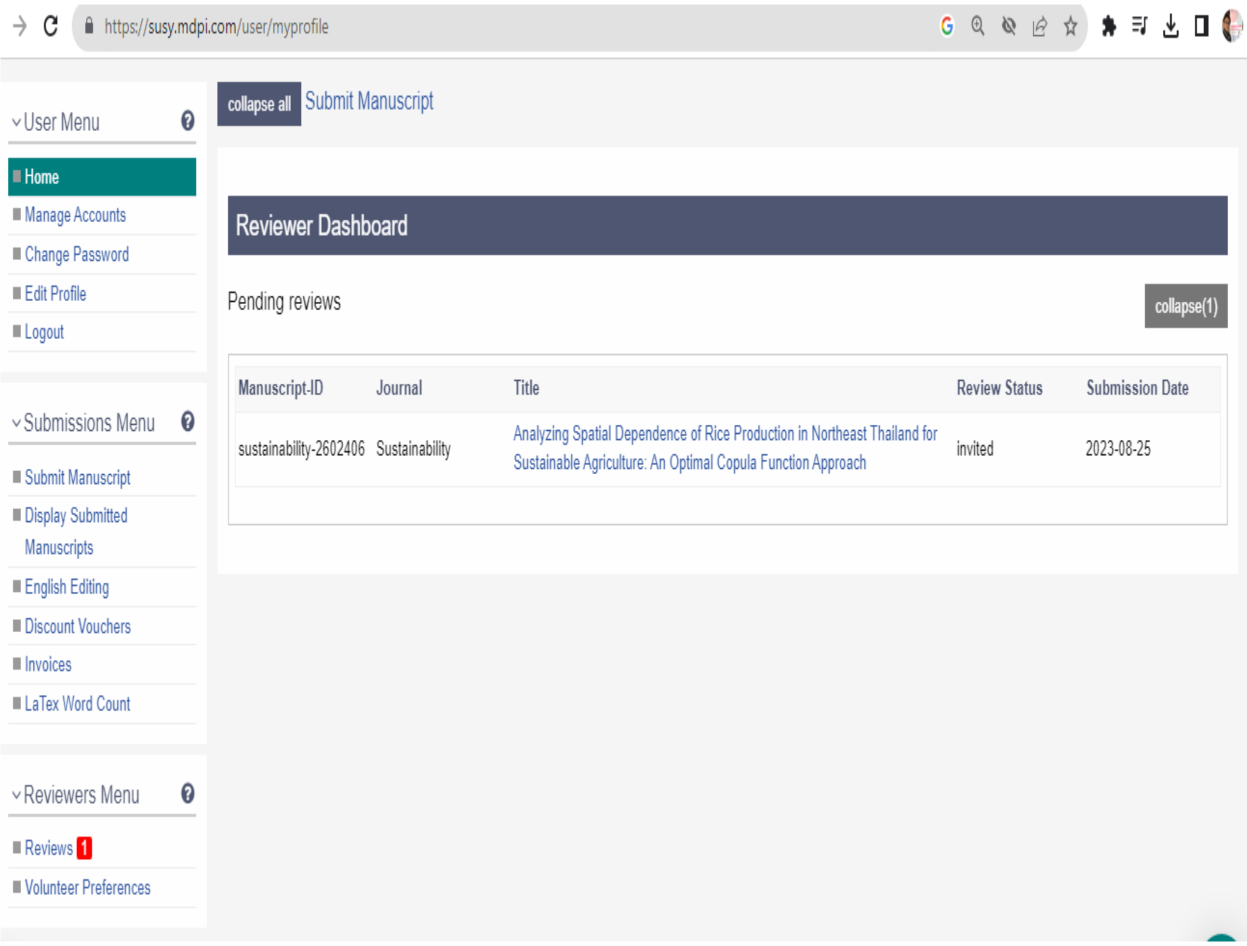

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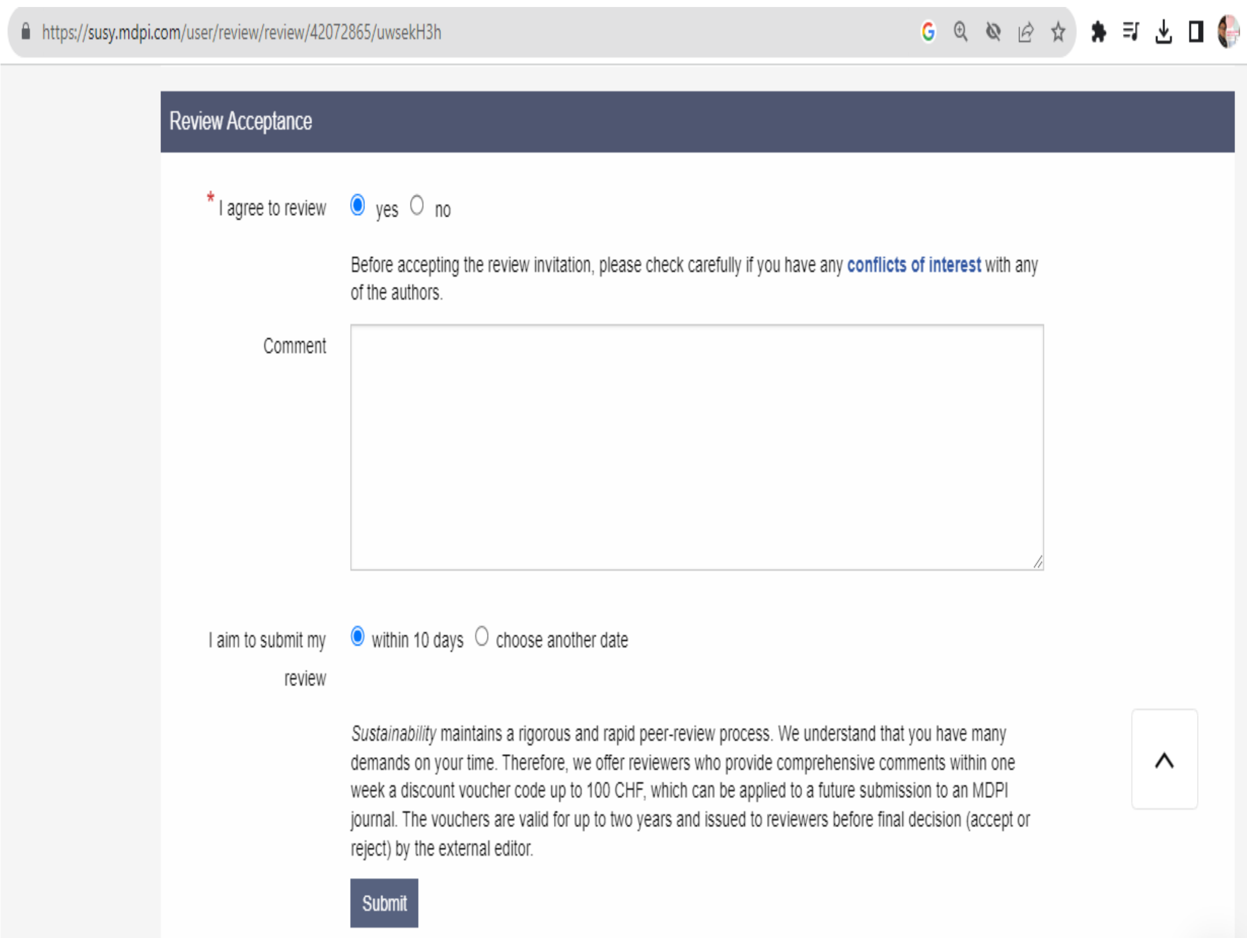

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Authors: Suneerat Srisopa , Peerapong Luamka , Saowanee Rattanawan , Khanitta Somtrakoon , Piyapatr Busababodhin *

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Article

Analyzing Spatial Dependence of Rice Production in Northeast Thailand for Sustainable Agriculture: An Optimal Copula Function Approach

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Abstract: Rice, a critical economic and dietary staple, predominantly thrives in Northeast Thailand, the nation's principal rice-producing region. Despite this centrality, yields from this region have historically been suboptimal. With escalating concerns around climate change, understanding the regional weather suitability for rice cultivation becomes paramount in strategizing effective agricultural interventions. This research provides a comprehensive examination of the multifaceted spatial dynamics influencing rice production across twenty provinces in Northeast Thailand, emphasizing the profound interplay between meteorological factors and rice yields. Drawing from a robust dataset spanning four decades (1981-2021) sourced from the Regional Office of Agricultural Economics 4,Thailand. We applied a piecewise linear model to decode rice yield trends. The maximum likelihood estimation elucidated the marginal distribution of residuals, and an inverse transformation of this data paved the way for generating pseudo data across Elliptical, Archimedean, and Extreme copula families. Rigorous parametric bootstrap goodness-of-fit tests, coupled with meticulous cross-validation, were employed to determine the most fitting copula for each province. Our salient findings underline substantial spatial interdependencies in rice yields. Notably, the t-copula function emerged as a pivotal indicator of these inter-relations. Yet, in specific provinces, Extreme copulas, especially Gumbel and HuslerReiss, were more apt descriptors of rice yield dynamics. Further, the results spotlighted the pronounced influence of meteorological factors, particularly rainfall and temperature, on rice production, especially in regions like Ubon Ratchathani. By shedding light on these intricate relationships and regional disparities, this study offers a roadmap for devising sustainable agricultural strategies tailored to local nuances. As the global agricultural landscape grapples with the implications of climate change, the insights from this research will be instrumental in promoting resilience and adaptive practices in rice cultivation, ensuring optimized productivity across Thailand's diverse agricultural regions.

Keywords: Agricultural Product; Cross-validation; Copula Analysis; Spatial Dependence; Sustainability.

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1. Introduction

Rice cultivation holds a pivotal role in Thailand's economy and workforce. In 2017, Thai rice trade was valued at 174.5 billion baht, constituting approximately 12.9% of the nation's entire agricultural output [1]. Out of the 40% of Thais engaged in agriculture, an estimated 16 million are rice cultivators [2,3]. The nation has a rich heritage of rice farming, with half of its arable land dedicated to this crop [7]. Globally, Thailand ranks fifth in terms of land used for rice cultivation and stands as the second-highest rice exporter [4]. There are ambitions to augment the rice-cultivation area, aiming to add an additional 1.2 million acres to the current 23 million acres ([5,6]). The Thai Agriculture Ministry anticipates a yield of 27–28 million metric tons for the 2019–2020 season, though projections indicate a potential decline due to climatic adversities like floods and drought [8]. While Jasmine rice (khao hom mali) is a premium variety predominantly grown in Thailand, it's believed that only regions like Surin, Buriram, and Sisaket can produce its top-quality variant [9]. Jasmine rice has a relatively low yield but is typically valued at over double the price of other rice types in the international market[5]. However, due to persistent droughts, the United States Department of Agriculture(USDA) has predicted a decline of over 20% in output to 15.8 million metric tons in 2016. Although Thailand has the potential for three rice harvests annually, water shortages have led to government advisories to transition to crops requiring less water or skipping a harvest cycle [10]. Rice farming is notably water-intensive, consuming approximately 400,000 US gallons of water for every cultivated acre [11].

While the Central Region stands as the primary rice-producing area catering to both local and international markets, our attention in this section is directed towards the North-east Region, also known as Isan, located in the Lower Mekong Basin (see Figure 1). The popularity and high profitability of the Khao Dawk Mali 105 (KDML105) variety, along with the productivity of its glutinous counterpart (RD6), have infused a distinct fragrance throughout the Northeastern landscape since the 1980s. This widespread adoption has significantly contributed to commercial growth, elevating numerous rural families from poverty and catalyzing broader economic advancement in a region historically viewed as underdeveloped [12–14].

In 2022, Thailand was ranked as one of the top three rice-exporting countries in the world [15] but the yield of Thai rice is quite low when compared to the neighboring countries [16]. In Thailand, rice cultivation is generally carried out during the rainy season with rainfed system [17]. Factors affecting rice production in Thailand include the high cost of farm chemicals, raising labor costs, climate change, soil fertility and soil quality ([18], [17] and [16]). Natural soil quality is one of the most important factors that affect agricultural productivity because it supplies favorable growing conditions and specify the indigenous nutrient provide to the crop [18]. Soil characteristics also affect the availability of soil water to crops grown in water-restricted areas [18]. Northeast Thailand is the main area of rice cultivation in Thailand [19]. Eighty percent of Northeast Thailand is an undulating plateau with extremely low soil fertility ([17,20]). The basement rocks of the plateau in northeast Thailand are the sandstone or siltstone of the Mesozoic age which mostly is underlain by rock salt bed. The land surface consists of sediment derived from the mass movement of the weathered mantle of the bedrock [21]. The sandy texture of the soil are low fertility with low organic matter, low cations exchange capacity, low buffering capacity and low water-holding capacity in the soil ([20,22]).

Yanai et al. (2020) reported that there are low total carbon and total nitrogen contents and deficiency in the available phosphorus, exchangeable potassium, and available silicon contents in the soil of Northeast Thailand. [20] also reported that the soil organic carbon content in the paddy field in northeast Thailand only ranged from 0.34 to 31.2 g/kg for the four past decades [20]. The sandy soil together with the low precipitation and lack of irrigation water makes low rice yield in Northeast Thailand [20]. Moreover, saline soils and the residence of an ironstone layer in the Northeast plateau at the shallow depths of the soil is another characteristic of the soil that increase the fertility problem for rice field [21]. Saline soil in Northeast Thailand is the groundwater runoff of underground rock salt that cause low rice production and it is expected to enlarge in the future due to climate change ([23,24]). About 1.84 Mha in northeast Thailand soil are affected by saline soils including

Nakhon Ratchasima, Khon Kaen and Maha Sarakham Province [23]. According to the salty crust in the dry season, the Land Development Department, Thailand category saline soil into four groups including 1) very severely saline soil with salt crust more than 50%, 2) severely saline soil with salt crust ranging between 10–50%, 3) moderately saline soil with salt crust ranging between 1–10% and 4) slightly saline soil with salt crust less than 1% [24].

In light of the pivotal role rice cultivation plays in Thailand's economy, particularly in the Northeast region, understanding the nuanced spatial interdependencies is paramount for both the sustainable advancement of the sector and its resilience against potential adversities. Despite the wealth of data available, there remains a distinct need for an inte-grated and rigorous exploration of rice yield patterns over time, especially considering the evolving challenges posed by environmental factors and climate change. This study aims to bridge this gap. In the subsequent sections, we elucidate our analytical methodologies, present comprehensive results that highlight key trends and correlations, discuss their broader implications in the context of sustainable agriculture, and finally, draw conclusions that could guide policy, practice, and future research in the realm of rice cultivation in Thailand.

2. Materials and Methods

2.1. Study Area

Northeast Thailand occupies the Khorat Plateau, nestled between the Phetchabun Range to the west and the Mekong River to the east [25]. Typically, these lands are catego-rized into high, middle, and low terraces, each with distinct vulnerabilities to droughts and floods, affecting their suitability for cultivating rice and other field crops. The majority of the plateau's cultivable soils are sandy, acidic, and nutrient-poor, predominantly composed of quartz and kaolinite resulting from extensively weathered source materials. Once blan-keted by monsoonal dipterocarp forests, the gradual deforestation for agricultural purposes has led to reduced soil organic content and essential minerals, intensifying soil acidity. Additionally, varying levels of salt afflict much of this farmland, with intense salinity in the western hilly regions and milder concentrations in the flat areas near the Mun and Chi Rivers.

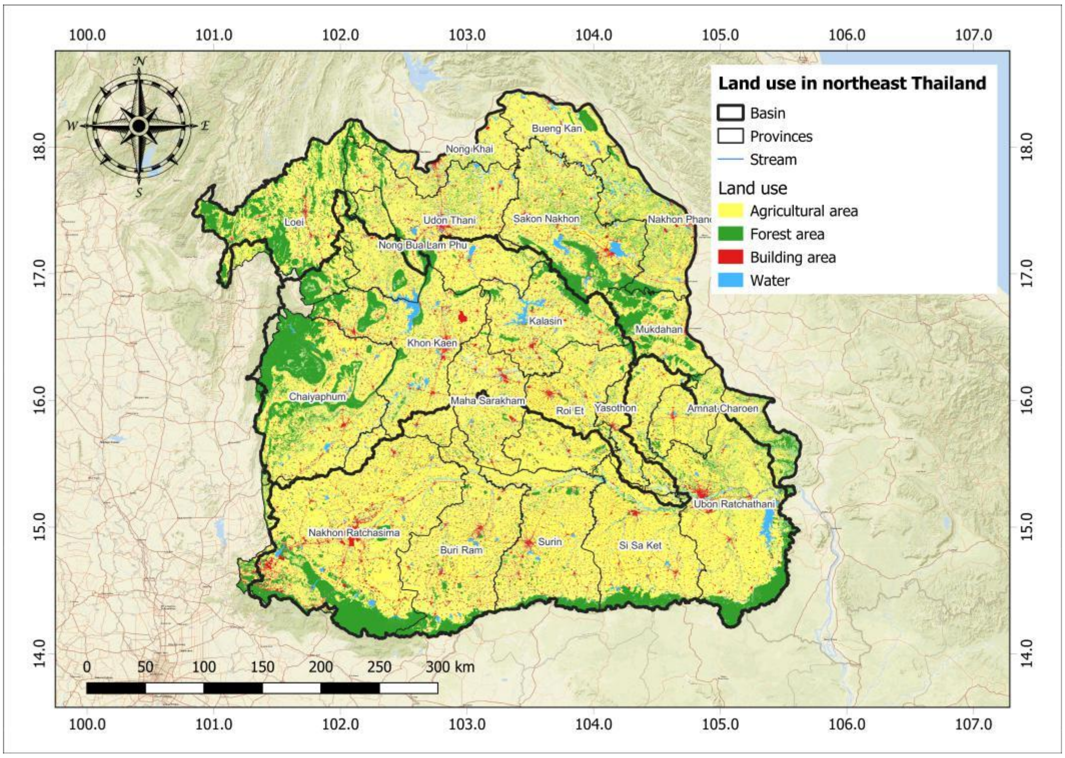


Figure 1. Land-used Map of Northeastern region of Thailand.

2.2. Data

In the Northeast, similar to other parts of the region, rice cultivation takes place in two primary seasons: the wet and dry seasons. The majority of the rice fields depend on rainwater, primarily producing during the wet season, which spans from May to October. The disparity between these seasons is notably more pronounced in Northeast Thailand compared to other regions in Mainland Southeast Asia [26]. While rainfall during the wet season can be unpredictable, it's often so abundant and frequent that it leads to localized flooding. Representing 46% of Thailand's agricultural holdings and 47% of its farmable land, the Northeast boasts an average holding size of 3.2 hectares. For a detailed breakdown of cultivated and harvested areas, productivity, and yield rates for both the wet and dry seasons in the Northeast from 1991-2021, see Table 2. Even though the Northeast's natural resources for rice production might not be as optimal as other areas, rice dominates the region's agriculture, covering over two-thirds of its land — a higher percentage than any other region. Other field crops such as cassava, sugarcane, and maize make up approximately 20%. This research further delves into the attribute types, notation, and predictor variables, which are elaborated on in Table 1.

Table 1. Attribute types, notation, and predictor variables.

Attribute Type	Attribute	Notation
Crops	cultivated area harvested area Productivity yield per rai	CA HA Product Yield
Meteorological variables	Average rainfall Cumulative rainfall Average temperature Average relative humidity	Ave_rain sum_rain Ave_tem Ave_rh

Table 2. Average (with Standard Deviation) of Cultivated Area (rai), Harvested Area (rai), Productiv-ity (ton), and Yield per Rai (kg) for Both Wet (WS) and Dry Seasons (DS) in Northeastern Regions: Data from Selected Years (1991-2021).

Province	Cultivated Area (rai)		Harvested Area (rai)		Productivities (ton)		Rice Yield (kg/rai)	
	WS	DS	WS	DS	WS	DS	WS	DS
Loei	393,926(53,702)	1,662(1,230)	371,510(57,125)	1,632(1,231)	145,701(23,869)	752(619)	394(67)	445(46)
Nong Bua Lamphu	823,122(99,552)	16,139(14,305)	763,880(99,585)	15,791(14,017)	245,059(36,952)	8,159(7,747)	321(77)	482(29)
Udon Thani	2,147,493(390,027)	35,891(29,239)	2,023,943(383,539)	35,281(29,290)	594,182(113,770)	16,323(14,030)	302(57)	443(64)
Nong Khai	933,689(258,760)	54,839(35,050)	848,730(228,442)	53,618(34,884)	254,835(60,158)	26,874(19,190)	308(64)	471(47)
Beung Kan	500,391(29,027)	11,780(2,703)	455,976(25,074)	11,564(2,691)	144,782(11,616)	5,891(1,379)	318(8)	509(24)
Nakhon Phanom	1,106,682(199,664)	35,901(28,505)	1,010,922(223,786)	34,853(28,683)	305,629(118,503)	15,967(14,464)	294(69)	418(58)
Sakon Nakhon	1,785,697(249,175)	35,875(29,927)	1,668,439(271,236)	35,033(29,830)	498,748(143,502)	16,248(15,533)	295(75)	410(49)
Mukdahan	385,658(71,628)	783(681)	366,835(72,341)	773(676)	119,826(40,913)	325(302)	320(77)	409(56)
Amnat Charoen	958,035(59,555)	2,919(2,556)	916,653(59,789)	2,903(2,534)	290,514(44,576)	1,316(1,289)	316(82)	412(37)
Khon Kaen	2,107,690(313,767)	109,823(73,990)	1,886,594(293,233)	107,302(73,121)	574,822(145,962)	57,689(43,000)	301(62)	519(42)
Maha Sarakham	1794,322(289,312)	106,649(75,330)	1,635,388(271,187)	105,038(74,272)	514,926(165,127)	62,146(46,164)	308(47)	573(62)
Roi Et	2,668,835(321,624)	117,168(103,382)	2441,921(276,889)	115,230(101,628)	758,475(215,672)	65041(58383)	307(69)	539(65)
Kalasin	1,263,580(202,954)	191,112(102,641)	1,191,222(191,708)	189,589(102,549)	403,758(102,119)	111,261(65,004)	335(67)	566(44)
Yasothon	1,117,988(148,852)	41,548(46,718)	1043,662(130,064)	410,69(45,928)	312,005(93,538)	21,354(24,289)	294(62)	486(60)
Chaiyaphum	1,346,462(272,579)	50,578(63,399)	1,179,523(23,2843)	49,964(63,150)	381,358(119,242)	26637(33475)	317(74)	501(52)
Nakhon Ratchasima	3,119,621(459,219)	118,456(136,333)	2,792,024(411,608)	116,254(132,905)	851,798(241,230)	69476(81889)	300(81)	550(55)
Buriram	2,734,872(228,312)	19,467(29,617)	2,553,609(247,623)	19,235(29,165)	806,889(180,418)	9,304(14,457)	314(79)	429(54)
Surin	2,783,108(379,726)	24,441(32,817)	2,633,325(357,709)	24,119(32,428)	860,704(229,943)	10,721(15,069)	324(65)	415(61)
Sisaket	2,492,575(389,718)	39,409(38,229)	2378,476(388,682)	38,507(37,078)	769,446(235,285)	18269(18857)	318(76)	423(60)
Ubon Ratchathani	3,544,253(391,610)	90,541(57,060)	3,385,282(410,877)	89,879(56,976)	959,868(270,565)	37,688(29,255)	281(76)	379(58)

Note: Convert 6.25 rai to 1 ha.

For the WS, as observed in Table 2, Ubon Ratchathani, Nakhon Ratchasima, Surin, Burirum, and Roi-Et rank in the top five in terms of cultivated area (rai), harvest area (rai), and productivity (ton). However, they don't lead in terms of rice yield (kg/rai). The top five provinces for rice yield (kg/rai) include Loei, Kalasin, Surin, Mukdahan, and Nong Bua Lamphu. In contrast, for the DS, as indicated in Table 2, Kalasin, Nakhon Ratchasima, Roi Et, Khon Kaen, and Maha Sarakham consistently dominate the top five positions for cultivated area (rai), harvest area (rai), productivity (ton), and rice yield (kg/rai). This underlines the need to investigate the weather's impact on rice productivity across different regions. In this research, copula methodology has been chosen to analyze the correlations among these datasets. Additionally, trend analysis is employed to examine the association between predictor and outcome variables, especially when the relationship isn't uniform across the entire predictor variable range.

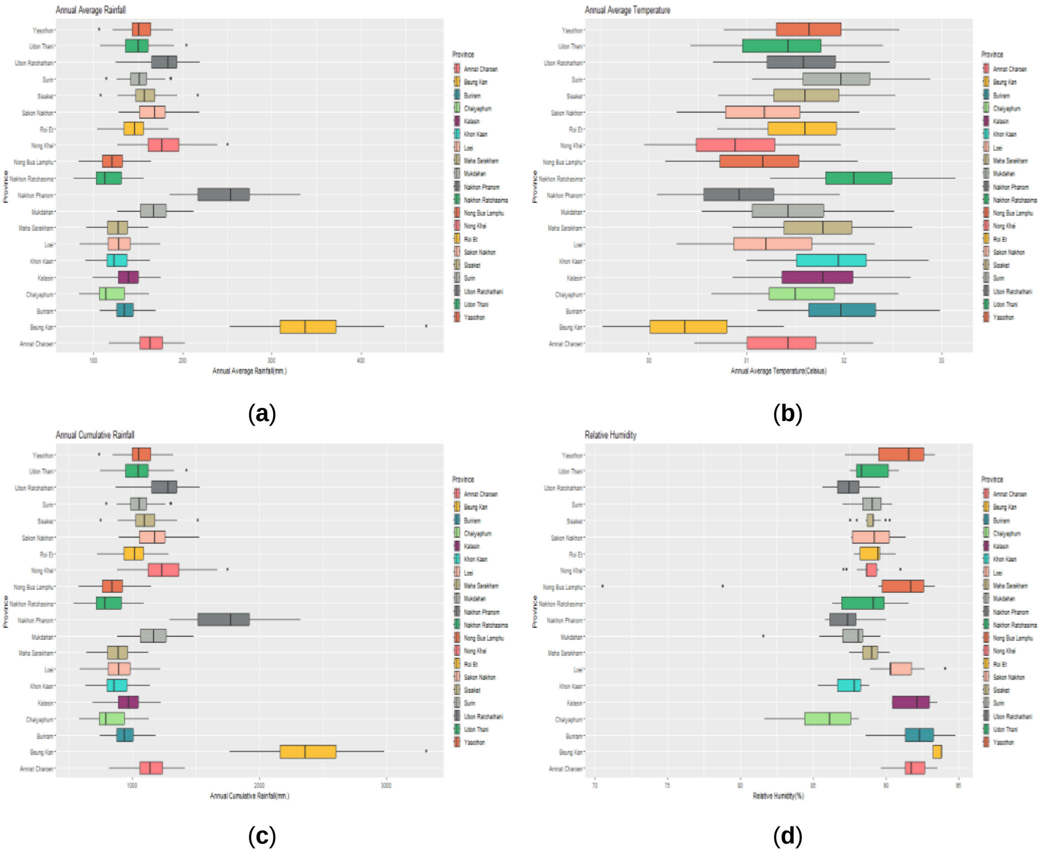


Figure 2. Box-Plot Illustrating Key Meteorological Metrics for Northeast Area (1981-2021): (**a**) Mean Rainfall (mm), (**b**) Mean Temperature ($^{\circ}$C), (**c**) Total Rainfall Accumulation (mm), and (**d**) Relative Humidity (%).

2.3. Methodology

2.3.1. Trend Analysis

The segmented regression model, also termed as a piecewise linear model, emerges as a powerful methodology to delineate the relationship between a predictor and its corresponding response variable, especially when said relationship doesn't maintain a constant presence throughout the predictor variable's full range. At its core, this model fuses various linear segments that intersect at designated junctions, often labeled as breakpoints or knots. The foundational equation for a segmented regression model, characterized by a singular breakpoint, can be expressed via Eq. (1):

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 (X_i - \tau) \times I(X_i > \tau) + \epsilon_i. \quad (1)$$

Within this equation, Y_i symbolizes the response variable, while X_i stands for the predictor variable.   designates the breakpoint, and I() acts as the indicator function (amounting to 1 when $X_i > \tau$, and 0 in other scenarios). The parameters β_0, β_1, and β_2 are subject to estimation, and $_i$ indicates the error term. Here, β_1 demarcates the line's slope leading up to the breakpoint, while $\beta_1 + \beta_2$ outlines the slope post-breakpoint. In essence,

β_2 elucidates the shift in slope at the breakpoint's location. These models extend a robust mix of adaptability and clarity, making them invaluable when dissecting intricate, non-linear data relationships, especially in contexts demanding the pinpointing of thresholds or breakpoints [27]. A depiction of variations in rice yield spanning from 1981 to 2021, framed within dual productivity-area combinations during wet seasons, accompanied by segmented regression lines for the Ubon Ratchathani province, can be observed in Figure 3.

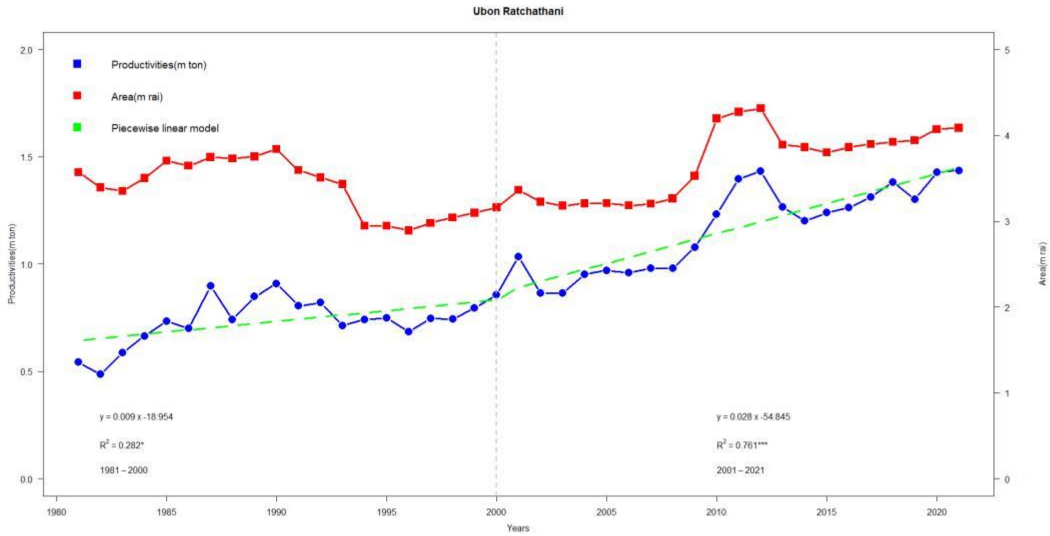


Figure 3. Changes in rice yield from 1981 to 2021 in two combinations of productivity and area for wet seasons with segmented regression lines at Ubon Ratchathani province.

2.3.2. Copula Function

In recent times, the field of Copula has seen rapid advancements, demonstrating significant potential in analyzing multivariate joint distributions and conducting multivariate frequency assessments. The primary strength of Copula lies in its ability to capture the interdependence among variables, enabling the computation of joint probabilities without being affected by the marginal tendencies of the variables in question. Essentially, it seamlessly amalgamates several univariate marginal distributions to generate their associated joint distribution. The copula function stands as a multivariate distribution where all its univariate margins align with U(0, 1). Considering a random vector (X_1, .., X_n), it is characterized by a joint distribution function H(X_1, .., X_n) and a continuous marginal distribution function (F_i (X_1) = u_i). Here, U_i possesses a uniform distribution over [0, 1] for i = 1, ..., d. Consequently, a unique d-dimensional copula C emerges. This section delves into the core principles underpinning copula theory [28–31].

In essence, a copula serves as a bridging function, linking a multivariate distribution function to its unidimensional marginal counterparts. This relationship is visually represented by the marginal probability distribution of a set of random variables, complemented by the varied interdependencies existing among these variables. The preference for copula analysis in this context stems from the non-linear nature of the correlations between provinces.

2.3.3. Copulas Families

Sklar's Theorem, proposed in 1959 by Sklar [28], describes the relationship between marginal distributions and heterogeneous distributions, known as the "copula". Thus, any cumulative distribution function (CDF), (F(X_1, X_2), of two random variables (X_1, X_2) can be states as

$$F(X_1, X_2) = C(F_1(x_1), F_2(x_2)), \tag{2}$$

where $F_1(x_1)$ and $F_2(x_2)$ are the marginal CDFs of variables X_1 and X_2, and C is a bivariate copula function.

Among all copula families, the Elliptical copula family and the archimedean copula family have been widely used in many areas. There is a variety of forms for both two copula families. In this study, the elliptical copulas (Normal copula and t copula), the Archimedes copulas (Clayton copula, Frank copula and Joe copula) and the extreme value copula(Gumbel copula, Gumbel-Hougaard copula and Husler-Reiss copula) are selected to analyze the joint probability of data for their simplicity and wide representation [32,33]. The copula function allows for the separation of a component describing only the structure of dependence from a total random vector distribution. In other words, copula functions are functions that combine the multidimensional cumulative distribution of a random variable with its one-dimensional limit distributors [34,35].

Table 3. The family of copula

Family	Copula Name	Function	Range
Elliptical	Student-t	$C(u, u, ..., u; \nu, \Sigma) = t_{\nu,\Sigma}(t^{-1}(u), t^{-1}(u), ..., t^{-1}(u))$	$-\infty < x < \infty$
	Normal	$C_\rho(u, v) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v))$	$-\infty < x < \infty$
Archimedean	Clayton	$C_\theta(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}$	$-1<\theta<\infty$
	Frank	$C_\theta(u, v) = -\frac{1}{\theta} \ln \left(1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1}\right)$	$-\infty<\theta<\infty$
	Joe	$C_\theta(u, v) = 1 + (u^{-\theta} - 1) + (v^{-\theta} - 1)$	$1\leq\theta<\infty$
Extreme	Gumbel	$C_\theta(u, v) = \exp\left(-((-\log(u))^{\theta} + (-\log(v))^{\theta})^{1/\theta}\right)$	$1\leq\theta<\infty$
	Galambos	$C_\theta(u, v) = u \cdot v \cdot \exp\left(-(-\log(u))^{\sigma} + (-\log(v))^{\sigma}\right)$	$0<\theta<\infty$
	Husler-Reiss	$C_\theta(u, v) = u\ v\ \Phi\sqrt{2\theta}\ \log(u^{-1/2}) + \log(v^{-1/2})$	$0<\theta<\infty$

In this study, we analyze the spatial correlations (spatial dependence) of the data between the ranking data with the Kendall's correlation coefficient as Eq.(3) under the null hypothesis of independence of X and Y [36];

$$\tau = \frac{2}{n(n-1)}\left[\sum_{i<j} sgn(x_i - x_j) sgn(y_i - y_j)\right]. \tag{3}$$

Then, we selected each pair of the highest spatial correlations to analyze the copula function as Eq. (4) follows.

$$F(x_1, x_2, ..., x_n) = C(F_1(x_1), F_2(x_2), ..., F_n(x_n)), \tag{4}$$

when $F_1(x_1)$, $F_2(x_2)$, ..., $F_n(x_n)$ are marginal distribution function, then Copula function, C, is unique [37].

2.4. Goodness-of-Fit Statistical Tests

The goodness-of-fit test is a statistical method used to assess the correlation between variables and determine if the collected data conform to a specific distribution. This test evaluates the performance of both marginal and joint probability functions. It plays a crucial role in hypothesis testing to check the normality of residuals and to compare two samples (observed and from the marginal distribution) to verify if they originate from identical distributions. In this study, the estimation of empirical non-exceedance probabilities for crop dataset and meteorological dataset utilized the Kolmogorov-Smirnov test and Cramer-von Misés test these tests were employed to evaluate the performance of the joint probabilities in the bivariate case.

2.4.1. Kolmogorov-Smirnov test (K-S test)

The Kolmogorov-Smirnov (K-S) test is favored because it doesn't hinge on assumptions regarding data distribution. It measures the largest discrepancy between the observed and theoretical cumulative distribution functions. As defined by [38], the K-S test metric (D_{n,n^τ}) serves as a criterion to evaluate the acceptability of parameters:

$$D_{n,n'} = \sup_x |F_{1,n}(x) - F_{2,n'}(x)|.$$

Here, $F_{1,n}$ represents the observed distribution; $F_{2,n'}$ stands for the theoretical distribution, and sup is the supremum function. In executing the goodness-of-fit test, we adopt the null hypothesis; it's only validated if the deviation from the theoretical is less than the anticipated amount for the sample in question.

2.4.2. Cramer-von Misés test (CvM)

To assess the fit of the extreme value copula function, we employ the Cramer-von Mises test, as detailed in [40]. This test uses a parametric bootstrap, as represented in Eq. (5):

$$S_n^{gof} = \int_{[0,1]^d} n(C_n(u) - C_{\theta_n}(u))^2 dC_n(u) = \sum_{i=1}^{n} (C_n(u_i) - C_{\theta_n}(u_i))^2. \quad (5)$$

An estimated $p-$value derived from S_n^{gof} can be achieved through a parametric bootstrap. The asymptotic soundness of this approach is further explored in [39].

2.5. Selection models

This research employs the XV-CIC statistic to determine the most suitable copulas, utilizing the Leave-One-Out Cross Validation (LOOCV) method for evaluating performance and model generalization capacity, as highlighted by [41]. The model's efficacy can be gauged using the formula $-2(\log L_{CV}) + 2(df)$, where $\log L_{CV}$ represents the average log-likelihood across the cross-validation sets, and df denotes the model's effective parameter count, factoring in the degrees of freedom from the cross-validation process.

3. Results

Sustainability is a multifaceted concept deeply influenced by human viewpoints, reflecting various aims and dimensions across a range of stakeholders. Its measurability often requires harmonizing diverse societal interests, including those advocating for future generations. To understand how crop values depend on factors that affect rice productivity, we employed seven unique two-dimensional copula models as outlined in the previous section. These models included the Student-t, Normal, Clayton, Frank, Joe, Gumbel, Galambos, and Husler-Reiss copulas. We derived the parameters for these selected copulas using a two-stage maximum likelihood technique known as the inference functions for margins (IFM) method. This was applied to both the normal and t-Student boundary distributions.

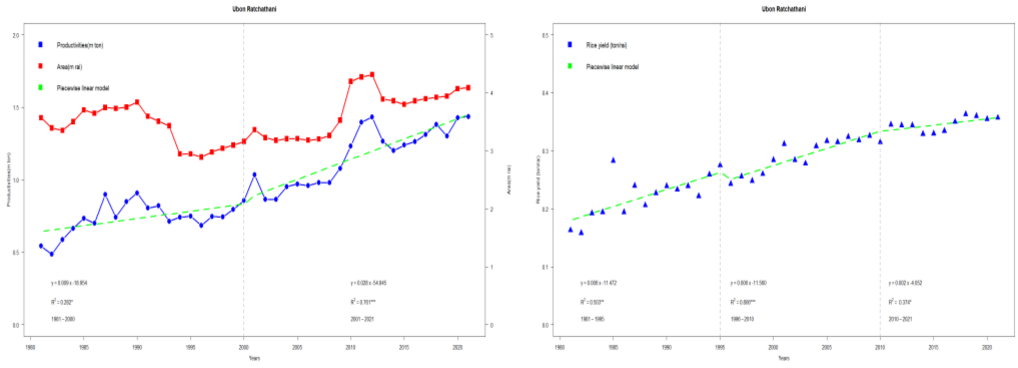
3.1. Data Analysis

A summary of crop data from the Northeast regions between 1981-2021, including cultivated area (rai), harvested area (rai), productivities (ton), and yield (kg./rai), can be found in the supplementary material (Tables S2 - S4). Additionally, a comparison between rice productivity and other crop data, encompassing cultivated area (rai), harvested area (rai), and yield per rai (kg.) for selected provinces from 1981-2021 is illustrated in Figures 4 through 7.

Rice production and yield in select provinces saw a significant rise from 1981, starting at 13.4 million tons and reaching 38.1 million tons by 2011, marking an impressive growth over a span of 40 years (as depicted in Figures 4 through 7). The initial 20 years witnessed a moderate yearly growth, which nearly doubled post the year 2000. However, post-2011, there's been an observable decline and fluctuation in production. This growth between 1981 to 2011 can be attributed to two factors:

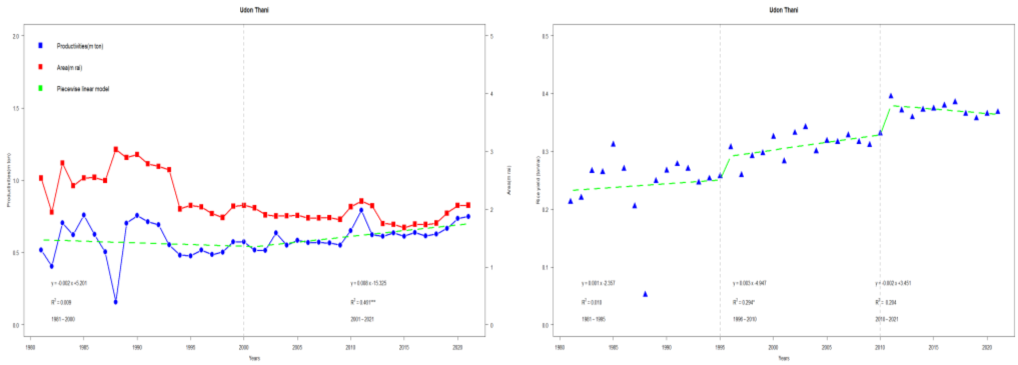
1. An expansion in rice cultivation areas, growing from 7.3 million hectares to 12.0 million hectares (a jump of 64%).

2. A surge in yield rates, rising from 1.8 tons per hectare to 3.2 tons per hectare. This represents a 78% increase, averaging an annual growth rate of 35.9 kg per hectare.



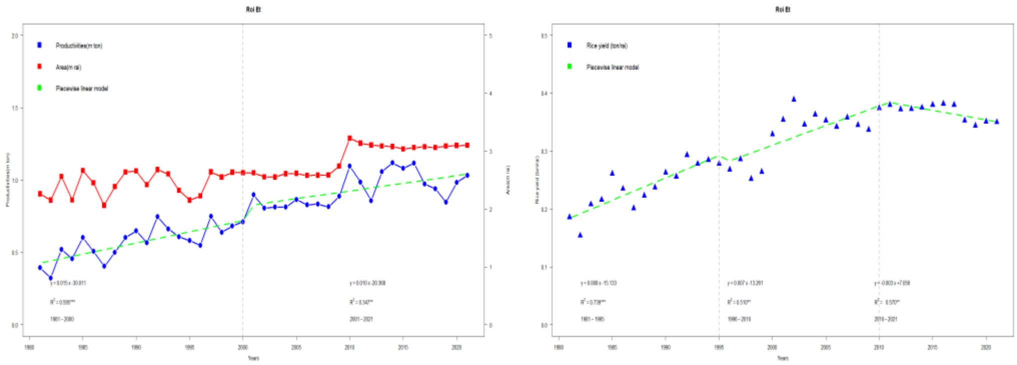
(**a**) (**b**)

Figure 4. Comparison of rice production and yield for Ubon Ratchathani Province. (**a**) Rice production and cultivation areas from 1991 to 2021. (**b**) Evolution of rice production and yield over the period 1981 to 2021.



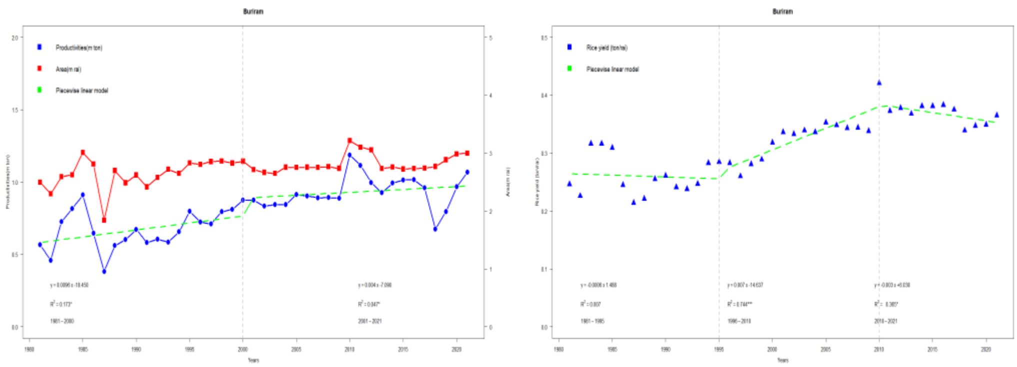
(**a**) (**b**)

Figure 5. Comparison of rice production and yield for Udonthani Province. (**a**) Rice production and cultivation areas from 1991 to 2021. (**b**) Evolution of rice production and yield over the period 1981 to 2021.



(**a**) (**b**)

Figure 6. Comparison of rice production and yield for Roi-Et Province. (**a**) Rice production and cultivation areas from 1991 to 2021. (**b**) Evolution of rice production and yield over the period 1981 to 2021.



(**a**) (**b**)

Figure 7. Comparison of rice production and yield for Burirum Province. (**a**) Rice production and cultivation areas from 1991 to 2021. (**b**) Evolution of rice production and yield over the period 1981 to 2021.

Digging deeper into the details, we note that the 1980s were marked by an expansion in rice cultivation areas. This trend plateaued during the 1990s through the early 2000s but then picked up pace rapidly between 2005 and 2011. Unfortunately, post-2011, the cultivated area saw some fluctuations, eventually dipping to 8.7 million hectares by 2016. In terms of yield, the initial decade starting from 1981 experienced a slower growth rate of 20.3 kg per hectare annually, culminating at 1.95 tons per hectare in 1990 (as shown in Figures 4(b) to 7(b)). The following 21 years up to 2011 marked an increase rate of 53.5 kg per hectare annually, which translates to a 1.7% yearly surge. But, the subsequent seven years leading up to 2021 did not witness any further rise in yield. The causes behind these shifts in production will be explored in subsequent sections.

3.2. Dependence Analysis

To investigate the interplay between rice production and yield in designated provinces, we utilized seven distinct two-dimensional copula models, as previously described. Figure 8 displays the connection between yields and the selected provinces. In contrast, Figure 9 emphasizes the linkage between crop variables and key meteorological elements.

Figure 8 reveals a strong correlation for neighboring areas, influenced by water man-agement practices within each watershed. Meanwhile, Figure 9 demonstrates the impact of critical meteorological variables, such as cumulative rainfall (mm.) and average tempera-ture, on yield and production.

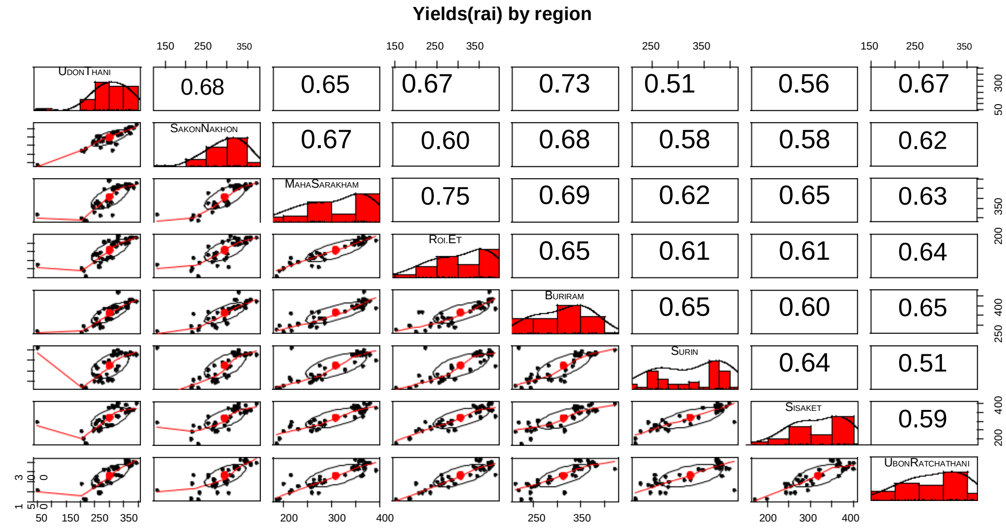


Figure 8. Relationship of Yields (kg./rai) Across Regions.

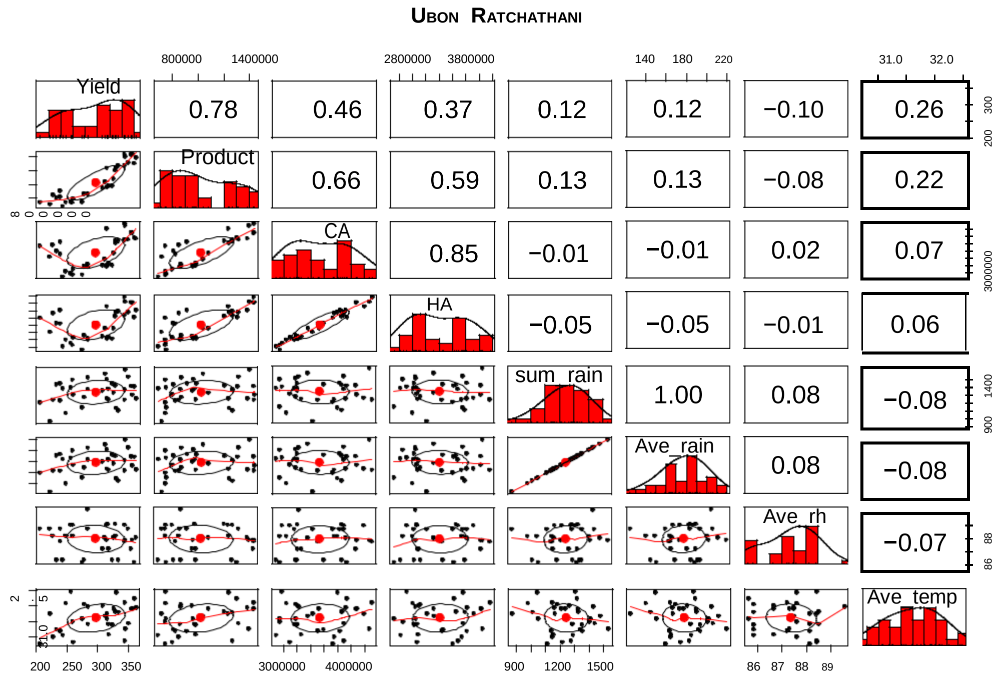


Figure 9. Association Between Crop Data and Meteorological Variables in Ubon Rachathani Province.

As previously mentioned, to discern the dependencies of crop values on variables influencing rice productivity, we utilized seven distinct two-dimensional copula models, as detailed in the prior section. The parameters for the chosen copulas were estimated using a two-stage maximum likelihood estimation technique, known as the IFM method, applied to two boundary distributions: the normal and t-Student distributions. The choice of these distributions was influenced by existing literature recommendations suggesting their applicability.

Results detailing the estimated parameters of probability distribution for production and yield across various provinces are provided in Tables 4 to 5, categorized based on the main rivers (Khong, Chi, and Mun). Table 6 displays the estimated parameters of probabil-ity distribution for both crop and meteorological variables specific to Ubon Ratchathani province. Each table highlights the fitting distribution and pertinent statistics.

Table 4. The estimated parameters of probability distribution for Product by each provinces.

Province	Distribution	shape/mean	scale/sd	ω^2 (p-value)
Loei	logis	768998.3604	123771.7007	0.0577(0.1375)
Nong Bua Lamphu	logis	2007.4995	4.9104	0.0471(0.7927)
Udon Thani	lnorm	12.4216	0.2380	0.1294(0.0418)
Nong Khai	gamma	14.9621	-	0.1772(0.0012)
Bueng Kan	Normal	144781.8182	11075.6497	0.0234(0.5597)
Sakon Nakhon	lnorm	13.5186	0.3099	0.0807(0.1095)
Nakhon Phanom	gamma	12.3479	0.0000	0.0401(0.2396)
Mukdahan	logis	525093.3304	97158.1500	0.0932(0.0635)
Amnat Charoen	lnorm	12.3988	0.1430	0.1194(0.0122)
Khon Kaen	weibull	4.7141	445198.1241	0.1270(0.0001)
Maha Sarakham	weibull	5.3287	882503.0686	0.0338(0.2151)
Roi Et	lnorm	12.6159	0.3055	0.0794(0.1042)
Kalasin	Normal	2001.50	11.5434	0.0631 (0.7896)
Yasothon	lnorm	11.6354	0.3469	0.0866(0.6288)
Chaiyaphum	weibull	4.8952	635372.2350	0.1099(0.2394)
Nakhon Ratchasima	lnorm	12.5638	0.3859	0.1316(0.0087)
Buriram	Normal	864636.3000	226791.0613	0.0361 (0.8377)
Surin	weibull	4.1253	556319.2191	0.0729(0.365)
Sisaket	logis	147454.0443	12211.2426	0.0411(0.831)
Ubon Ratchathani	logis	601413.2941	59138.3478	0.0342(0.0965)

Table 5. The estimated parameters of probability distribution for Yields by region

Region	Distribution	shape/mean	scale/sd	ω^2 (p-value)
UdonThani	logis	305.9399	33.9950	0.0455(0.4727)
SakonNakhon	weibull	7.7314	313.9020	0.0477(0.1078)
MahaSarakham	logis	312.6092	37.4440	0.3508(0.0000)
Roi-Et	weibull	5.9746	332.0968	0.2649(0.0073)
Buriram	weibull	6.9120	336.0878	0.1052(0.2718)
Surin	logis	326.8991	37.7011	0.3615(0.0000)
Sisaket	weibull	6.6396	342.0744	0.1775(0.2417)
UbonRatchathani	weibull	5.9564	304.0702	0.1152(0.3641)

Table 6. The estimated parameters of probability distribution for Crop and Meteorologic variables

Region	Distribution	shape/mean	scale/sd	ω^2 (p-value)
Yield	weibull	7.8399	316.5515	0.1285(0.0356)
Product	lnorm	13.8086	0.2379	0.1475(0.1573)
CA	norm	1021846.2940	245561.0823	0.1454(0.2007)
HA	lnorm	15.0353	0.1203	0.1707(0.0049)
sum_rain	weibull	9.7045	1305.8484	0.0267(0.8354)
Ave_rain	weibull	9.7058	186.5552	0.0268(0.8350)
Ave_rh	weibull	95.9435	87.8542	0.0819(0.0131)
Ave_temp	norm	31.6076	0.4487	0.0466(0.5889)

The subsequent step in our analysis was to validate if the relationships illustrated by the estimated copulas were an accurate reflection of real-world data, and whether they are apt for empirical modeling. To evaluate how well the estimated copulas match the empirical data related to rice production and yield, we implemented the described methodology.

One way to gauge the accuracy of copula parameter estimation is to compare the coefficients inferred from the chosen copula with the empirical Kendall coefficients, denoted as $\hat{\tau}$. We obtained estimates of the Kendall coefficient (τ) for all copulas via a simulation method. These results can be found in Tables 7 to 9.

Table 7. The results of the copula function between Maha Sarakham and Roi-Et

Region		τ^{2}	Copula	Estimated θ (s.e.)	S (p-value)	xv-CIC
Maha Sarakham	Roi-Et	0.7718	Normal	0.9135(0.0239)	0.0380(0.0065)	30.5789
			Clayton	2.9843(0.6855)	0.1232(0.0005)	10.0482
			Frank	15.1213(3.3589)	0.0223(0.0694)	34.4935
			Joe	4.0775(0.8554)	0.0820(0.0075)	20.4052
			Gumbel	3.4157(0.6181)	0.0031(0.0893)	17.5138
			Galambos	2.7020(0.6365)	0.0032(0.0893)	13.8879
			Husler-Reiss	3.1999(0.9922)	0.0036(0.0893)	10.6794

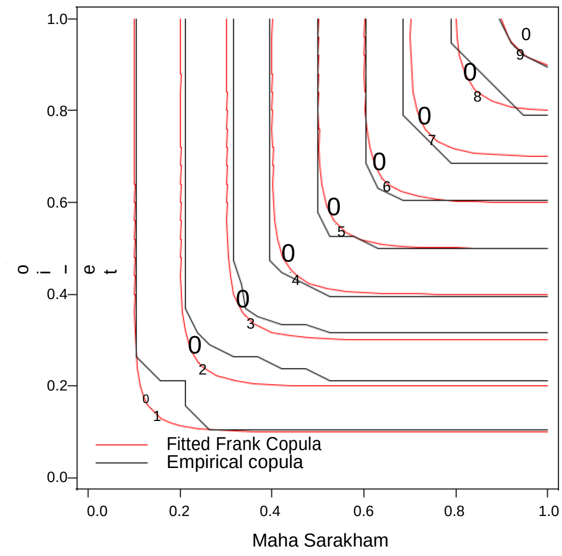


Figure 10. Comparison of empirical copulas and fitted copula between Maha Sarakham and Roi-Et province.

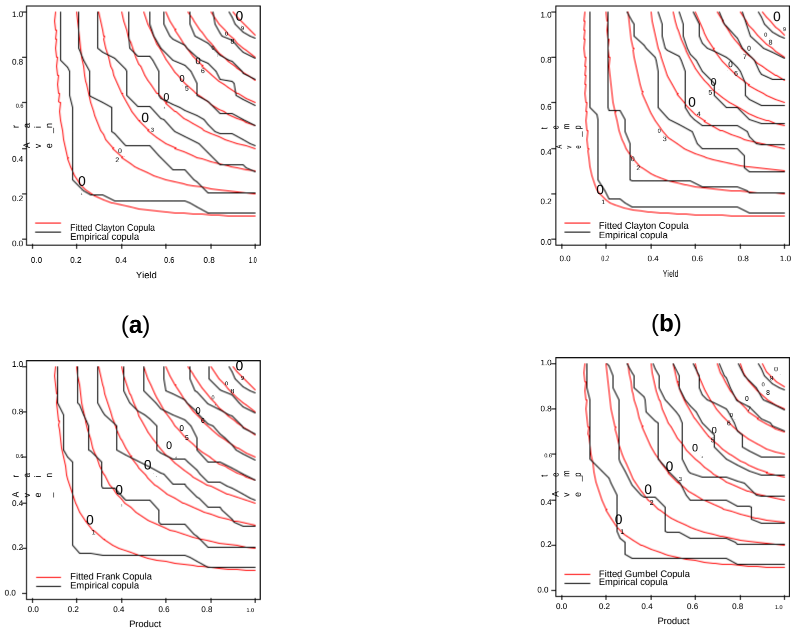
Conversely, Table 8 displays the values of the Kendall correlation coefficient $\hat{\tau}$, as de-rived from the sample data. All these estimated correlations are positive and hold statistical significance. When considering pairs of agricultural products, the Maha Sarakham and Roi-Et province pair showcases the strongest correlation. In contrast, the Srisaket and Ubon Ratchathani pair indicates the weakest relationship. We obtained estimates of the Kendall coefficient for all copulas using the simulation technique, and these findings are detailed in Tables 7 through 9.

Table 8. The results of the optimal Copula functions for yields in each regions.

Region		τ^{2}	Copula	Estimated θ (s.e.)	S (p-value)	xv-CIC
Udon Thani	Sakon Nakhon	0.6789	Gumbel	3.1713(0.5749)	0.0074(0.0484)	28.8867
Maha Sarakham	Roi Et	0.7477	Frank	12.9791(3.0980)	0.0239(0.1184)	31.9820
Buriram	Surin	0.6527	Frank	9.5504(0.9222)	0.0384(0.0574)	20.7038
	Sisaket	0.5980	Frank	8.0084(1.8498)	0.0316(0.1803)	18.3651
	UbonRatchathani	0.6503	Frank	10.0841(1.6224)	0.0386(0.0564)	20.7577
Surin	Sisaket	0.6421	Clayton	3.4850(1.0619)	0.0299(0.1953)	25.3581
	UbonRatchathani	0.5858	Clayton	2.8313(1.0641)	0.0383(0.1773)	19.8037
Sisaket	UbonRatchathani	0.5148	Clayton	2.0705(0.6233)	0.0648(0.0325)	12.1426

Table 9. The results of the copula function between correlated variables at Ubon Ratchathani province

Variables		τ^2	Copula	Estimated θ (s.e.)	S (p-value)	xv-CIC
Yield	Ave_rain	0.1199	Clayton	0.5174 (0.3934)	0.0167 (0.5739)	0.3488
	Ave_temp	0.2639	Clayton	0.9662 (0.3923)	0.0252(0.4021)	3.6437
Product	Ave_rain	0.1266	Frank	1.1641(1.0939)	0.0358 (0.0574)	0.0375
	Ave_temp	0.2165	gumbel	1.2641(0.1598)	0.0152(0.9194)	0.7778



(**a**) (**b**)

(**c**) (**d**)

Figure 11. Comparison of empirical copulas and fitted copula between Yields and meteorological data at Ubon Ratchathani province. (**a**) Yield and Average Rainfall (mm.), (**b**) Yield and Average Temperature($^{\circ}$), (**c**) Yield and Cumulative rainfall (mm.) and (**d**) Yield and Relative humidity(%).

The findings in Tables 8, 9, and Figure 11 corroborate the assessment of how well the copulas fit using the Kendall coefficient τ and xv-CIC value. For the observation pairs Maha Sarakham and Roi-Et, Burirum and Surin, as well as Sisaket and Ubon Ratchathani, the Frank copula offers the most optimal fit. Conversely, the Clayton copula appears to be the best match for pairs like Surin and Srisaket, and Sisaket and Ubon Ratchathani, while the Gumbel copula is best suited for the Udonthani and Sakon Nakorn pair. In the case of Ubon Ratchathani province, when examining the relationship between correlated variables, the Clayton copula best represents the link between yield and average rainfall, the Frank copula aptly captures the connection between production and average rainfall, and the Gumbel copula is most fitting for the relationship between production and average temperature.

4. Discussion

To assess land suitability for rice has considered crop requirement and the selected multi land qualities used for the land evaluation. In the result and data validation depending on the variant factor such as rainfall data, flood area and soil fertility etc. The intricate relationship between rice production, yield, and various influencing factors, particularly in the provinces of Thailand, provides valuable insights into the dynamics of agricultural productivity. Drawing upon the extensive analyses and results, several key points emerge that warrant discussion.

The distinctiveness in rice production and yield trends across various provinces underscores the regional variations in Thailand's agricultural landscape. Maha Sarakham and Roi-Et's strong dependence contrasts sharply with the relatively weaker correlation observed between Srisaket and Ubon Ratchathani. These variations could be attributed to factors such as local agricultural practices, water resource management, soil fertility, and regional climate conditions. The utilization of different copulas (Frank, Clayton, and Gumbel) to best fit these relationships further accentuates the unique characteristics of each province's agricultural dynamics. The findings highlight the profound impact of meteorological factors, specifically average rainfall and temperature, on rice production and yield, particularly in Ubon Ratchathani. As climate change continues to influence global weather patterns, understanding these correlations becomes paramount for future agricultural planning and risk management.

The research validates the efficacy of the two-dimensional copula models in capturing the dependencies between diverse variables. The comparison of coefficients implied by the selected copulas with empirical Kendall coefficients $\hat{r}$ demonstrates the reliability of this methodology in agricultural research. The Frank, Clayton, and Gumbel copulas, in particular, emerge as powerful tools to model the intricate relationships across provinces and meteorological factors. The observed trends over the past few decades, coupled with the results from the copula analysis, carry significant implications for the future of Thai agriculture. The period of rapid growth in rice area and yield from 1981 to 2011, followed by the recent fluctuations and decline, indicates potential challenges ahead. As the rice-growing areas are increasingly influenced by external factors such as climate change and water resource management, targeted interventions may be necessary to ensure sustainability. Moreover, the government and agricultural bodies might need to reconsider water-intensive practices, given the crucial role of meteorological factors in rice productivity. Policymakers should prioritize strategies that cater to regional nuances as depicted by the different relationships across provinces. Investment in research to further understand local variations and the driving factors behind them could lead to tailored interventions, ensuring optimized productivity across Thailand's diverse agricultural regions.

In conclusion, this research provides a comprehensive exploration into the dynamics of rice production and yield in Thailand. The application of copula models has offered nuanced insights, emphasizing the importance of a region-specific approach and the profound influence of meteorological factors. As the global agricultural landscape grapples with the challenges of a changing climate, such insights will be invaluable for future planning and sustainability efforts.

5. Conclusion

Sustainable agriculture stands at the crossroads of environmental stewardship, economic viability, and social desirability. As global concerns over climate change intensify, the need to embrace sustainable practices in agriculture, particularly in rice cultivation, has never been more pressing. Conservation of resources, protection of the environment, and a commitment to agricultural stewardship not only align with sustainability principles but also hold the promise of enhancing global food production. However, the broader ramifications of sustainable agriculture on the larger food industry, rural communities, and societal structures remain areas of ongoing exploration.

Delving into Thailand's agricultural tapestry, this study presents a meticulous analysis of the relationship between rice production, yield, and multiple determinants across selected provinces. Harnessing the precision of two-dimensional copula models—Frank, Clayton, and Gumbel in particular—the research unravels the intricate dependencies woven between these variables. A salient takeaway is the regional variation in agricultural trends, with meteorological factors, namely average rainfall and temperature, profoundly influencing rice yields, a trend most evident in Ubon Ratchathani.

Further insights reveal pronounced disparities in rice productivity dynamics between provinces such as Maha Sarakham and Roi-Et in comparison to Srisaket and Ubon Ratchathani. These differences shed light on the pivotal roles played by local agricultural methodologies, efficient water resource management, and soil fertility. In an era marked by the challenges posed by climate change, discerning these regional nuances becomes essential for shaping adaptive agricultural strategies and bolstering risk management.

The rigorous empirical validation of the selected copulas through the lens of Kendall coefficients $\hat{\tau}$ reinforces the methodological strength underpinning this research. These data-driven revelations have far-reaching implications for charting the trajectory of Thailand's agricultural aspirations. A holistic approach that encompasses regional specificities, recognizes localized variations, and acknowledges the sweeping impact of weather and climate on agriculture is paramount for Thailand's journey toward sustainable agricultural advancement.

In summation, this research offers a kaleidoscopic view into the multifaceted world of rice production in Thailand, underscoring the transformative potential of copula models in agricultural research. As the agricultural tapestry of Thailand continues to evolve in the face of global and regional challenges, the insights garnered from this study will serve as pivotal touchstones for informed, sustainable decision-making.

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