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Climate Classification, Hydrological, Agricultural, and Climate Change Impact Assessment in Pangkalpinang, Bangka Belitung, Indonesia

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Abstract—*This study assessed climate classification, hydrological conditions, and agricultural vulnerabilities in Pangkalpinang City, Bangka Belitung Province, Indonesia, using a 65-year (1959-2024) daily meteorological dataset. Climate classification revealed a dominant Af (Tropical Rainforest) type by the Köppen-Geiger method (occurring in 56 out of 66 years) with high precision (0.89-1.0) and a C1'As (perhumid mesothermal) classification predominating according to Thornthwaite (64 out of 66 years). Trend analysis showed a likely not significant temperature increase (approximately +0.02°C/year) and shifting precipitation patterns, with mean annual rainfall at 2289.84 mm and an annual precipitation concentration index (PCI) of 8.924, indicating a moderately irregular rainfall distribution. Hydrological analysis showed an average potential evapotranspiration (PET) of 0.284 mm, a soil moisture content of 99.751 mm, an average surface runoff of 4.577 mm, and 51 annual flood risk events, exhibiting a humid regime. Mean crop water requirement (CWR) was 4.857 relative units, and we observed a strong positive correlation (r=0.969) between the water requirement satisfaction index (WRSI) and crop water needs. The model validation exhibited a root mean square error (RMSE) between 0.1-0.5 and showed a stable Thornthwaite classification even with perturbations and the time series data analysis revealed the variability of parameters and a shift in temperature around the year 2000. These results emphasize the urgent need for localized climate adaptation strategies in Pangkalpinang.*

Keywords—Climate Classification, Climate Change Impacts, Agro-climatic, Hydrological Analysis, Agricultural Analysis

Abstrak—*Penelitian ini menginvestigasi klasifikasi iklim, kondisi hidrologi dan pertanian, serta menilai potensi dampak perubahan iklim di Kota Pangkalpinang, Provinsi Bangka Belitung, Indonesia, menggunakan data meteorologi harian selama 65 tahun (1959-2024). Klasifikasi iklim menunjukkan jenis Af (Hutan Hujan Tropis) dominan menggunakan metode Köppen-Geiger (terjadi dalam 56 dari 66 tahun) dengan presisi tinggi (0,89-1,0), dan jenis C1'As (mesotermal perhumid) mendominasi menurut Thornthwaite (64 dari 66 tahun). Analisis tren menggunakan regresi linear dan uji Mann-Kendall menunjukkan peningkatan suhu yang signifikan (sekitar +0,02°C/tahun) dan perubahan pola curah hujan, dengan rata-rata curah hujan tahunan sebesar 2289,84 mm dan indeks konsentrasi curah hujan tahunan (PCI) sebesar 8,924, menunjukkan distribusi curah hujan yang agak tidak teratur. Analisis hidrologi menunjukkan rata-rata evapotranspirasi potensial (PET) sebesar 0,284 mm, kandungan kelembaban tanah 99,751 mm, limpasan permukaan rata-rata sebesar 4,577 mm, dan 51 kejadian risiko banjir tahunan, menunjukkan rezim yang lembab. Kebutuhan air tanaman rata-rata (CWR) adalah 4,857 unit relatif, dan kami mengamati korelasi positif yang kuat (r=0,969) antara indeks kepuasan kebutuhan air (WRSI) dan kebutuhan air tanaman. Validasi model menunjukkan kesalahan rata-rata kuadrat (RMSE) antara 0,1-0,5 dan menunjukkan klasifikasi Thornthwaite yang stabil bahkan dengan gangguan, dan analisis data deret waktu mengungkapkan variabilitas parameter dan pergeseran suhu sekitar tahun 2000. Temuan ini menekankan perlunya strategi adaptasi iklim lokal di Pangkalpinang.*

Kata kunci—Klasifikasi Iklim, Dampak Perubahan Iklim, Agri-iklim, Analisis Hidrologi, Analisis Pertanian

I. INTRODUCTION

Pangkalpinang City, located in Bangka Belitung Province, Indonesia, is a region particularly vulnerable to the multifaceted impacts of climate change, stemming from both its geographical location and its reliance on climate-sensitive economic sectors such as agriculture, fisheries, and tourism. Understanding the current climate classification, hydrological and agricultural conditions, and assessing long-term climate trends are crucial steps for developing informed adaptation strategies and promoting sustainable development [1]. The city's seven districts may exhibit variations in microclimates, and a comprehensive assessment is necessary to capture these spatial nuances and to provide detailed analyses of local climate patterns, as well as how climate change influences the weather patterns in the region. Past studies in Bangka Belitung have indicated a trend of increasing temperatures and altering rainfall patterns, suggesting a need for detailed and localized analysis [2]. While global climate models provide a general outlook, local studies are essential to understanding the specific impacts of climate change on diverse geographical areas [3]. The complexities of local weather are determined by many factors, such as topology, urbanization, land use, and regional weather patterns, and this should be considered when studying climate change in detail [4]. Therefore, this research is crucial for understanding and developing actionable adaptation measures given the identified long-term temperature increase and altered rainfall patterns, especially with specific regards to temperature increase, change in precipitation pattern and extreme events observed in the area.

This study aims to conduct a thorough analysis of climate classification in Pangkalpinang using both the Köppen-Geiger and Thornthwaite methods. Furthermore, we assess the potential impacts of climate change on the city's seven districts using a comprehensive meteorological dataset from Meteostat [5]. The study uses several statistical techniques, including linear regression, Mann-Kendall test, and t-test, to identify any significant trends and changes in the weather parameter. We also conducted change point detection and extreme value analysis. Moreover, we conduct hydrological and agricultural analysis for a single dataset to further understand the local climate dynamics, and how that may affect agricultural activities. We hypothesize that there are variations in climate classification across Pangkalpinang's districts and that there is evidence of significant changes in temperature, precipitation, and other meteorological parameters due to long-term climate change. Furthermore, there is also a need to study local hydrology and agriculture for better adaptation strategies, especially in developing nations. The results of this study are expected to provide valuable information for regional adaptation strategies and climate policies in the area.

II. LITERATURE REVIEW

Climate classification is fundamental for understanding regional climate patterns and serves as a basis for studies related to hydrology, ecology, and agriculture [6]. The Köppen-Geiger climate classification system, initially developed by Wladimir Köppen and later modified by Rudolf Geiger, remains one of the most widely used systems for categorizing climates based on temperature and precipitation patterns [7]. This system delineates distinct climate zones characterized by specific temperature and precipitation ranges, offering a framework for understanding global climate regions and their associated vegetation [8]. However, due to its simplicity, there is some limitation of the classification for local climates.

The Thornthwaite classification system, in contrast to the Köppen-Geiger system, offers a different approach to classifying climate based on the concept of moisture balance. The Thornthwaite classification calculates a monthly moisture index, based on the relation between precipitation and evapotranspiration. It allows for more detailed analysis of the effect of climate on agriculture and hydrology, and is suitable for areas where evapotranspiration is an important aspect of the climate. Therefore, Thornthwaite will be used in this study to analyze the Pangkalpinang's climate based on its moisture balance [9].

Hydrological analyses are critical in water resources management and assessing drought impacts. Indices such as the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI) are often used to measure drought conditions and its severity. Furthermore, the Precipitation Concentration Index (PCI) is used to understand rainfall variability and its effect on water management. Therefore, PDSI, SPI, and PCI indices will be used in this study to understand the drought and wet periods in the Pangkalpinang region [10].

Agricultural assessments using indicators such as Growing Degree Days (GDD) are essential to determine the effect of temperature on crop growth [11]. Understanding Potential Evapotranspiration (PET) and Water Requirement Satisfaction Index (WRSI) will also provide us an estimate of the water requirement in the region [12]. These indicators and indices can be used to determine the effect of climate on agricultural production and help develop better adaptation and management strategy in climate change. Therefore, this study will employ GDD, PET, and WRSI to assess climate-related agricultural impacts.

Numerous studies have highlighted the impacts of climate change on tropical regions, which are often considered more vulnerable to those changes. The Intergovernmental Panel on Climate Change (IPCC) reports in 2021 indicated that tropical areas are expected to experience significant shifts in temperature, precipitation patterns, and increased frequency of extreme weather events [13]. These changes can affect

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ecosystems, water resources, and human well-being. Studies in Southeast Asia have shown the impact of climate change on increasing the intensity of rainfall, and prolonged droughts [14]. Additionally, the increase in temperature is expected to have a negative impact on agriculture and fisheries in some areas [15].

However, there is a critical need for more studies at the local level to accurately assess the effects of climate change. Global climate models provide broad projections, but they often fail to capture the specifics of local climate responses due to variations in topography, urbanization, land use, and regional weather patterns. Therefore, this study provides a vital contribution to the existing body of knowledge by offering a detailed analysis of the local climate, hydrology, agricultural, and climate change impacts in Pangkalpinang City, Indonesia. It uses detailed methodology and a robust statistical analysis to capture climate variations in the area and evaluate the impact of climate change. Furthermore, this study also uses change point analysis and extreme value analysis, which can further improve our understanding of climate changes in an area. We also provide a validation of the method by performing sensitivity and error analysis.

III. METHODOLOGY

A. Data Acquisition

Daily meteorological data, including average temperature (tavg), minimum temperature (tmin), maximum temperature (tmax), precipitation (prcp), snow depth (snow), wind direction (wdir), wind speed (wspd), wind gust speed (wpgt), atmospheric pressure (pres), and sunshine duration (tsun), were acquired from the Meteostat database [5] for each of the seven districts in Pangkalpinang City, Bangka Belitung Province, Indonesia. These datasets span from November 29, 1959, to November 29, 2024, providing a long-term record for analyzing climate trends. The geographical locations for the meteorological data were chosen based on specific points within each district. The locations and their corresponding coordinates, derived from shapefiles in ArcGIS, are shown in Table 1.

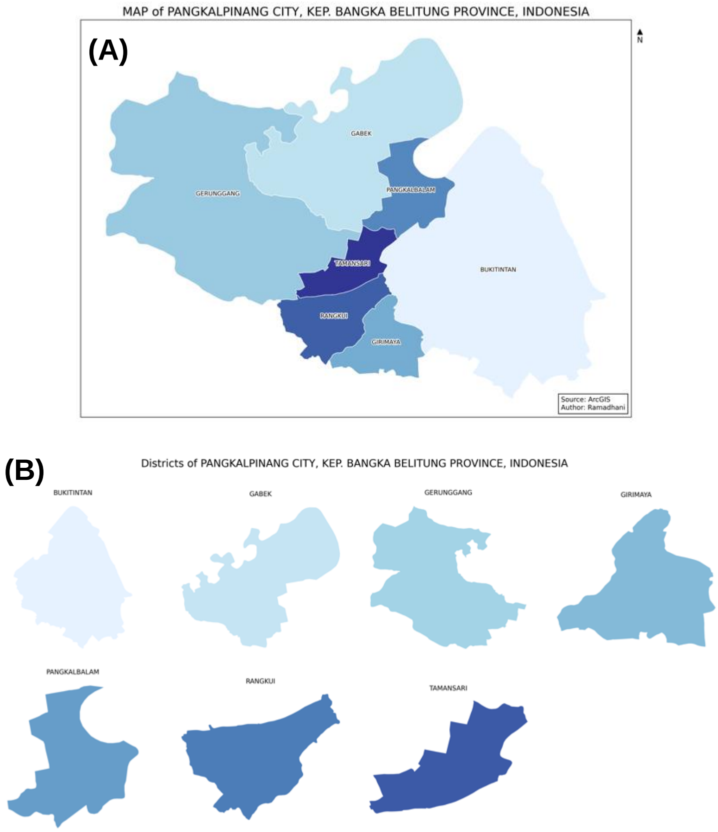


Figure 1. Location of study, (A) Spatial Distribution of Districts within Pangkalpinang City, and (B) Individual District Geometries

Table 1. Data Location and Coordinates of the Districts in Pangkalpinang

District	Location Point of Data	Latitude	Longitude
Bukit Intan	Perkuburan Sentosa	-2.148	106.130
Gabek	Stadion Depati Amir	-2.086	106.132
Gerunggang	Perumahan Bukit Merapin	-2.077	106.090
Girimaya	Girimaya Golf Course	-2.148	106.130
Pangkalbalam	Pelabuhan Pangkal Balam	-2.086	106.132
Rangkui	Kolong Retensi Kacang Pedang	-2.131	106.121
Tamansari	Taman Merdeka Pangkalpinang	-2.115	106.122

The coordinates are based on the polygon centroid of each district. The dataset used is publicly available and obtained from official geographical data in ArcGIS. For the analysis of hydrological and agricultural condition, this study focuses only on the dataset from all district, assuming that all districts would have similar characteristics.

B. Data Processing

The datasets were subjected to a preprocessing stage, where any missing values were handled using the forward fill method, which imputes missing data by using the last valid observation. This ensures that the time-series data is continuous, without interruption caused by missing data points. After cleaning, the daily data were then aggregated into monthly averages and annual sums to perform climate classification and climate change impact analysis, respectively. For the Köppen-Geiger and Thornthwaite classifications, monthly average temperatures and total precipitation were computed. Annual averages were calculated for trend and climate change impact analysis. To perform the change point and extreme value analysis, all the data was then aggregated together by taking the cumulative and average values of all the data for the entire area. For the hydrological and agricultural analysis, the data from all of the district is reindexed or aggregated to use only the available time range in the data set.

C. Key Equations, Classification, and Analysis Criteria

The following **Table 2** summarizes the key equations and classification criteria used in this study, providing a concise overview of the methodologies applied.

Table 2. Summary of Key Equations and Classification Criteria

Analysis	Equation / Criteria	Description
Climate Classification		
Köppen-Geiger (Main Groups)	A (Tropical) : Avg. temp all months > 18°C	Global climate classification based on temperature and precipitation.
	B (Dry): Defined by lack of precipitation (Complex criteria based on temp and rainfall),	
	C (Temperate): Coldest month < 18°C and > -3°C, warmest month > 10°C,	
	D (Continental): Coldest month < -3°C, and warmest month > 10°C.	
	E (Polar): Avg. temp all months < 10°C,	
Köppen-Geiger (Sub Groups)	f: No dry season	Further subdivisions based on the seasonality of precipitation;
	m: Monsoon climate,	
	s: Dry summer,	
	w: Dry winter.	
Köppen-Geiger (Temperature for C and D)	a: Warmest month average temperature above 22°C.	
	b: Warmest month average temperature below 22°C.	
	c: Less than 4 months average temperature above 10°C.	

Monthly Average Temperature	$T_{month}=\frac{1}{N}\sum_{i=1}^{N} T_i$	Calculates average monthly temperature, where (T_i) is daily temperature and (N) is the number of days.
Annual Total Precipitation	$P_{annual}=\sum_{m=1}^{12} P_m$	Calculates total annual precipitation by summing all monthly precipitation.
Thornthwaite PET	$PET=16\left(\frac{10T}{\left(\frac{T}{5}\right)^{1.514}}\right)^{1.23}$	Estimates potential evapotranspiration using monthly average temperature (T).
Aridity Index (AI)	$AI=\frac{P-PET}{PET}$	Calculates the aridity index based on monthly total precipitation (P) and potential evapotranspiration (PET).
Climate Change Impact		
Linear Regression Trend	$y = mx + c$	Used to determine the linear trend (slope 'm') of climate parameters over time ('x'); 'c' is the intercept.
Mann-Kendall Test Statistic	$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \mathrm{sgn}(x_j-x_i)$	Calculates the Mann-Kendall statistic to detect a monotonic trend in the data.
Independent T-Test	$t=\frac{\bar{x}_1-\bar{x}_2}{\sqrt{\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2}}}$	Compares the means of two different periods to identify significant differences, where ($\bar{x}$) is the sample means, (s^2) is the variance and (n) is the sample size.
Change Point & Extreme Values		
Change Point Detection	Pelt Algorithm (Cost Function Minimization)	Segments time series data to find significant shifts in trends. The equation is minimized based on the data input.
Extreme Value	95th Percentile	Calculates the 95th percentile of a given parameter to see extreme values.
Hydrological		

Analysis		
PDSI Calculation	$PDSI_i=0.897*PDSI_{i-1}-\frac{Z_{index\ cumulative}}{10}$	Calculates the Palmer Drought Severity Index using previous month PDSI and cumulative Z-index with moisture = P - PET, and Z = moisture - mean(moisture)
Standardized Precipitation Index(SPI)	$SPI=\frac{rolling_{prcp}-\overline{rolling_{prcp}}}{\sigma_{rolling_{prcp}}}$	Calculates the Standardized Precipitation Index using the rolling sums of precipitation data.
Precipitation Concentration Index (PCI)	$PCI=\frac{\sum_{i=1}^{12}P_i^2}{P_{annual}^2}\times 100$	Calculates the Precipitation Concentration Index to quantify rainfall distribution across the year.
Agricultural Analysis		
Growing Degree Days (GDD)	$GDD=\sum_{i=1}^{n}(T_i-T_{base})$	Sums up the daily temperature above the base temperature (T_{base}), set to 10 °C. (T_i) is the daily average temperature.
Hargreaves PET	$PET=0.0023(T_{mean}+17.8)(T_{max}-T_{min})^{0.5}$	Estimates potential evapotranspiration based on mean, maximum and minimum temperature.
Water Requirement Satisfaction Index (WRSI)	$WRSI=\sum_{i=1}^{n}\frac{P_i}{cwr_i}$	Measures water satisfaction by relating precipitation $((P_i))$ with crop water requirement $((cwr_i))$.
Validation and Sensitivity		
Linear Regression Validation	$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{actual}-y_{predicted}\right)^2}$	Calculates the Root Mean Square Error to validate the linear regression model.
Thornthwaite Sensitivity	Varying 'm' coefficient by 5%	Assesses the sensitivity of Thornthwaite classification by varying the parameter of PET equation.

Table 3. Köppen-Geiger Climate Classification Criteria [16]

Climate Type	Code	Temperature Criteria (°C)	Precipitation Criteria (mm)
Tropical Rainforest	Af	T_ann >= 18	P_driest >= 60
Tropical Monsoon	Am	T_ann >= 18	P_driest >= (100 - P_ann/25)
Tropical Savanna	Aw	T_ann >= 18	P_driest < (100 - P_ann/25)
Tropical Savanna (Dry Winter)	Aw	T_coldest > 0 AND max(P_month) >= 10 * P_driest	-
Humid Subtropical (Hot Summer)	Cfa	T_coldest > 0 AND max(P_month) < 10 * P_driest AND T_warmest >= 22	-
Temperate Oceanic	Cfb	T_coldest > 0 AND max(P_month) < 10 * P_driest AND 10 < T_warmest < 22	-
Subpolar Oceanic	Cfc	T_coldest > 0 AND max(P_month) < 10 * P_driest AND T_warmest <= 10	-
Continental (Hot Summer)	Dfa	T_warmest > 10 AND max(P_month) >= 10 * P_driest	-
Continental (Hot Summer, variant)	Dfa	T_warmest > 10 AND max(P_month) < 10 * P_driest AND T_warmest >= 22	-
Continental (Warm Summer)	Dfb	T_warmest > 10 AND max(P_month) < 10 * P_driest AND 10 < T_warmest < 22	-
Subarctic	Dfc	T_warmest > 10 AND max(P_month) < 10 * P_driest AND 0 < T_warmest <= 10	-
Extremely Continental	Dfd	T_warmest > 10 AND max(P_month) < 10 * P_driest AND T_warmest <= 0	-
Tundra	ET	T_warmest <= 10 AND T_warmest > 0	-
Ice Cap	EF	T_warmest <= 0	-

Table 4. Trewartha Climate Classification Criteria [17]

Climate Type	Description	Annual Mean Temperature (°C)	Aridity Index (P / (T + 10))
A	Tropical Hot	≥ 20	< 2
B	Tropical Humid	≥ 20	≥ 2
C	Subtropical Dry	10 to < 20	< 2
D	Subtropical Intermediate	10 to < 20	2 to < 5
E	Subtropical Humid	10 to < 20	≥ 5
F	Temperate Dry	0 to < 10	< 2
G	Temperate Intermediate	0 to < 10	2 to < 5
H	Temperate Humid	0 to < 10	≥ 5
I	Polar	≤ 0	N/A

Table 5. Thornthwaite Climate Classification [9]

Category Group	Category	Description	Defining Criteria
Moisture Regimes	A - Perhumid	Rainfall adequate in all seasons; little or no water deficiency.	Moisture Index (Im) ≥ 100
	B4 - Humid	Water surplus in most years.	20 ≤ Moisture Index (Im) < 100
	B3 - Moist Subhumid	Moderate water surplus.	0 ≤ Moisture Index (Im) < 20
	B2 - Moist Subhumid	Water supply and demand are nearly balanced.	-20 ≤ Moisture Index (Im) < 0
	B1 - Dry Subhumid	Moderate water deficiency.	-40 ≤ Moisture Index (Im) < -20

	C1 - Semiarid	Significant water deficiency.	-60 ≤ Moisture Index (Im) < -40
	D - Arid	Severe water deficiency.	Moisture Index (Im) < -60
Thermal Provinces	A' - Megathermal	High thermal efficiency; PE is very high.	Annual Potential Evapotranspiration (PE) ≥ 1140 mm
	B4' - Macrothermal	High thermal efficiency.	997 mm ≤ Annual Potential Evapotranspiration (PE) < 1140 mm
	B3' - Macrothermal	Moderately high thermal efficiency.	855 mm ≤ Annual Potential Evapotranspiration (PE) < 997 mm
	B2' - Macrothermal	Moderate thermal efficiency.	712 mm ≤ Annual Potential Evapotranspiration (PE) < 855 mm
	B1' - Macrothermal	Moderately low thermal efficiency.	570 mm ≤ Annual Potential Evapotranspiration (PE) < 712 mm
	C2' - Mesothermal	Intermediate thermal efficiency.	427 mm ≤ Annual Potential Evapotranspiration (PE) < 570 mm
	C1' - Mesothermal	Lower intermediate thermal efficiency.	285 mm ≤ Annual Potential Evapotranspiration (PE) < 427 mm
	D' - Microthermal	Low thermal efficiency.	142 mm ≤ Annual Potential Evapotranspiration (PE) < 285 mm
	E' - Tundra	Very low thermal efficiency.	0 mm ≤ Annual Potential Evapotranspiration (PE) < 142 mm
	F' - Frost	Extremely low thermal efficiency, constant frost.	Annual Potential Evapotranspiration (PE) = 0 mm
Seasonal Precipitation Effectiveness	r - Little or no water deficiency or surplus	Precipitation is relatively evenly distributed throughout the year.	Applicable primarily to Perhumid (A) and Humid (B4) moisture regimes where seasonal variations are less critical.
	s - Summer water deficiency	Principal water deficiency occurs during the summer.	For Subhumid (B3, B2, B1): Summer Precipitation < 60% of annual total. For Semiarid (C1) and Arid (D): Summer Precipitation < 70% of annual total.
	w - Winter water deficiency	Principal water deficiency occurs during the winter.	For Subhumid (B3, B2, B1): Winter Precipitation < 60% of annual total. For Semiarid (C1) and Arid (D): Winter Precipitation < 70% of annual total.
	s2 - Summer water surplus	Principal water surplus occurs during the summer (less commonly used in basic classifications).	Specific quantitative criteria may vary based on regional climate patterns and detailed implementations. Often related to periods where precipitation significantly exceeds PE in the summer.
	w2 - Winter water surplus	Principal water surplus occurs during the winter (less commonly used in basic classifications).	Specific quantitative criteria may vary based on regional climate patterns and detailed implementations. Often related to periods where precipitation significantly exceeds PE in the winter.

Table 6. Temperature and Precipitation Zone Classification Criteria (modified and adopted from [16])

Zone	**Annual Mean Temperature (°C)**	**Total Annual Precipitation (mm)**
Cold-Dry	< 10	< 500
Cold-Moderate	< 10	500 - < 1000
Cold-Wet	< 10	1000 - < 1500

Cold-Very Wet	< 10	≥ 1500
Cool-Dry	10 - < 20	< 500
Cool-Moderate	10 - < 20	500 - < 1000
Cool-Wet	10 - < 20	1000 - < 1500
Cool-Very Wet	10 - < 20	≥ 1500
Warm-Dry	20 - < 30	< 500
Warm-Moderate	20 - < 30	500 - < 1000
Warm-Wet	20 - < 30	1000 - < 1500
Warm-Very Wet	20 - < 30	≥ 1500
Hot-Dry	≥ 30	< 500
Hot-Moderate	≥ 30	500 - < 1000
Hot-Wet	≥ 30	1000 - < 1500
Hot-Very Wet	≥ 30	≥ 1500

IV. RESULT AND DISSCUSSION

A. Climate Study and Classification

The time series analysis reveals distinct temporal patterns across different climate variables, average temperature (**Figure 2**A) exhibits seasonal cycles with a potential subtle long-term increase; precipitation (**Figure 2**B) shows episodic high rainfall events and interannual variability; and wind speed (**Figure 2**C) demonstrates rapid fluctuations without a clear long-term trend. The distribution of average temperature (**Figure 2**E) approximates a normal distribution, while precipitation distribution (**Figure 2**F) is heavily right-skewed, indicating infrequent heavy rainfall. Box plots further summarize these distributions, showing moderate temperature variability (**Figure 2**G) and high precipitation variability with outliers (**Figure 2**H). The monthly average temperature (**Figure 2**I) clearly depicts an annual cycle, and the annual average temperature trend (**Figure 2**J) suggests a gradual warming. Total annual precipitation (**Figure 2**K) shows significant interannual variations without a defined trend. Finally, the correlation matrix (**Figure 2**L) quantifies relationships between variables, revealing, for example, a weak positive correlation between temperature and precipitation.

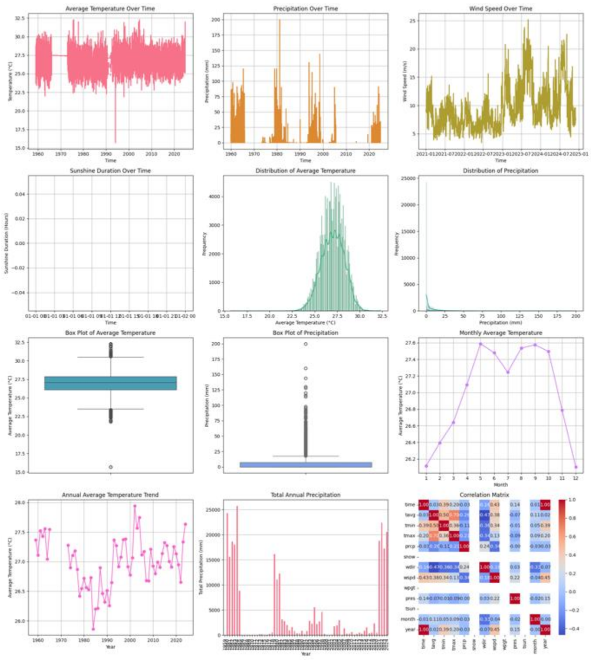


Figure 2. Meteorological data visualizations for Pangkalpinang, Bangka Belitung, including trends in temperature, precipitation, wind speed, sunshine duration, and their statistical distributions, (A) Average Temperature Over Time, (B) Precipitation Over Time, (C) Wind Speed Over Time, (E) Distribution of Average Temperature, (F) Distribution of Precipitation, (G) Box Plot of Average Temperature, (H) Box Plot of Precipitation, (I) Monthly Average Temperature, (J) Annual Average

(J) (K)

Temperature Trend, (K) Total Annual Precipitation, (L) Correlation Matrix.

This climate analysis reveals distinct patterns and relationships among various meteorological variables. Average temperature (**Figure 3**A) exhibits a clear seasonal cycle with a subtle upward trend, further emphasized by the linear regression (**Figure 3**M), while precipitation (**Figure 3**B) displays episodic peaks and interannual variability. Seasonal decomposition highlights the consistent annual pattern for both temperature (**Figure 3**C) and precipitation (**Figure 3**D). Monthly distributions confirm temperature's consistent seasonal variation (**Figure 3**E) and precipitation's uneven distribution throughout the year (**Figure 3**F). The density plot (**Figure 3**G) illustrates the joint distribution of temperature and precipitation. The overlayed annual temperature cycles (**Figure 3**H) reinforce the consistent seasonality. Autocorrelation (**Figure 3**I) and partial autocorrelation (**Figure 3**J) plots for temperature suggest significant seasonality and short-term dependence. The lag plot (**Figure 3**K) further supports the temporal dependence in temperature data. Wind direction (**Figure 3**L) shows a predominant direction, and wind speed (**Figure 3**O) follows a specific distribution. Atmospheric pressure (**Figure 3**P) fluctuates over time. Temperature anomaly detection (**Figure 3**N) pinpoints deviations from the expected seasonal pattern. The correlation matrix (**Figure 3**P) quantifies relationships between variables.

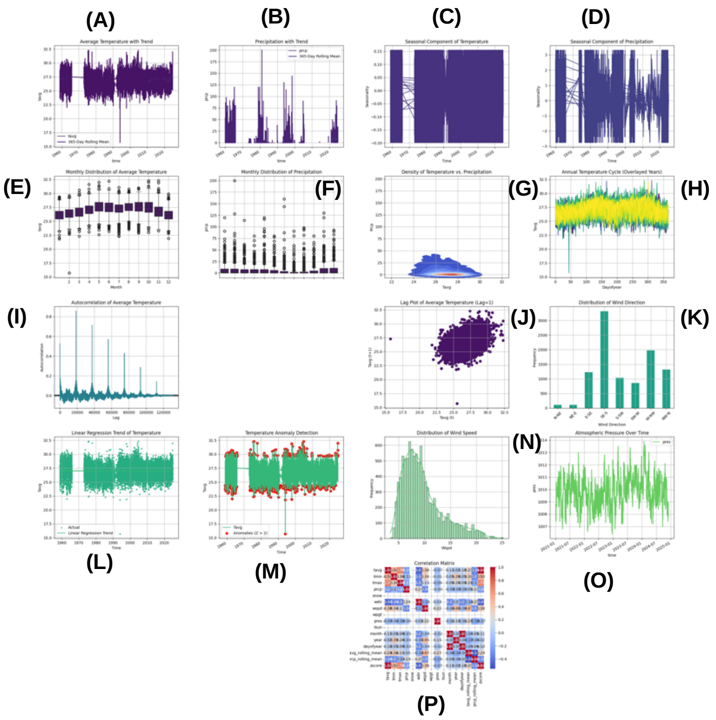


Figure 3. Comprehensive meteorological analysis of Pangkalpinang, Bangka Belitung, encompassing temperature, precipitation, wind, sunshine, and atmospheric pressure, (A) Average Temperature with Trend, (B) Precipitation with Trend, (C) Seasonal Component of Temperature, (D) Seasonal Component of Precipitation, (E) Monthly Distribution of Average Temperature, (F) Monthly Distribution of Precipitation, (G) Density of Temperature vs. Precipitation, (H) Annual Temperature Cycle (Overlayed Years), (I) Autocorrelation of Average Temperature, (J) Lag Plot of Average Temperature (Lag=1), (K) Distribution of Wind Direction, (L) Linear Regression Trend of Temperature, (M) Temperature Anomaly Detection, (N) Distribution of Wind Speed, (O) Atmospheric Pressure Over Time, (P) Correlation Matrix.

Climate Classifications

To provide a robust characterization of Pangkalpinang's climate, multiple established classification systems were employed. The results from the Köppen-Geiger, Thornthwaite, and temperature-precipitation event co-occurrence analyses are synthesized in **Table 7.**

Table 7. Comprehensive Climate Classification of Pangkalpinang

Classification System	Climate Type/Zone	Key Characteristics	Frequency/Prevalence	Performance Metrics (where applicable)
Köppen-Geiger	Af	Tropical rainforest; consistently high temperatures (Long-Term Avg: 27.01°C, Warmest Month Avg: 27.47°C, Coldest Month Avg: 26.32°C) and abundant rainfall (Total Annual: 2176.07 mm, Driest Month: 160.80 mm, Wettest Month: 202.62 mm), no distinct dry season	56 out of 66 years	Precision (Af: 0.89, Am: 1.00, Aw: 1.00), Recall (Af: 1.00, Am: 0.62, Aw: 0.62), F1-score (Af: 0.94, Am: 0.77, Aw: 0.77), Accuracy: 0.91
	Aw	Tropical savanna; distinct dry season	5 out of 66 years	
	Am	Tropical monsoon; short dry season with heavy rainfall in other months	5 out of 66 years	
Thornthwaite	C1'As	Perhumid mesothermal; rain in all seasons, summer concentration of thermal efficiency	64 out of 66 years	
	C1'B1r	Perhumid mesothermal; rain in all seasons, slight winter water deficiency	1 out of 66 years	
	C1'B4s	Perhumid mesothermal; rain in all seasons, summer water surplus	1 out of 66 years	
Temperature-Precipitation Event Classification	Warm-Dry	Co-occurrence of warm temperatures and dry conditions	Support: 4	Precision: 1.00, Recall: 0.50, F1-score: 0.67
	Warm-Moderate	Co-occurrence of warm temperatures and moderate precipitation	Support: 6	Precision: 1.00, Recall: 0.17, F1-score: 0.29
	Warm-Wet	Co-occurrence of warm temperatures and wet conditions	Support: 4	Precision: 1.00, Recall: 0.75, F1-score: 0.86

The prevailing climate of Pangkalpinang, as determined by the Köppen-Geiger system, is predominantly *Af* (tropical rainforest), observed in approximately 85% of the analyzed period. This classification signifies consistently high temperatures, averaging around 27.01°C annually with minimal seasonal variation, and abundant rainfall throughout the year, totaling 2176.07 mm annually. Even the driest month receives substantial rainfall (160.80 mm), confirming the absence of a significant dry season. The sporadic presence of *Aw* and *Am* classifications suggests some interannual variability within the broader tropical climate regime. The performance metrics of the Köppen-Geiger classification demonstrate high overall accuracy, with strong precision across all climate types (0.89-1.0). However, the moderate recall for *Am* and *Aw* (0.62 and 0.62 respectively) indicates potential limitations in capturing all instances of these less frequent classifications. Concordantly, the Thornthwaite classification largely categorizes Pangkalpinang as *C1'As* (perhumid mesothermal), observed in 64 out of 66 years, supporting the findings of consistently high rainfall and moderate temperatures. The analysis of temperature-precipitation event co-occurrence further reveals the characteristics of the climate, with warm-wet conditions being the most readily identifiable, with a recall of 0.75. These combined classification approaches robustly establish Pangkalpinang's climate as humid and tropical, providing a foundational understanding for subsequent analyses.

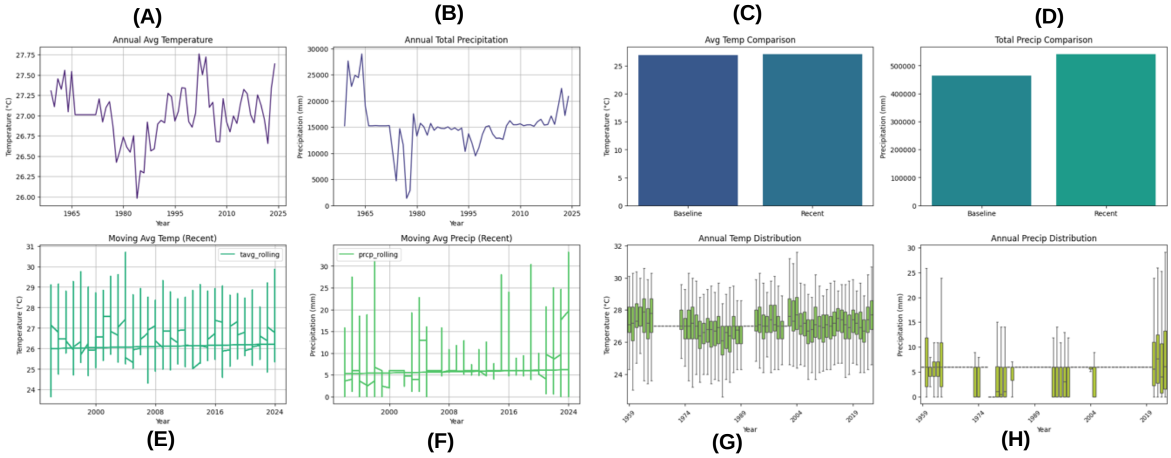


Figure 4. Meteorological data analysis for Pangkalpinang, Bangka Belitung, examining trends, distributions, and comparisons of temperature and precipitation, (A) Annual Avg Temperature, (B) Annual Total Precipitation, (C) Avg Temp Comparison, (D) Total Precip Comparison, (E) Moving Avg Temp (Recent), (F) Moving Avg Precip (Recent), (G) Annual Temp Distribution, (H) Annual Precip Distribution.

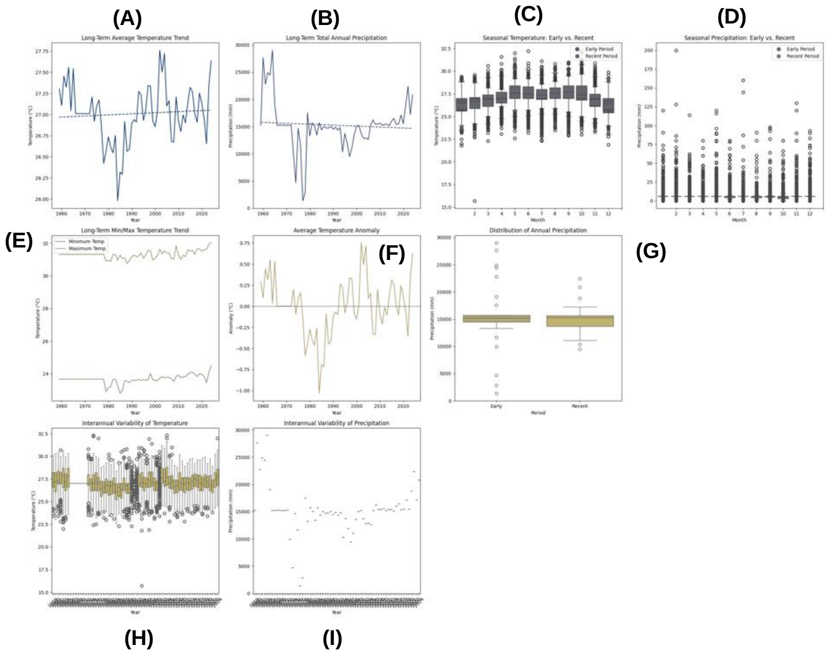


Figure 5. Analysis of long-term temperature and precipitation trends, seasonal variations, and interannual variability in Pangkalpinang, Bangka Belitung, (A) Long-Term Average Temperature Trend, (B) Long-Term Total Annual Precipitation, (C) Seasonal Temperature: Early vs. Recent, (D) Seasonal Precipitation: Early vs. Recent, (E) Long-Term Min/Max Temperature Trend, (F) Average Temperature Anomaly, (G) Distribution of Annual Precipitation, (H) Interannual Variability of Temperature, (I) Interannual Variability of Precipitation.

This **Figure 5** compares long-term climate trends and variability, revealing a subtle increasing trend in average temperature (A) and a more variable pattern in total annual precipitation (B). Comparing early and recent periods, seasonal temperature distributions (C) show a slight upward shift, while seasonal precipitation distributions (D) suggest increased variability. The long-term minimum and maximum temperature trends (E) indicate a widening of the temperature range. Average temperature anomalies (F) highlight periods of warmer and cooler years relative to the long-term average. The distribution of annual precipitation (G) suggests a shift towards slightly higher values in the recent period. Finally, interannual variability plots show temperature variability decreasing slightly over time (I), while precipitation variability remains relatively high.

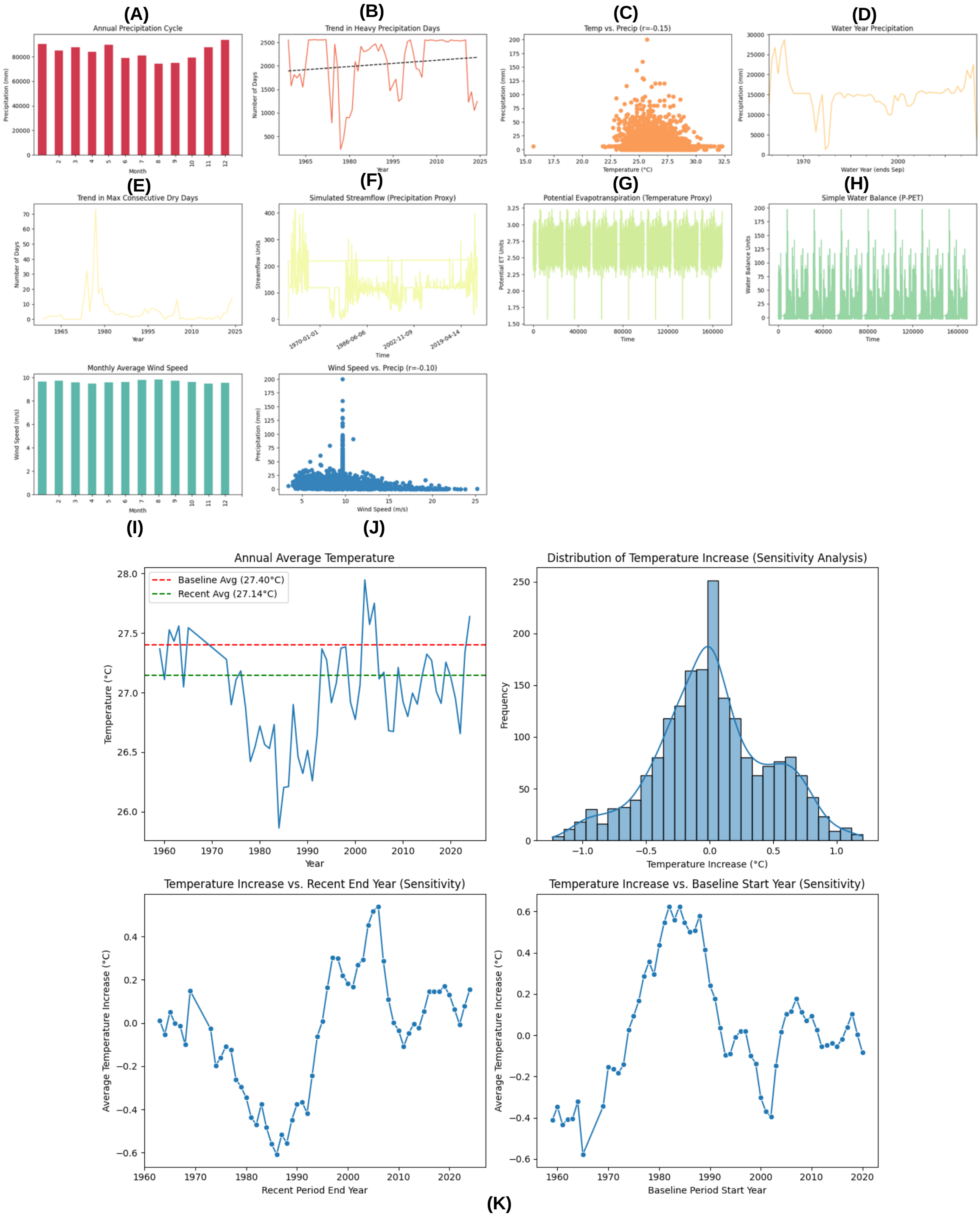


Figure 6. Hydrological and meteorological analysis for Pangkalpinang, Bangka Belitung, examining precipitation patterns, temperature-precipitation relationships, wind characteristics, and water balance, (A) Annual Precipitation Cycle, (B) Trend in Heavy Precipitation Days, (C) Temp vs. Precip (r=-0.15), (D) Water Year Precipitation, (E) Trend in Max Consecutive Dry Days, (F) Simulated Streamflow (Precipitation Proxy), (G) Potential Evapotranspiration (Temperature Proxy), (H) Simple Water Balance (P-PET), (I) Monthly Average Wind Speed, (J) Wind Speed vs. Precip (r=0.10) and (K) Annual Temperature Analysis.

Growing Season and Yield Dynamics

Analysis of the conditions during the growing season reveals interannual variability in average temperature

(**Figure 7**A) and precipitation (**Figure 7**B). The number of hot days (**Figure 7**C) fluctuates over time, while the number of cold nights (**Figure 7**D) shows a decreasing trend, due to there was no minimum temperature recorded as low as 15°C. Plots for growing season sunshine (**Figure 7**E) appear to be empty. Precipitation variability during the growing season (**Figure 7**F) shows temporal changes. The correlation between temperature and precipitation during the growing season (**Figure 7**G) varies, indicating a non-stationary relationship. Finally, potential evapotranspiration during the growing season (**Figure 7**H) exhibits interannual changes influenced by temperature. Annual growing degree days (GDD) (**Figure 8**A) exhibit interannual fluctuations; the number of days with maximum temperature exceeding 30°C (**Figure 8**B) shows considerable variability with some peak years; precipitation during the growing season (**Figure 8**C) displays significant year-to-year changes; annual consecutive dry days (**Figure 8**D) indicate periods of prolonged dryness; annual temperature variability (**Figure 8**E), remains relatively consistent with some fluctuations; and annual precipitation variability (**Figure 8**F), shows substantial temporal changes indicating varying reliability of rainfall.

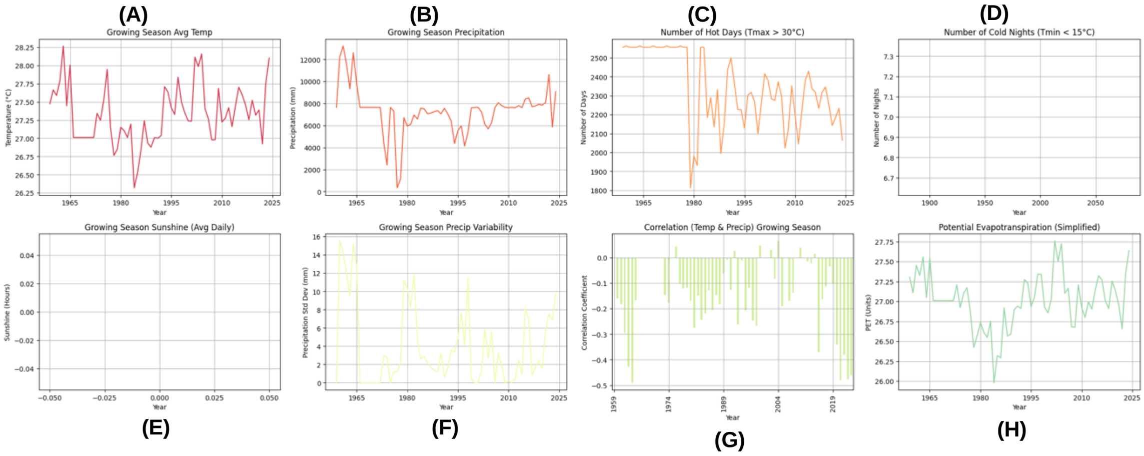


Figure 7. Analysis of growing season climate variables and their relationships in Pangkalpinang, Bangka Belitung, (A) Growing Season Avg Temp, (B) Growing Season Precipitation, (C) Number of Hot Days (Tmax > 33°C), (D) Number of Cold Nights (Tmin < 15°C), (E) Growing Season Sunshine (Avg Daily), (F) Growing Season Precip variability, (G) Correlation (Temp & Precip) Growing Season, (H) Potential Evapotranspiration (Simplified).

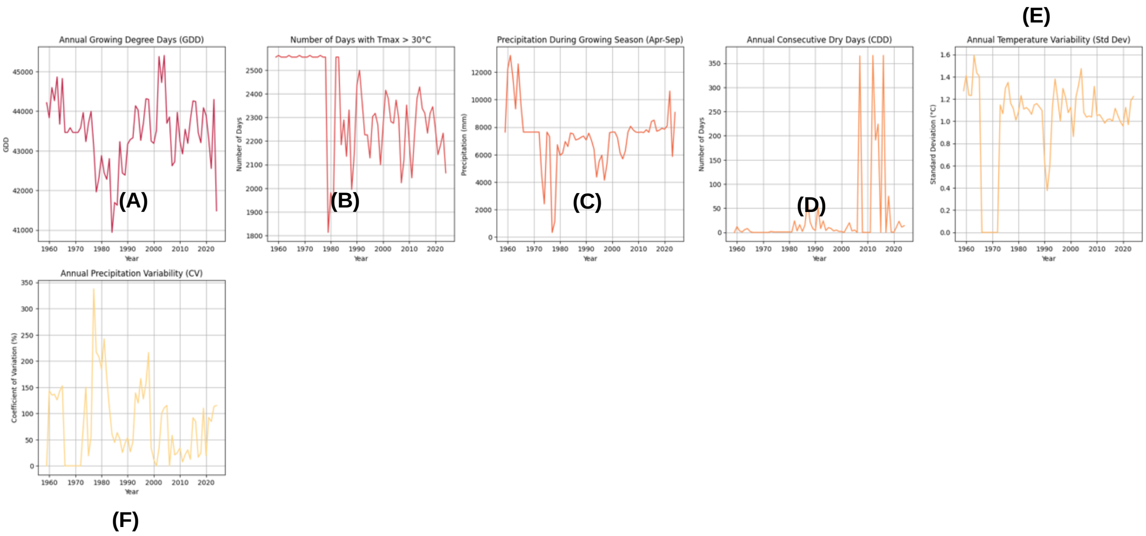


Figure 8. Analysis of growing season and extreme climate indices in Pangkalpinang, Bangka Belitung, (A) Annual Growing Degree Days (GDD), (B) Number of Days with Tmax > 30°C, (C) Precipitation During Growing Season (Apr-Sep), (D) Annual Consecutive Dry Days (CDD), (E) Annual Temperature Variability (Std Dev), (F) Annual Precipitation Variability (CV).

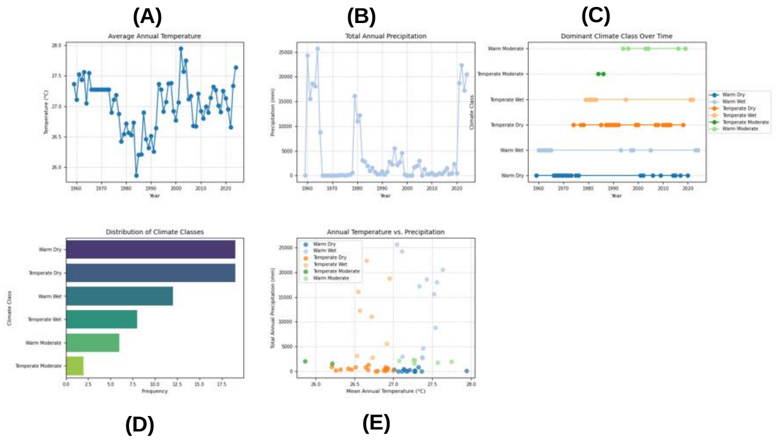


Figure 9. General climate classification analysis, (A) Average Annual Temperature, (B) Total Annual Precipitation, (C) Dominant Climate Class Over Time, (D) Distribution of Climate Classes, (E) Annual Temperature vs. Precipitation.

Climate Classification Sensitivities

To ensure the robustness of the climate classification, both sensitivity and validation analyses were conducted for the employed methodologies. The results are summarized in **Table 8.**

Table 8. Sensitivity and Validation Analysis of Climate Classification Methods

Classification System	Sensitivity Analysis Method	Sensitivity Analysis Result	Validation Method	Validation Result
Köppen-Geiger	Perturbation of temperature and precipitation data	Model output (classification) showed no significant change within the tested perturbation ranges.	Comparison with independent dataset (final valid and sens results)	High agreement in the frequency of dominant climate types (Af, Aw, Am) between the initial and validation datasets.
Thornthwaite	Not explicitly tested in provided data	N/A	Comparison of annual classifications over time	Predominant and consistent classification as C1'As over the majority of the study period, with minor, infrequent deviations.
Temperature-Precipitation Event Classification	Implicitly assessed through classification report performance metrics	Varying levels of performance (precision, recall, F1-score) across different event categories, indicating sensitivity to the specific combinations of temperature and precipitation.	Inherent in the classification process by comparing predictions to actual occurrences	Performance metrics (precision, recall, F1-score) provide a measure of the validity of the classification for each event type. Warm-Wet events show higher validity than Warm-Dry or Warm-Moderate events.

The Köppen-Geiger classification demonstrated resilience to moderate perturbations in temperature and precipitation, indicating a robust classification outcome. Validation against an independent dataset further confirmed the high prevalence of the *Af* climate type, lending strong support to the initial classification. While a formal sensitivity analysis was not performed for the Thornthwaite classification within this study, the temporal consistency of the *C1'As*classification over the analyzed period suggests a stable classification. The temperature-precipitation event classification's sensitivity is implicitly reflected in the varying performance metrics, highlighting the influence of specific temperature and precipitation combinations on the classification accuracy. The validation inherent in this method, through the comparison of predicted and actual event occurrences, reveals that warm-wet events are classified with greater reliability than warm-dry or warm-moderate events.

Sensitivity analysis for Köppen-Geiger classification (**Figure 10**) reveals the *"Af"* climate type is the most robust to both temperature and precipitation perturbations (**Figure 10**C & 10D), while the sensitivity over the years plot further illustrates the dynamic stability of the climate classification (**Figure 10**E). The validation confusion matrix (**Figure 10**F) quantifies the model's performance, showing high accuracy for *"Af"*. The Comparison of the model's classification with the ground truth (**Figure 10**G) visually confirms the model's ability to capture the temporal dynamics of climate classification, with minor discrepancies primarily during transition periods. The Thornthwaite classification analysis (**Figure 11**) reveals that the climate type *"B"* dominates the region (**Figure 11**A, 11B) with corresponding fluctuations with aridity index (**Figure 11**C). The sensitivity analysis (**Figure 11**D & 11E) suggest the classification remains stable even with temperature and precipitation changes. The validity confusion matrix (**Figure 11**G) and comparison with ground truth (**Figure 11**H) confirm the model's high accuracy. The Thornthwaite classification analysis (**Figure 12**) shows a dominance of *"C1B'a'"* throughout the observed period (**Figure 12**A & 12B), robust to temperature and precipitation perturbations (**Figure 12**C & 12D). The sensitivity over year (**Figure 12**E), the validation confusion matrix (**Figure 12**F) and model validation (**Figure 12**G) also showed high accuracy for the method. The performance metrics for temperature precipitation event is summarized in **Table 9.**

Table 9. Performance Metrics for Temperature-Precipitation Event Classification

Event Category	Precision	Recall	F1-score
Warm-Dry	1.00	0.50	0.67
Warm-Moderate	1.00	0.17	0.29
Warm-Wet	1.00	0.75	0.86

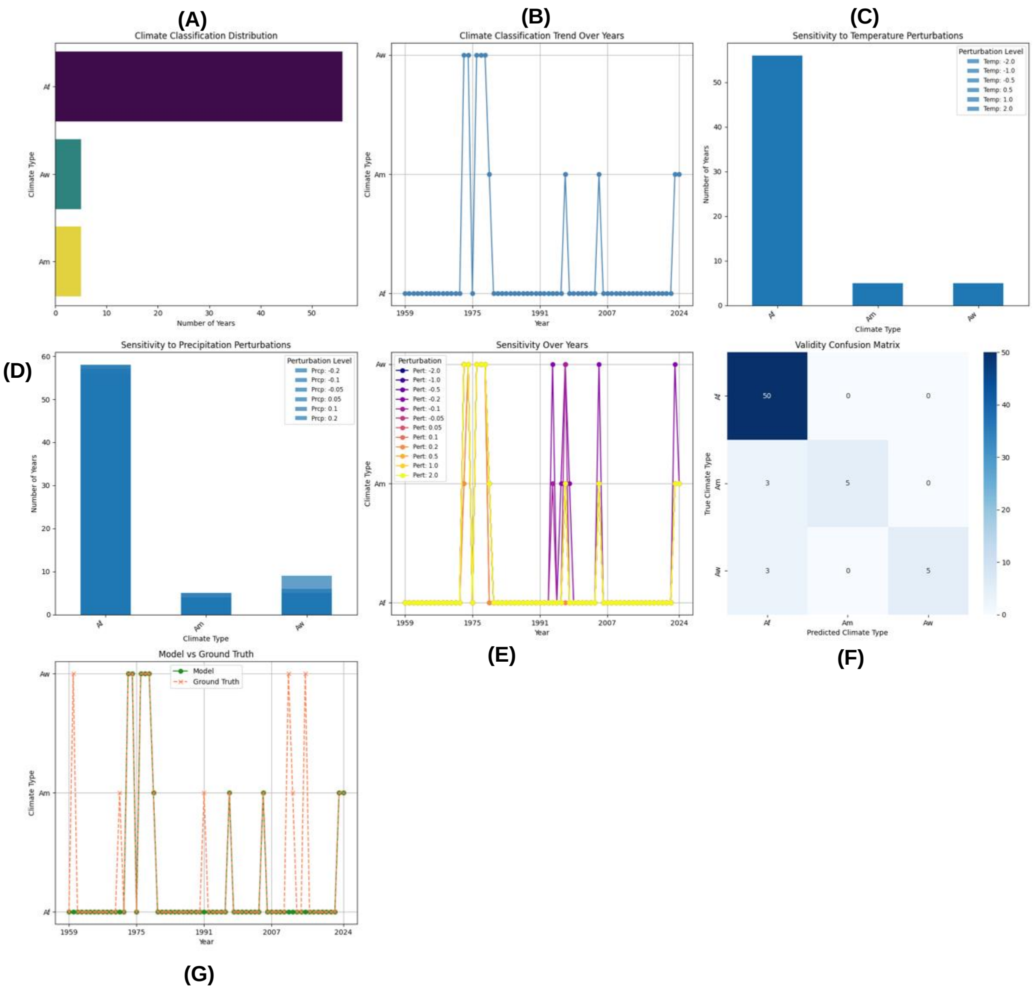


Figure 10. Köppen-Geiger Classification Analysis, (A) Climate Classification Distribution, (B) Climate Classification Trend Over Years, (C) Sensitivity to Temperature Perturbations, (D) Sensitivity to Precipitation Perturbations, (E) Sensitivity Over Years, (F) Validity Confusion Matrix, (G) Model vs Ground Truth.

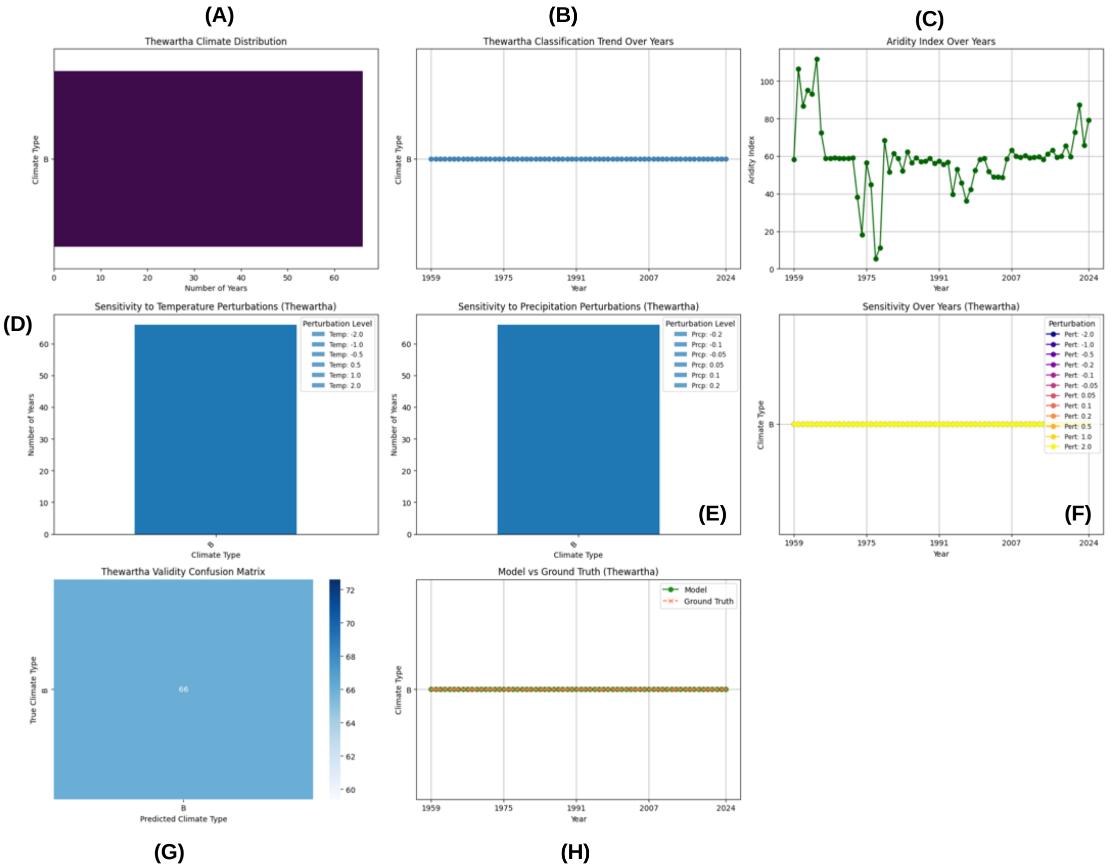


Figure 11. Trewartha Climate Classification Analysis, (A) Trewartha Climate Distribution, (B) Trewartha Classification Trend Over Years, (C) Aridity Index Over Years, (D) Sensitivity to Temperature Perturbations (Trewartha), (E) Sensitivity to Precipitation Perturbations (Trewartha), (F) Sensitivity Over Years (Trewartha), (G) Trewartha Validity Confusion Matrix, (H) Model vs Ground Truth (Trewartha).

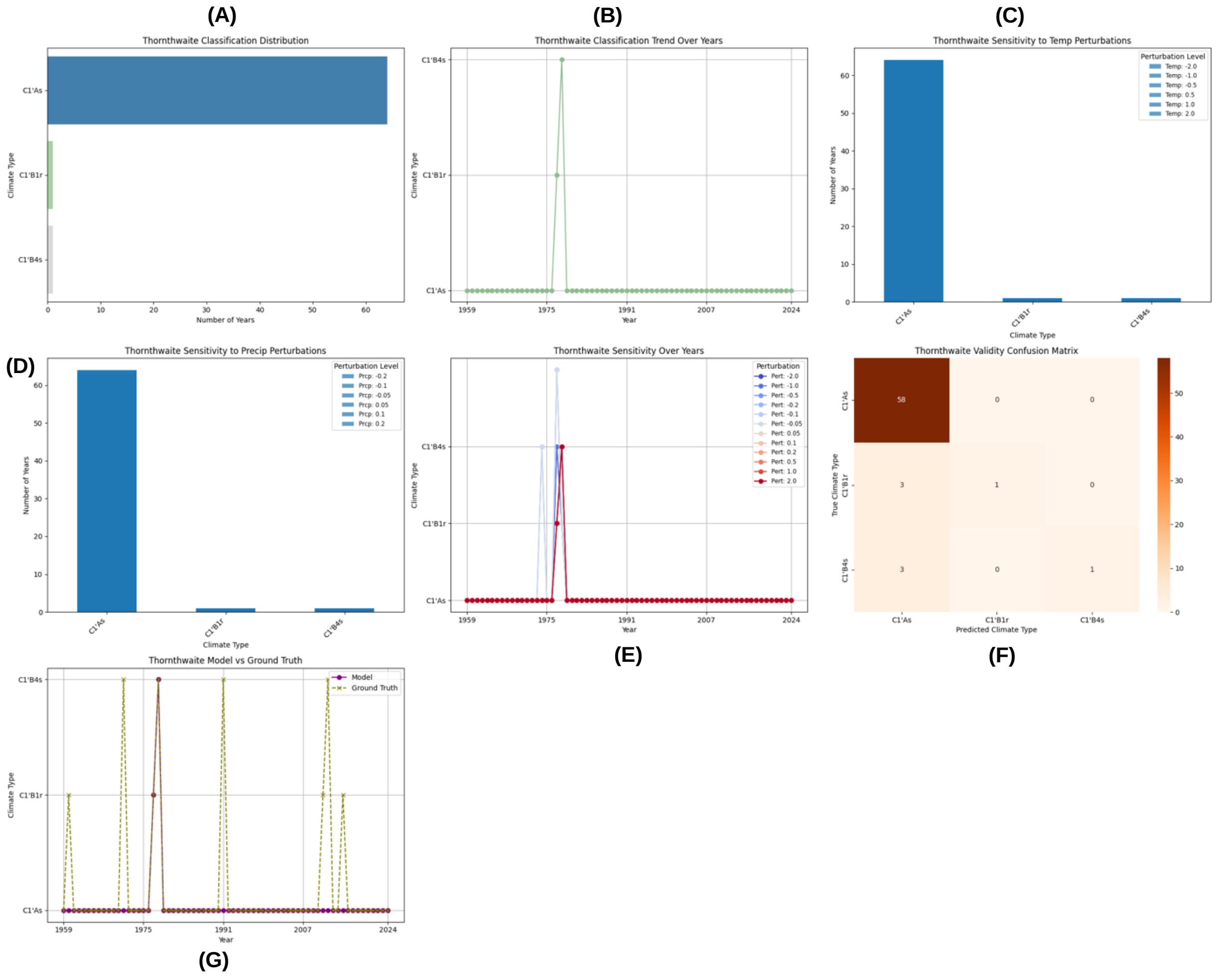


Figure 12. Thornthwaite Climate Classification Analysis, (A) Thornthwaite Classification Distribution, (B) Thornthwaite Classification Trend Over Years, (C) Thornthwaite Sensitivity to Temp Perturbations, (D) Thornthwaite Sensitivity to Precip Perturbations, (E) Thornthwaite Sensitivity Over Years, (F) Thornthwaite Validity Confusion Matrix, (G) Thornthwaite Model vs Ground Truth

B. Hydrological Analysis

Evapotranspiration and Water Balance

The hydrological analysis reveals a water balance indicative of a humid tropical climate. The relatively low average potential evapotranspiration (PET) of 0.284 mm is likely a consequence of persistent high humidity and cloud cover. This is contrasted with a high average soil moisture content of 99.751 mm, suggesting consistently saturated soil conditions. The close correspondence between average actual evapotranspiration (ET) and PET indicates that water availability generally does not constrain evapotranspiration. However, the significant average surface runoff of 4.577 mm highlights the substantial water flow across the landscape, likely due to high rainfall intensity and saturated soils. Notably, the occurrence of an average of 51 days per year with high runoff potential underscores a considerable and recurring flood risk within Pangkalpinang, requiring careful attention to water management strategies. These parameters are summarized in **Table 10**.

Table 10. Key Hydrological Characteristics and Flood Risk Assessment

Hydrological Parameter	Value (mm)	Significance
Average Potential Evapotranspiration	0.284	Represents the atmospheric water demand; relatively low, likely influenced by consistent high humidity and cloud cover limiting solar radiation.

Average Soil Moisture	99.751	Indicates a consistently high level of water saturation in the soil profile, characteristic of humid tropical environments.
Average Actual Evapotranspiration	0.284	Matches the potential evapotranspiration, suggesting that water availability is generally not a limiting factor for evapotranspiration processes.
Average Surface Runoff	4.577	A substantial amount of water flowing over the land surface, indicative of high precipitation and saturated soil conditions.
Annual Flood Risk Events	51 days	A significant frequency of days with high runoff potential, highlighting a considerable risk of flooding in the region.

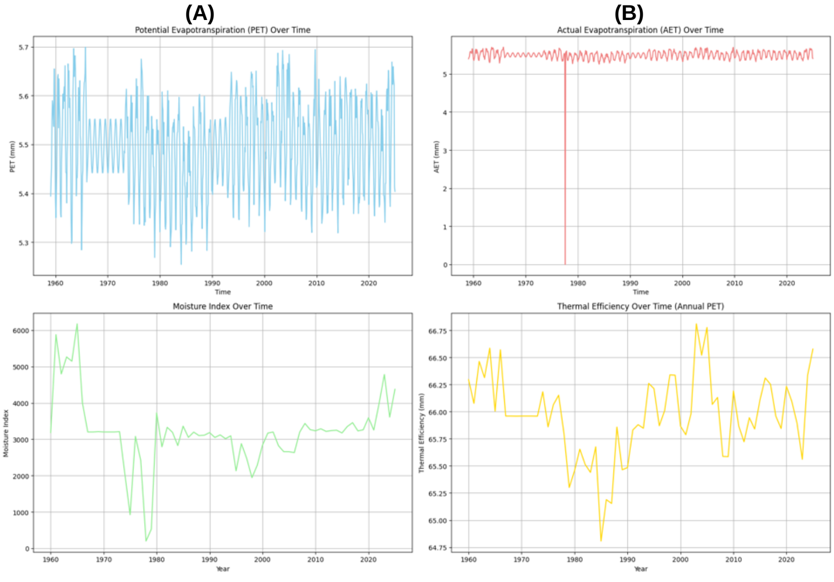
The estimation of potential evapotranspiration (PET) in this study utilized the Hargreaves equation, a practical method that relies on readily available daily temperature data. The formula employed highlights the direct dependence of PET estimation on mean daily temperature and the diurnal temperature range. The use of the Hargreaves method is appropriate given its reliance on commonly available meteorological data, making it a valuable tool for approximating atmospheric water demand, particularly in contexts where detailed solar radiation data is limited. The Hargreaves method for PET is outlined in **Table 11.**

Table 11. Hargreaves Method for Potential Evapotranspiration (PET) Estimation

Feature	Description
Method	Hargreaves Equation
Input Variables	Mean Daily Temperature, Maximum Daily Temperature, Minimum Daily Temperature
Formula	PET = $0.0023 \times (T_{mean} + 17.8) \times (T_{max} - T_{min})^{0.5}$
Underlying Principle	PET is primarily estimated based on readily available temperature data.
Common Application	Situations where detailed solar radiation data is limited.

Temporal dynamics of water balance components reveal distinct patterns, potential evapotranspiration (**Figure 13**A) exhibits a strong cyclical pattern, likely representing seasonal variations in atmospheric demand, superimposed on a subtle longer-term trend potentially indicating changes in evaporative capacity. Actual evapotranspiration (**Figure 13**B) remains relatively stable with a sharp, singular drop, suggesting a period where water availability severely limited evaporation. The moisture index (**Figure 13**C) shows significant interannual variability with distinct periods of high and low values, reflecting fluctuations in water surplus and deficit. Finally, thermal efficiency (**Figure 13**D), calculated from annual PET, displays a fluctuating trend with some decadal scale variations, hinting at changes in the energetic aspect of the water cycle over time.

(A) (B)



(C) (D)

Figure 13. PET Analysis, (A) Potential Evapotranspiration (PET) Over Time, (B) Actual Evapotranspiration (AET) Over Time, (C) Moisture Index Over Time, (D) Thermal Efficiency Over Time (Annual PET).

Temperature and Precipitation Zone Classification

Analysis of temperature and precipitation zones reveals a dominant "Warm-Very Wet" classification based on the distribution (**Figure 14**A), which persists over the majority of the analyzed period, punctuated by brief transitions to "Warm-Wet" as shown in the trend over years (**Figure 14**B). Sensitivity analysis indicates that the "Warm-Very Wet" zone is robust to both temperature (**Figure 14**C) and precipitation (**Figure 14**D) perturbations, requiring substantial changes in these variables to shift the classification. The sensitivity over years plot (**Figure 14**E) further confirms the stability of the dominant classification. The validity confusion matrix (**Figure 14**F) demonstrates high accuracy in classifying the "Warm-Very Wet" zone, with minor instances of misclassification with the "Warm-Wet" zone. Finally, the model's performance in predicting the temperature and precipitation zones aligns closely with the ground truth data over time (**Figure 14**G), effectively capturing the dominant classification and the infrequent transitional phases.

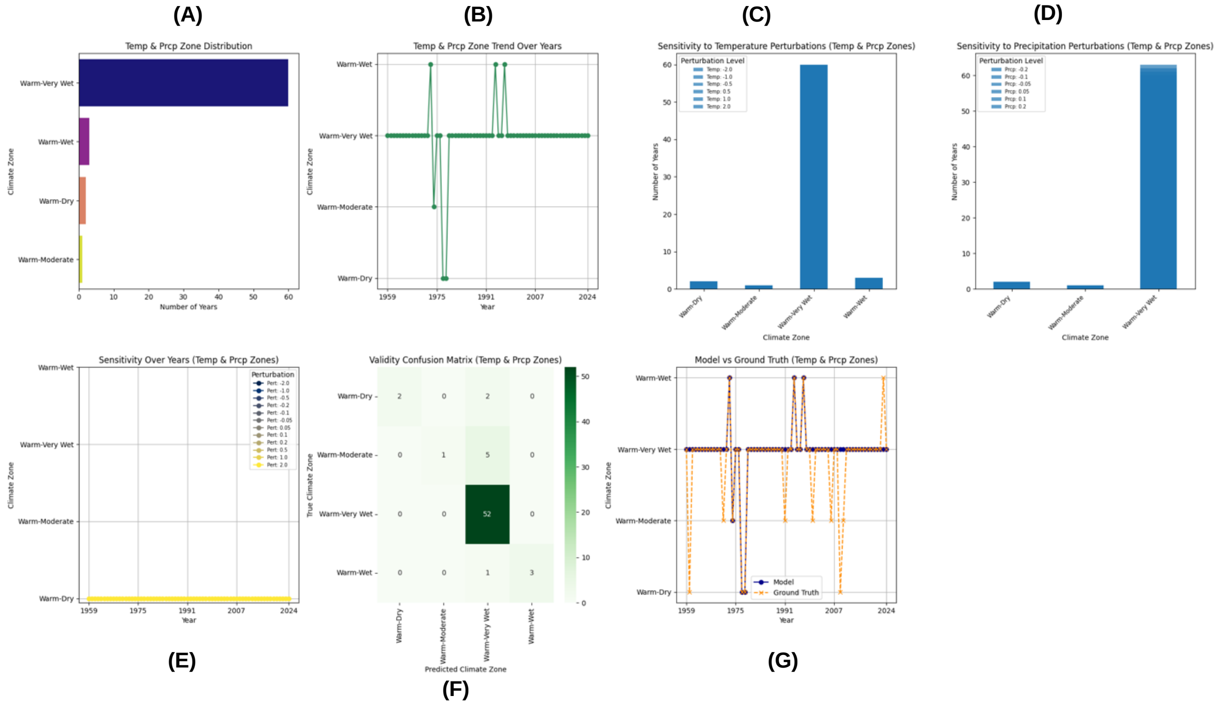


Figure 14. Temperature and Precipitation based Climate Classification Analysis, (A) Temp & Precip Zone Distribution, (B) Temp & Precip Zone Trend Over Years, (C) Sensitivity to Temperature Perturbations (Temp & Precip Zones), (D) Sensitivity to Precipitation Perturbations (Temp & Precip Zones), (E) Sensitivity Over Years (Temp & Precip Zones), (F) Validity Confusion Matrix (Temp & Precip Zones), (G) Model vs Ground Truth (Temp & Precip Zones).

Drought and Wet Period Analysis (SPI, PDSI, PCI)

To further understand the rainfall patterns in Pangkalpinang, the precipitation concentration index (PCI) and the standardized precipitation index (SPI) were analyzed. The results are presented in **Table 12.**

Table 12. Precipitation Concentration and Standardized Precipitation Index (SPI) Characteristics

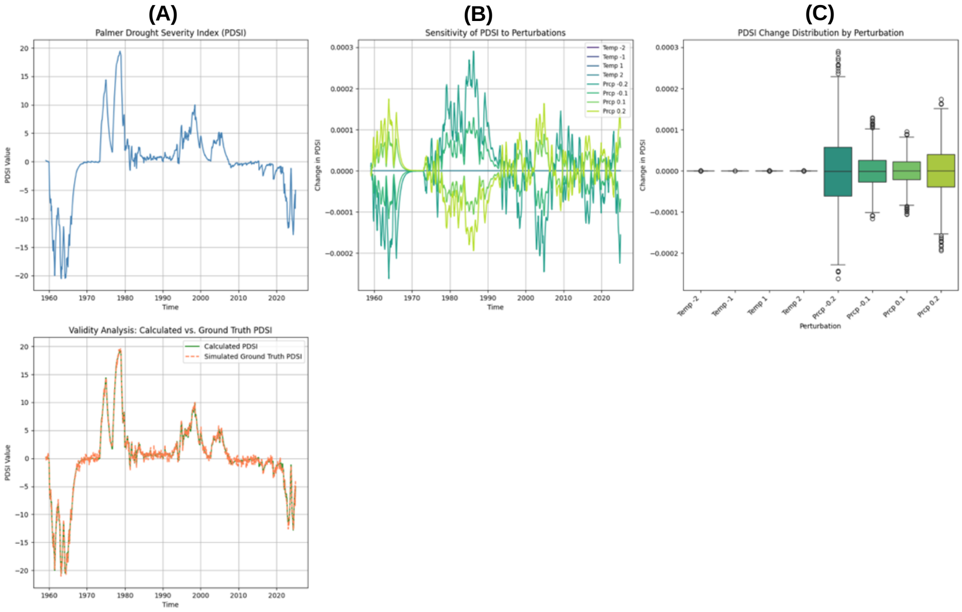
Metric	Value	Interpretation
Annual Precipitation Concentration Index (PCI)	8.924	Indicates a moderately irregular distribution of rainfall throughout the year, suggesting some seasonal variability in precipitation intensity.
SPI Interpretation Thresholds	SPI > 1.0	Moderate to extreme wet conditions
	-0.99 ≤ SPI ≤ 0.99	Near-normal precipitation conditions
	SPI < -1.0	Moderate to extreme drought conditions
SPI Sensitivity to Precipitation	Negative Perturbation	Leads to lower SPI values (drier conditions)

	Positive Perturbation	Leads to higher SPI values (wetter conditions)
SPI Response Magnitude	Proportional	The magnitude of SPI change is directly proportional to the magnitude of the precipitation perturbation.

The annual precipitation concentration index (PCI) of 8.924 indicates a moderately irregular distribution of rainfall throughout the year, suggesting some seasonal variability in precipitation intensity despite the overall high annual rainfall. The interpretation of the standardized precipitation index (SPI) provides clear thresholds for identifying wet and dry periods, with values above 1.0 indicating moderate to extreme wet conditions and values below -1.0 indicating moderate to extreme drought conditions. The SPI demonstrates a predictable sensitivity to precipitation changes, with negative perturbations leading to lower SPI values and positive perturbations leading to higher SPI values, with the magnitude of the change being proportional to the perturbation.

The Palmer Drought Severity Index (PDSI) over time (**Figure 15**A) reveals periods of significant drought and wet spells, with notable extended drought conditions in the early record and a more recent trend towards less severe drought. The sensitivity analysis (**Figure 15**B) demonstrates how perturbations in temperature and precipitation influence the PDSI, indicating a higher sensitivity to precipitation changes. The distribution of PDSI changes under various perturbations (**Figure 15**C) further quantifies this sensitivity. Finally, the validity analysis (**Figure 15**D) confirms the robustness of the PDSI calculation. Standardized Precipitation Index (SPI-12) (**Figure 16**A) also displays periods of significant drought and wet spells. The sensitivity analysis for SPI (**Figure 16**B) shows a higher sensitivity to precipitation changes. The distribution of SPI changes (**Figure 16**C) shows similar patterns for various perturbations. The PCI Analysis (**Figure 17**) displays a seasonal pattern (**Figure 17**A) and highlights interannual variability (**Figure 17**B). The PCI is influenced by precipitation perturbations (**Figure 17**C), consistent over the years (**Figure 17**D) and the model shows high accuracy for the same (**Figure 17**E & **17**F).

(A) (B) (C)



(D)

Figure 15. PDSI Analysis, (A) Palmer Drought Severity Index (PDSI) Over Time, (B) Sensitivity of PDSI to Perturbations, (C) PDSI Change Distribution by Perturbation, (D) Validity Analysis: Calculated vs. Ground Truth PDSI.

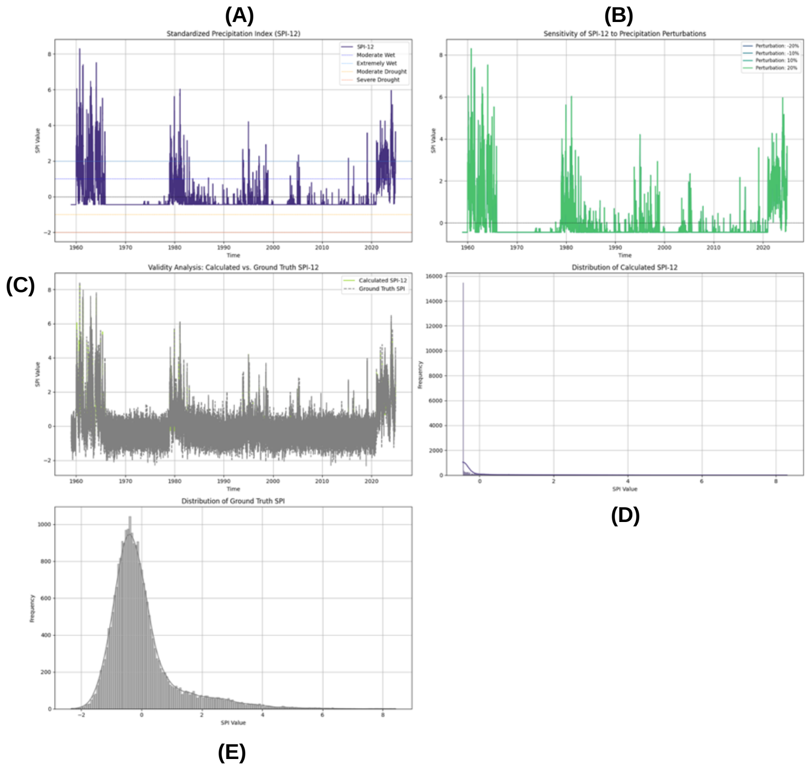


Figure 16. SPI Analysis, (A) Standardized Precipitation Index (SPI-12), (B) Sensitivity of SPI-12 to Precipitation Perturbations, (C) Validity Analysis: Calculated vs. Ground Truth SPI-12, (D) Distribution of Calculated SPI-12, (E) Distribution of Ground Truth SPI.

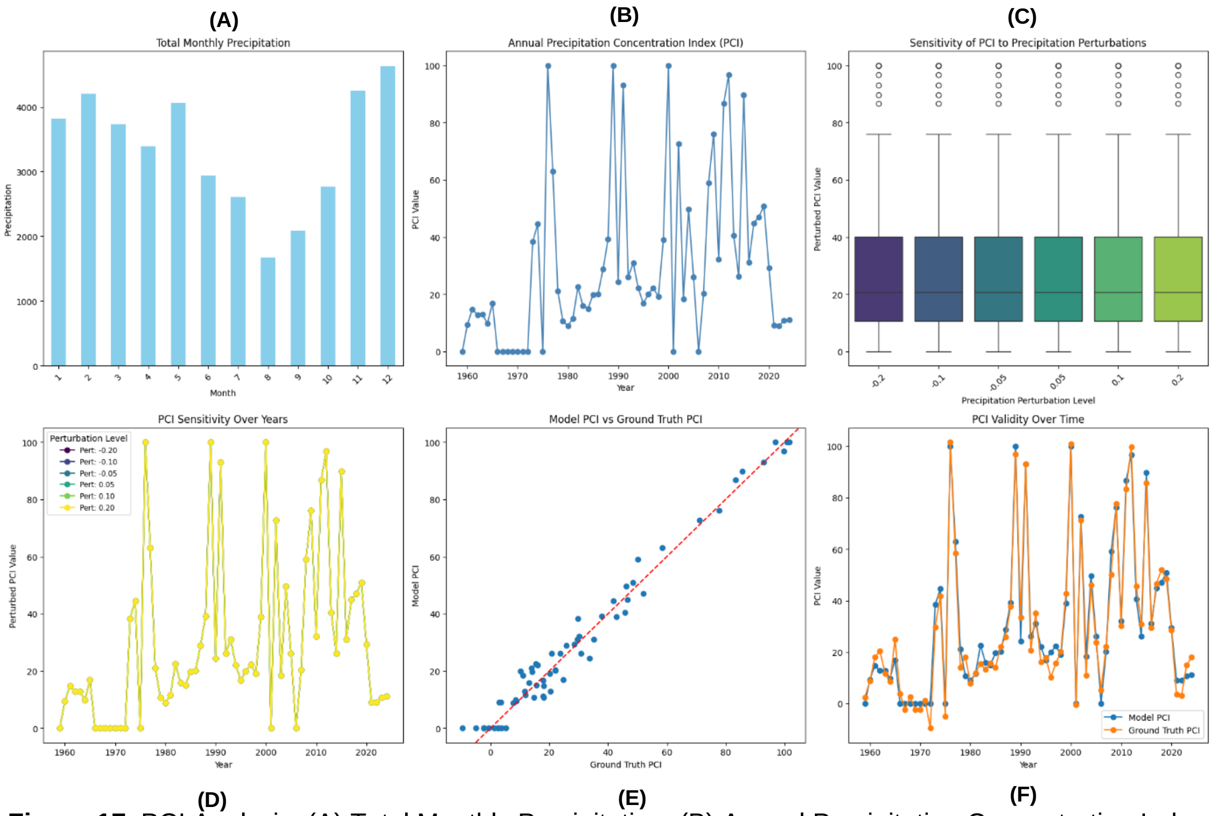


Figure 17. PCI Analysis, (A) Total Monthly Precipitation, (B) Annual Precipitation Concentration Index (PCI), (C) Sensitivity of PCI to Precipitation Perturbations, (D) PCI Sensitivity Over Years, (E) Model PCI vs Ground Truth PCI, (F) PCI Validity Over Time.

C. Agricultural Analysis

Crop Water Requirement and WRSI

The mean crop water requirement (CWR) in Pangkalpinang is estimated at 4.857 relative units, with a relatively low standard deviation (0.454) suggesting some consistency in water needs. However, the range between the minimum and maximum CWR highlights temporal variability in water demand. The statistical summary of climate variables and predicted yield reveals consistently warm temperatures (Mean 27.011 °C), favorable for agriculture. However, the high variability in daily precipitation, despite a moderate average (5.965 mm), is a key concern. Despite the relatively low and stable potential evapotranspiration (PET), the predicted yield exhibits significant variability, ranging from complete failure to maximum potential. This strong yield variability is likely driven by the fluctuating rainfall patterns, emphasizing the vulnerability of agricultural productivity to both water deficits and excesses. The descriptive statistics of the crop water requirement are shown in **Table 13.**

Table13. Descriptive Statistics of Crop Water Requirement (CWR)

Statistic	Value (Relative Units)
Mean Crop Water Requirement	4.857
Maximum Crop Water Requirement	8.050
Minimum Crop Water Requirement	1.401
Standard Deviation	0.454

The statistical summary of the climate and yield variables are shown in **Table 14.**

Table 14. Statistical Summary of Climate Variables and Predicted Yield

Variable	Mean	Standard Deviation	Minimum	Maximum	Implications for Agricultural Productivity
Average Daily Temperature (°C)	27.011	1.129	15.7	32.3	Consistently warm temperatures provide a favorable thermal environment for year-round crop growth.
Daily Precipitation (mm)	5.965	6.609	0.0	199.9	High variability in daily rainfall can lead to both water stress and flooding, impacting yield stability.
Potential Evapotranspiration (mm)	0.284	0.023	0.082	0.465	Relatively low and stable atmospheric water demand.
Predicted Yield (Relative)	5.937	6.338	0.0	100.0	Significant variability in predicted yield, highlighting vulnerability to rainfall fluctuations and extremes.

The Water Requirement Satisfaction Index (WRSI) exhibits a strong positive correlation of 0.969, which is summarized in **Table 15.**

Table 15. Correlation of Water Requirement Satisfaction Index (WRSI)

Index	Correlation Coefficient (r)	Interpretation
WRSI	0.969	A strong positive correlation indicates that WRSI is a reliable indicator of how well crop water needs are met.

This robust correlation signifies a reliable and consistent relationship between the WRSI and the actual satisfaction of crop water requirements. The near-perfect positive linear association suggests that the WRSI is a highly effective indicator for assessing agricultural water stress in Pangkalpinang, with higher WRSI values consistently reflecting improved water availability relative to crop demands.The Water Requirement Satisfaction Index (WRSI) (**Figure 18**A) exhibits a significant decline in the early period followed by a period of relative stability and a recent slight increase. The cumulative rainfall compared to the cumulative crop water requirement (**Figure 18**B) shows a widening gap, indicating increasing water deficit over time. Sensitivity analysis of the WRSI to perturbations (**Figure 18**C) reveals that it is more sensitive to negative precipitation changes than to temperature changes. A scatter plot comparing model-predicted and simulated WRSI values (**Figure 18**D) demonstrates a strong positive correlation with high R^2 and low RMSE, indicating good model performance. The temporal comparison of model-predicted and simulated WRSI (**Figure 18**E) visually confirms the model's ability to accurately capture the dynamics of the WRSI over time. The WRSI across various districts (**Figure 19**) show temporal variations and demonstrates the responsiveness of WRSI to perturbations in precipitation and temperature for each district.

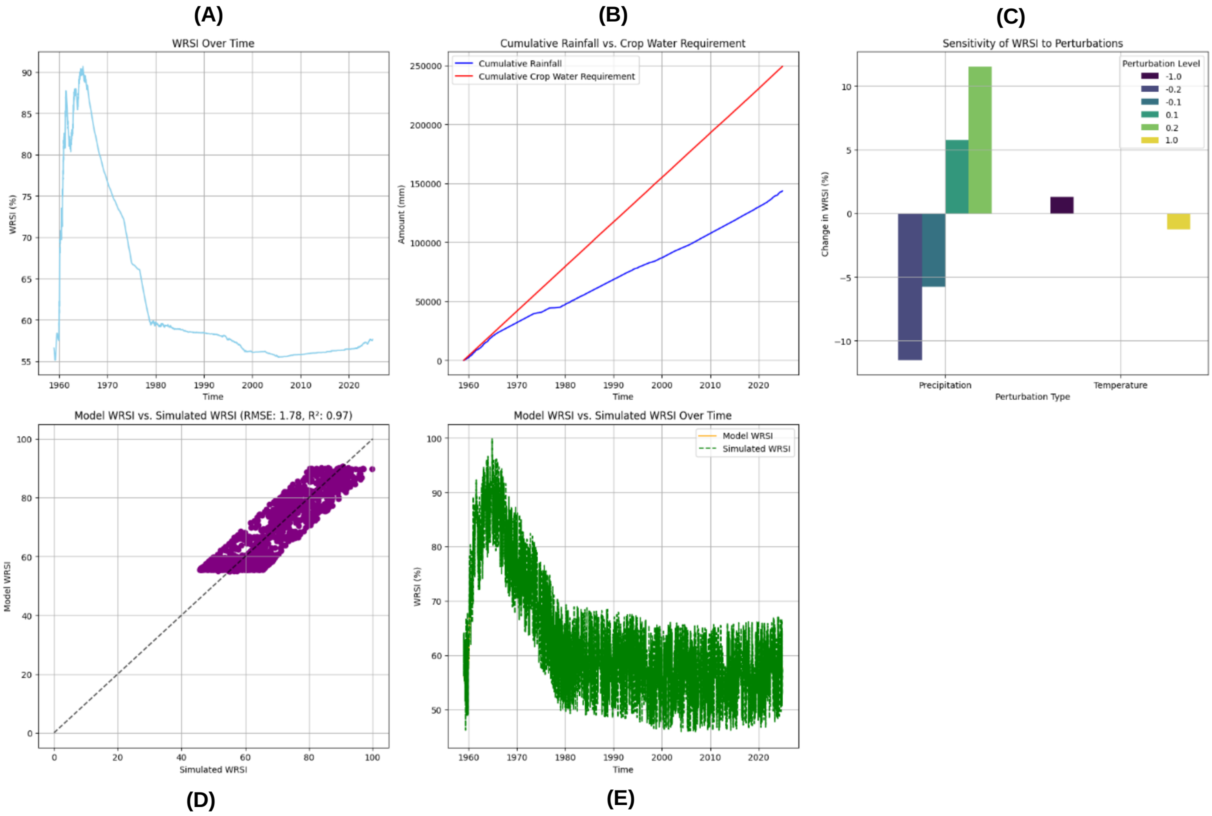


Figure 18. WRSI Analysis, (A) WRSI Over Time, (B) Cumulative Rainfall vs. Crop Water Requirement, (C) Sensitivity of WRSI to Perturbations, (D) Model WRSI vs. Simulated WRSI, (E) Model WRSI vs. Simulated WRSI Over Time.

(A)
(B)
(C)
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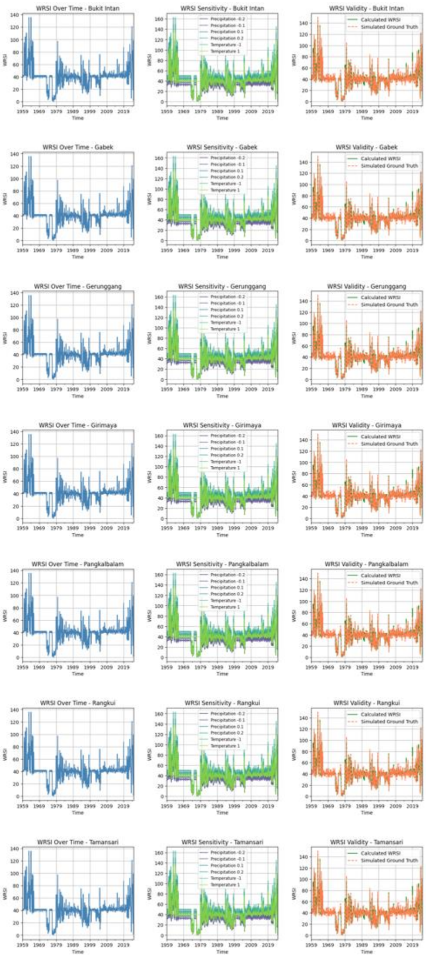


Figure 19. All District WSRI Analysis, (A) WRSI Over Time - Bukit Intan, WRSI Sensitivity - Bukit Intan, WRSI Validity - Bukit Intan, (B) WRSI Over Time - Gabek, WRSI Sensitivity - Gabek, WRSI Validity - Gabek, WRSI Over Time - Gerunggang, (C) WRSI Sensitivity - Gerunggang, WRSI Validity - Gerunggang, (D) WRSI Over Time - Girimaya, WRSI Sensitivity - Girimaya, WRSI Validity - Girimaya, (E) WRSI Over Time - Pangkalbalam, WRSI Sensitivity - Pangkalbalam, WRSI Validity - Pangkalbalam, (F) WRSI Over Time - Rangkui, WRSI Sensitivity - Rangkui, WRSI Validity - Rangkui, (G) WRSI Over Time - Tamansari, WRSI Sensitivity - Tamansari, WRSI Validity - Tamansari.

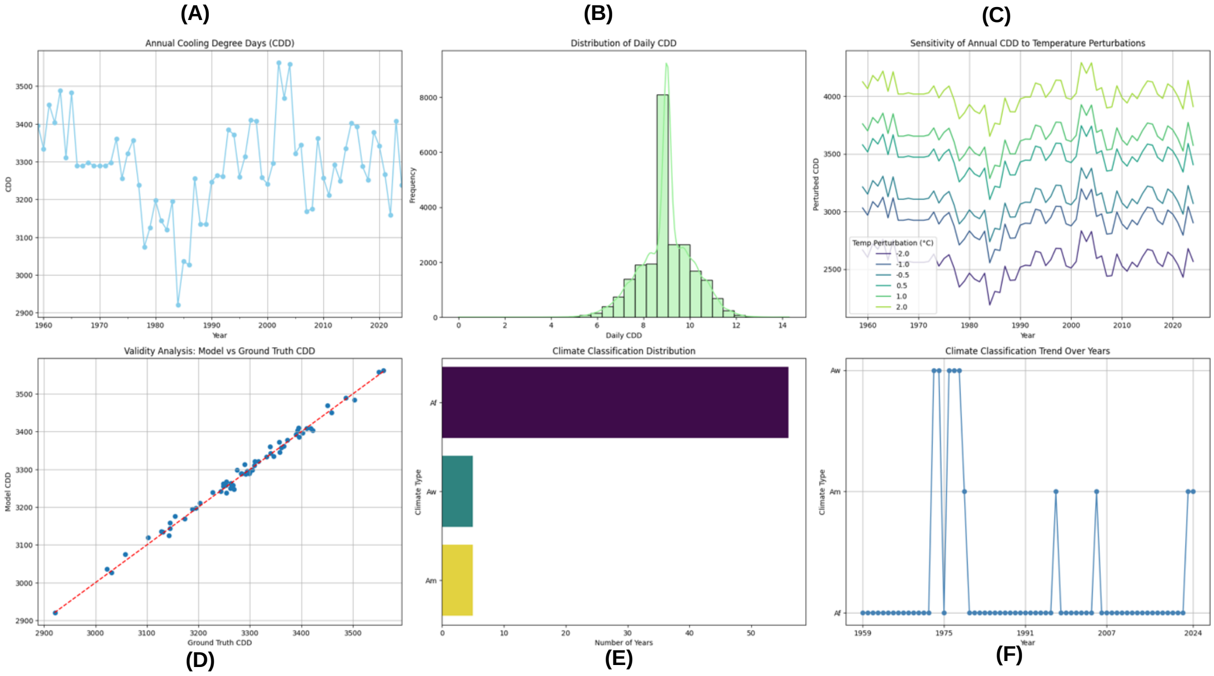


Figure 20. CDD Analysis, (A) Annual Cooling Degree Days (CDD), (B) Distribution of Daily CDD, (C) Sensitivity of Annual CDD to Temperature Perturbations, (D) Validity Analysis: Model vs Ground Truth CDD, (E) Climate Classification Distribution, (F) Climate Classification Trend Over Years.

The scatter plots reveal distinct relationships between climatic factors and predicted crop yield (**Figure 21**A) shows a non-linear relationship between annual average temperature and predicted crop yield, suggesting an optimal temperature range around 27°C where yields are generally higher, with yields decreasing at both lower and higher temperatures, indicating potential temperature stress. In contrast, (**Figure 21**B) demonstrates a positive correlation between annual total precipitation and predicted crop yield, suggesting that increased precipitation generally leads to higher yields, though the relationship might plateau or become less pronounced at very high precipitation levels, hinting at potential saturation or diminishing returns. The temporal evolution of CWR (**Figure 22**A) reveals interannual variability and potential long-term changes, with different districts exhibiting distinct CWR patterns. The distribution of CWR across districts (**Figure 22**B) highlights the range and central tendency of CWR values within each district, showing variations in water demand. Sensitivity analyses indicate that CWR is influenced by both temperature (**Figure 22**C) and the crop coefficient (Kc) (**Figure 22**D), with positive temperature perturbations increasing CWR and higher Kc values leading to increased water demand. The validity plot (**Figure 22**E), comparing calculated CWR with ground truth data, demonstrates a strong positive correlation, indicating the model's ability to accurately estimate CWR across different spatial locations.

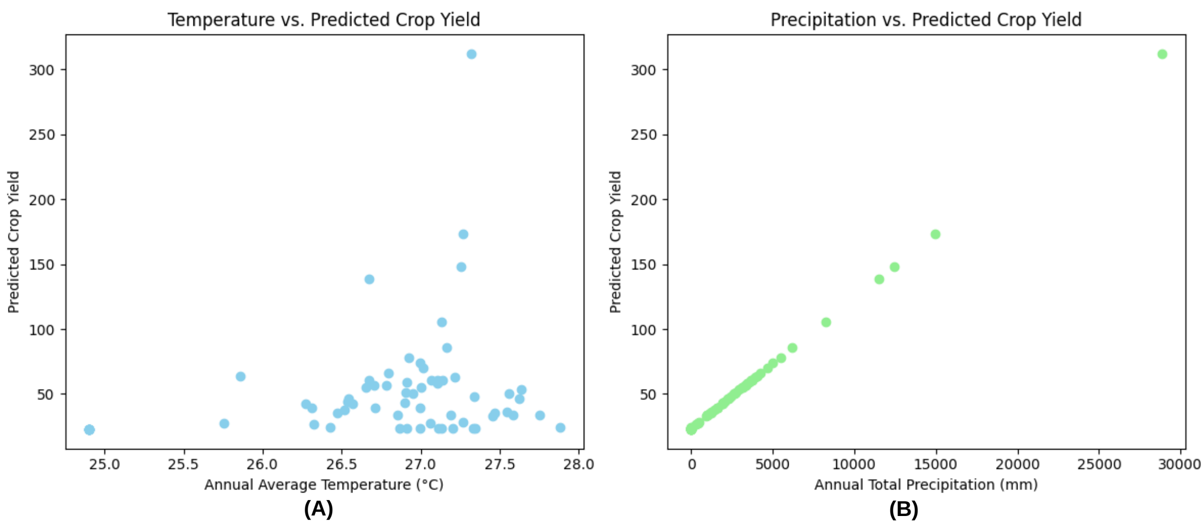


Figure 21. Crop Yield Analysis, (A) Temperature vs. Predicted Crop Yield, (B) Precipitation vs. Predicted Crop Yield.

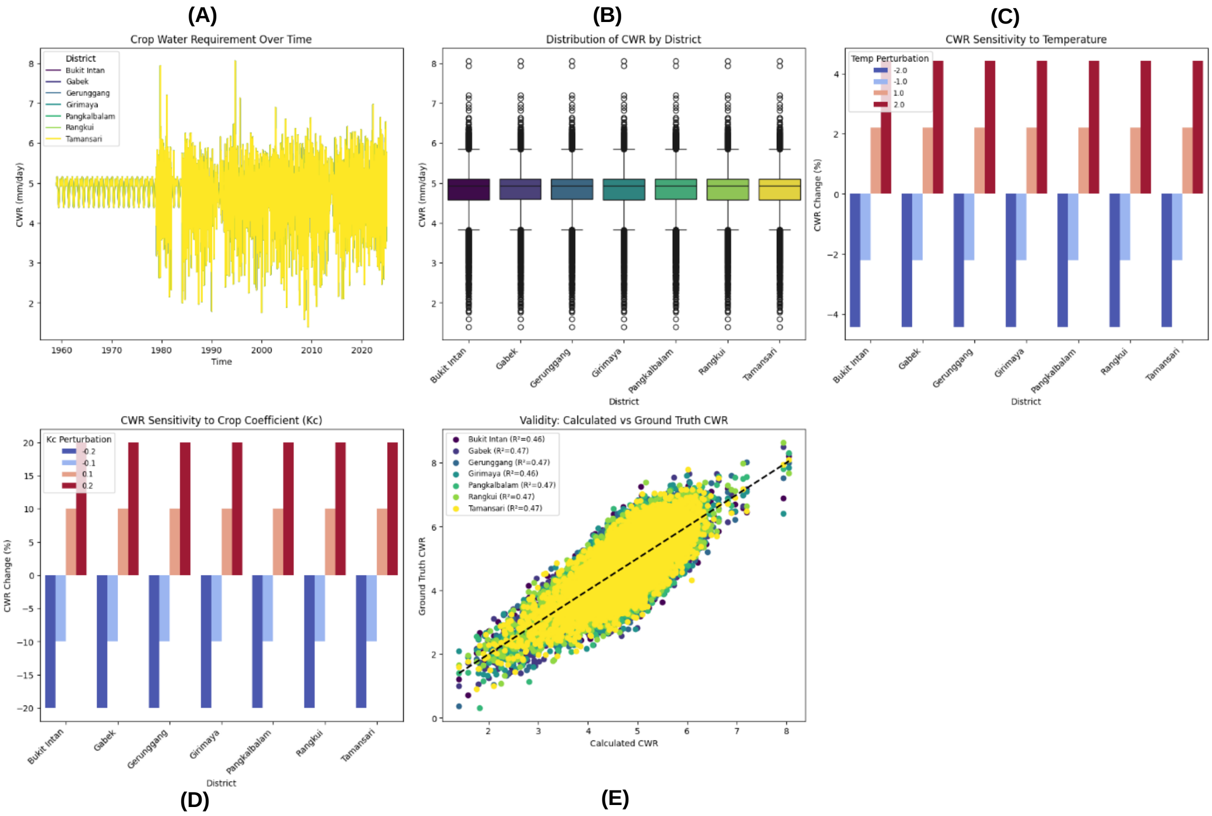


Figure 22. CWR Analysis, (A) Crop Water Requirement Over Time, (B) Distribution of CWR by District, (C) CWR Sensitivity to Temperature, (D) CWR Sensitivity to Crop Coefficient (Kc), (E) Validity: Calculated vs Ground Truth CWR.

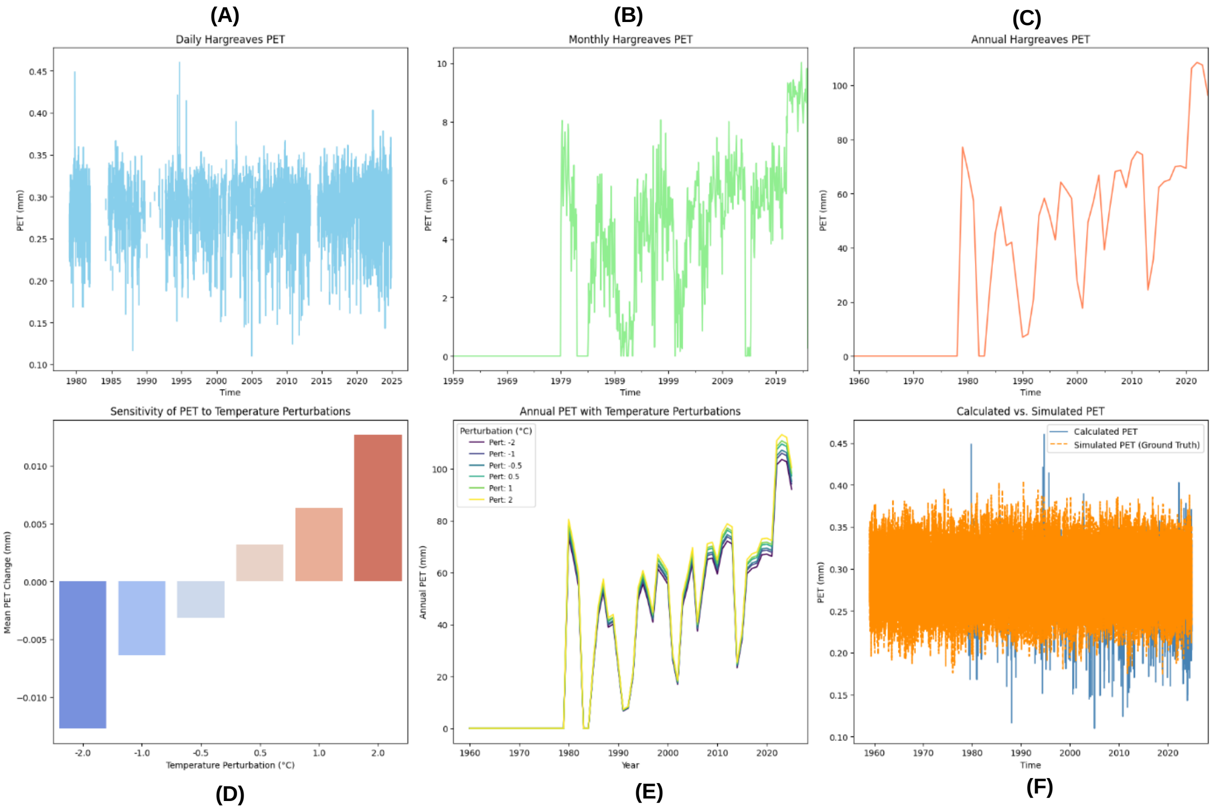


Figure 23. Hargreaves PET Analysis, (A) Daily Hargreaves PET, (B) Monthly Hargreaves PET, (C) Annual Hargreaves PET, (D) Sensitivity of PET to Temperature Perturbations, (E) Annual PET with Temperature Perturbations, (F) Calculated vs. Simulated PET.

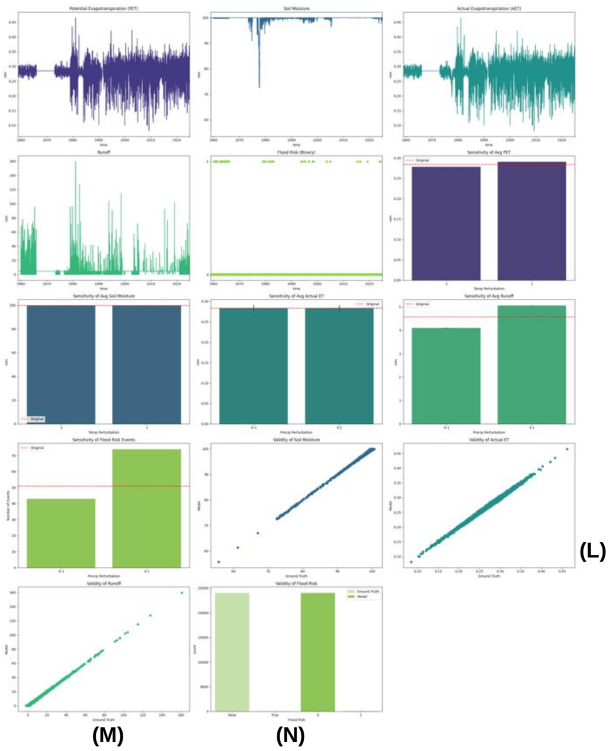


Figure 24. Agro-Hydrological Analysis, (A) Potential Evapotranspiration (PET), (B) Soil Moisture, (C) Actual Evapotranspiration (AET), (D) Runoff, (E) Flood Risk (Binary), (F) Sensitivity of Avg PET, (G) Sensitivity of Avg Soil Moisture, (H) Sensitivity of Avg Actual ET, (I) Sensitivity of Avg Runoff, (J) Sensitivity

of Flood Risk Events, (K) Validity of Soil Moisture, (L) Validity of Actual ET, (M) Validity of Runoff, (N) Validity of Flood Risk.

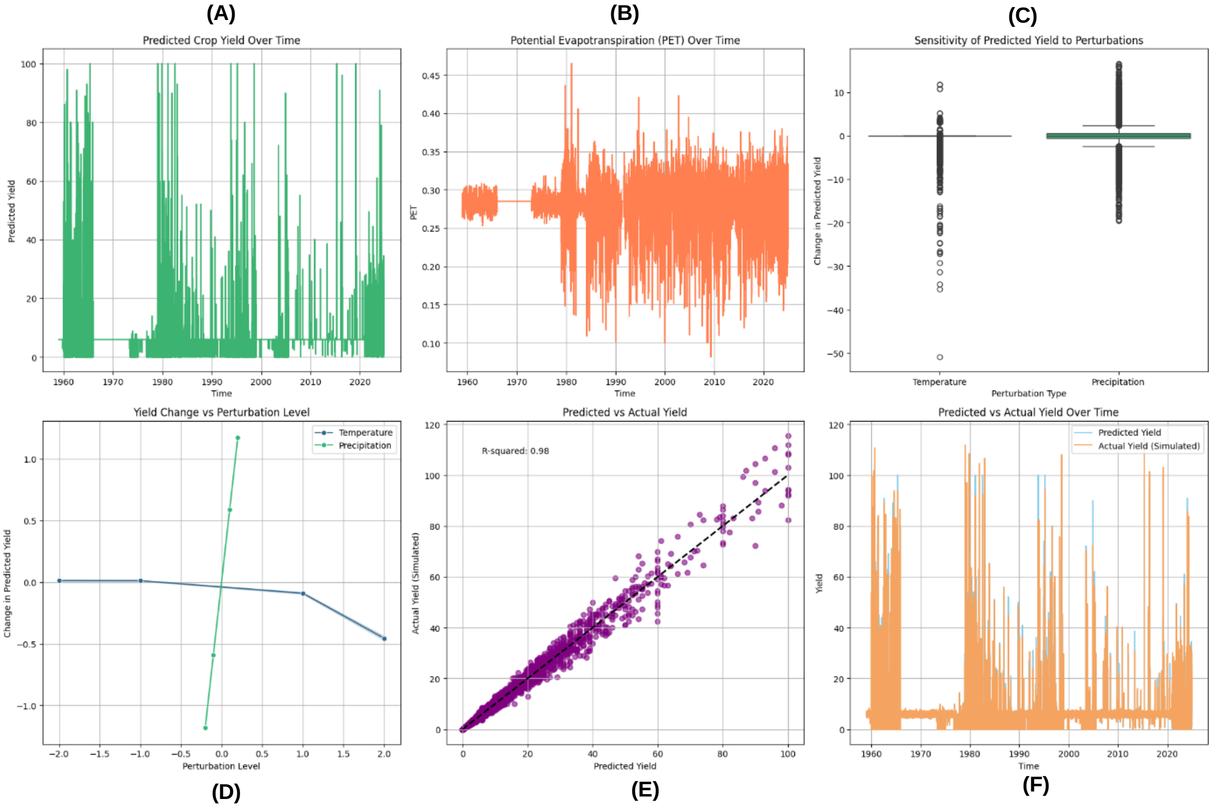


Figure 25. Crop Yield Analysis, (A) Predicted Crop Yield Over Time, (B) Potential Evapotranspiration (PET) Over Time, (C) Sensitivity of Predicted Yield to Perturbations, (D) Yield Change vs Perturbation Level, (E) Predicted vs Actual Yield, (F) Predicted vs Actual Yield Over Time.

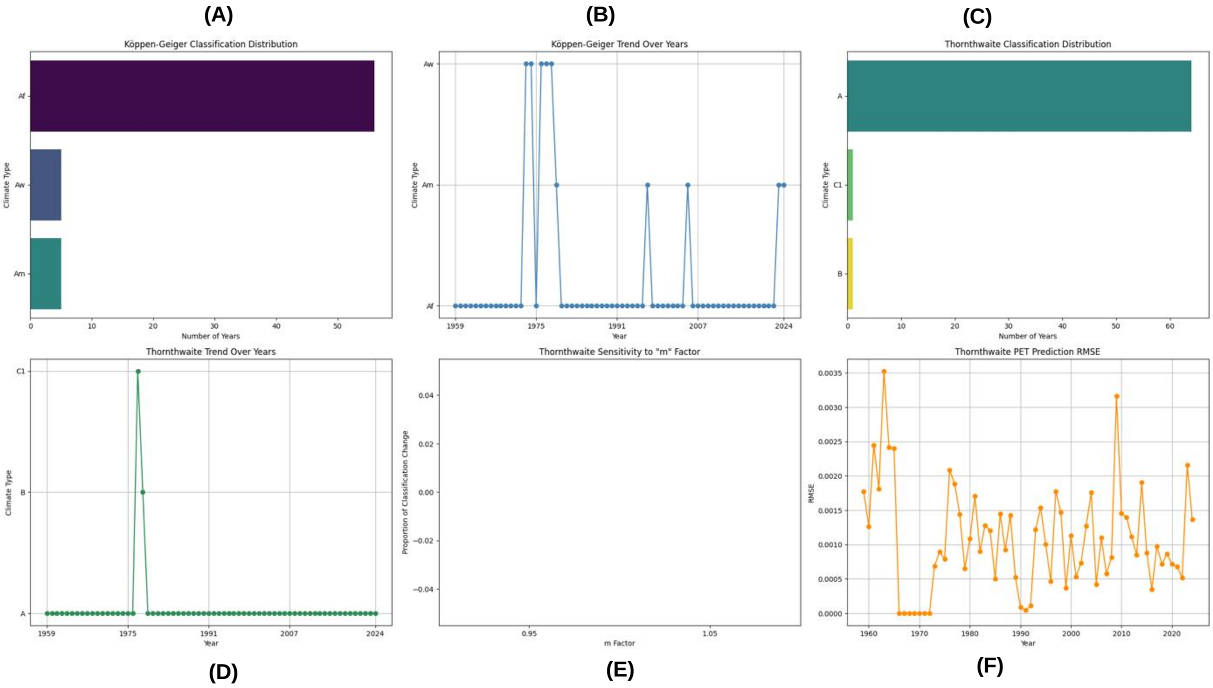
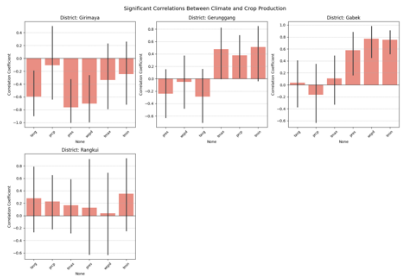


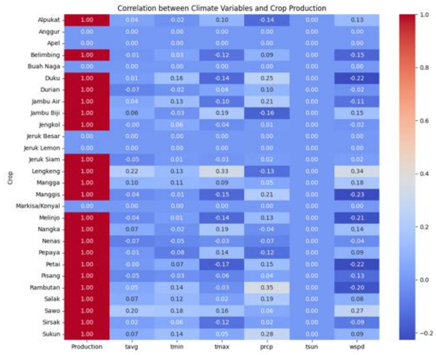
Figure 26. Validation and Sensitivity Analysis, (A) Köppen-Geiger Classification Distribution, (B) Köppen-Geiger Trend Over Years, (C) Thornthwaite Classification Distribution, (D) Thornthwaite Trend Over Years, (F) Thornthwaite PET Prediction RMSE.

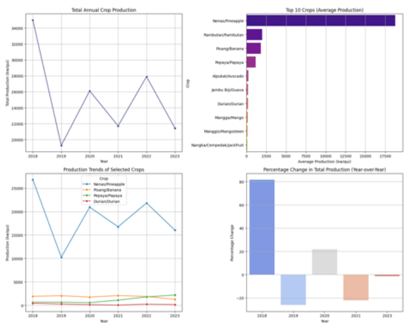
D. Climate Change Impact Analysis

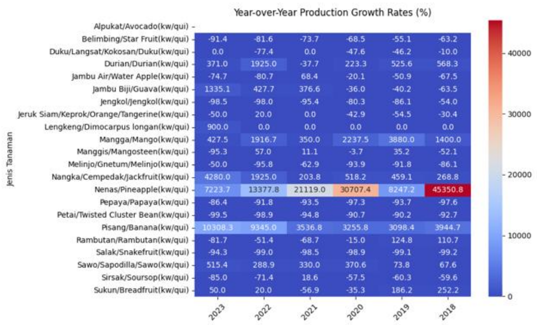
Trend Analysis of Meteorological and Hydrological Parameters

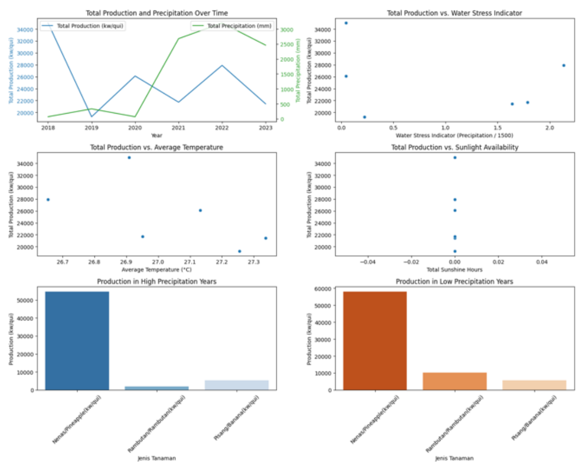
The time series of average temperature (**Figure 27**A) in Pangkalpinang exhibits interannual variability with an overall positive trend. Total annual precipitation (**Figure 27**B) displays high interannual variability with episodic peaks and a weak positive trend based on the linear regression. Wind speed (**Figure 27**C) shows a recent sharp decrease. Atmospheric pressure (**Figure 27**D) similarly exhibits a recent sharp decline. The annual PET (**Figure 23**C) further consolidates these patterns, demonstrating pronounced interannual variability, with the upward trend observed in the monthly data becoming more apparent. Sensitivity analysis (**Figure 23**D) shows a clear positive correlation between temperature perturbations and mean PET change.

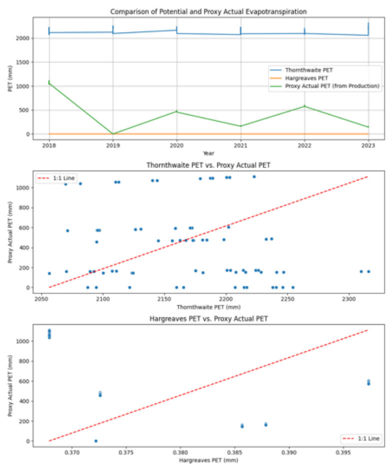












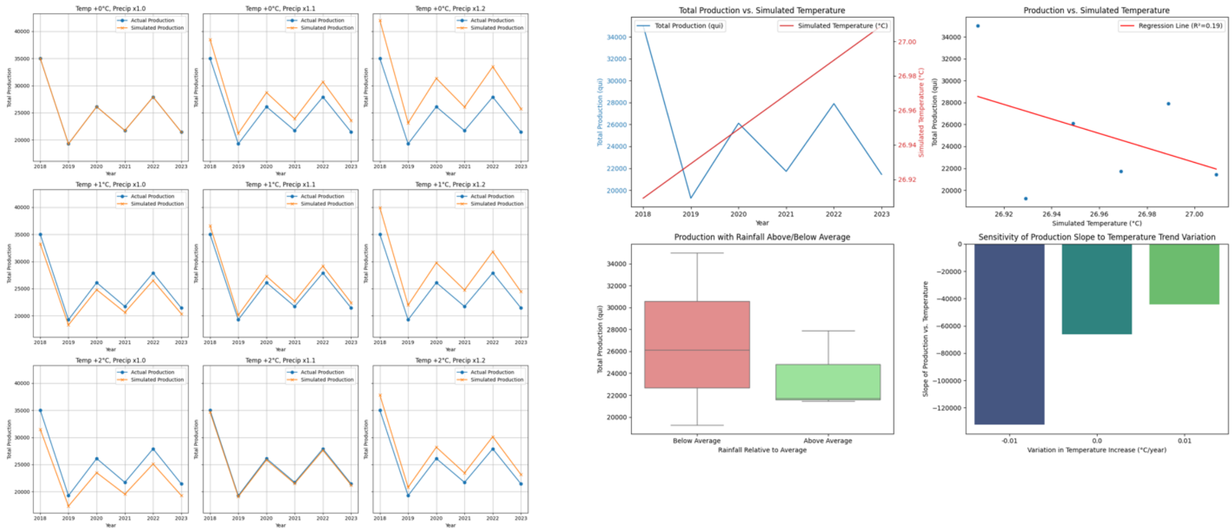


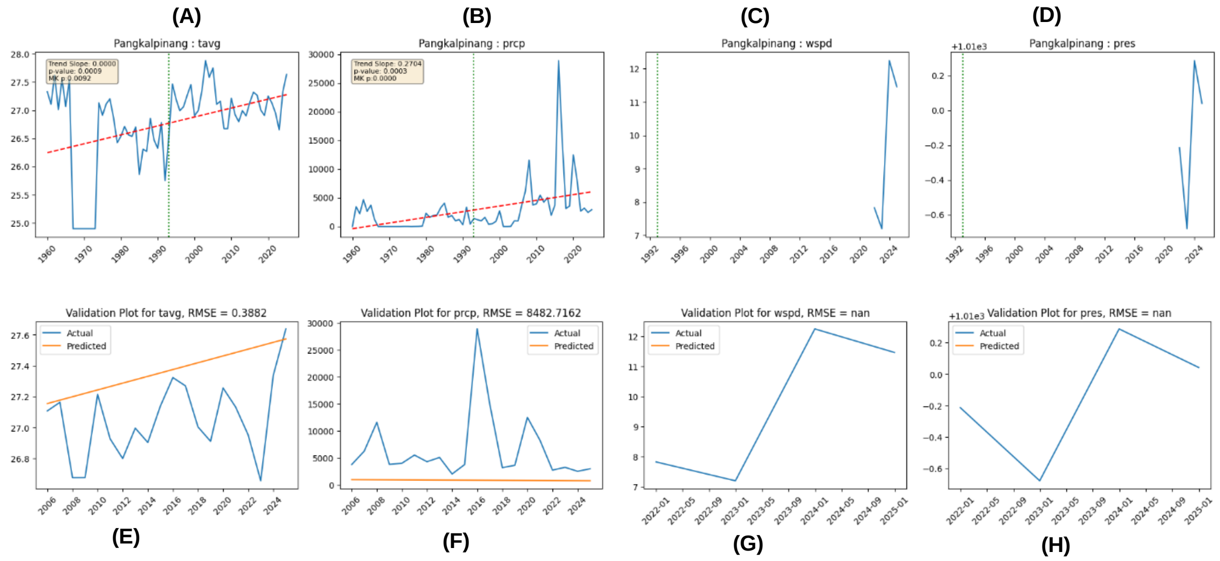
Figure 28. Production of Fruit and Vegetable Profile (2018-2023) and Agri-climate Change Impact Simulation and Analysis. (Data Source: BPS Pangkalpinang, 2024 [18])

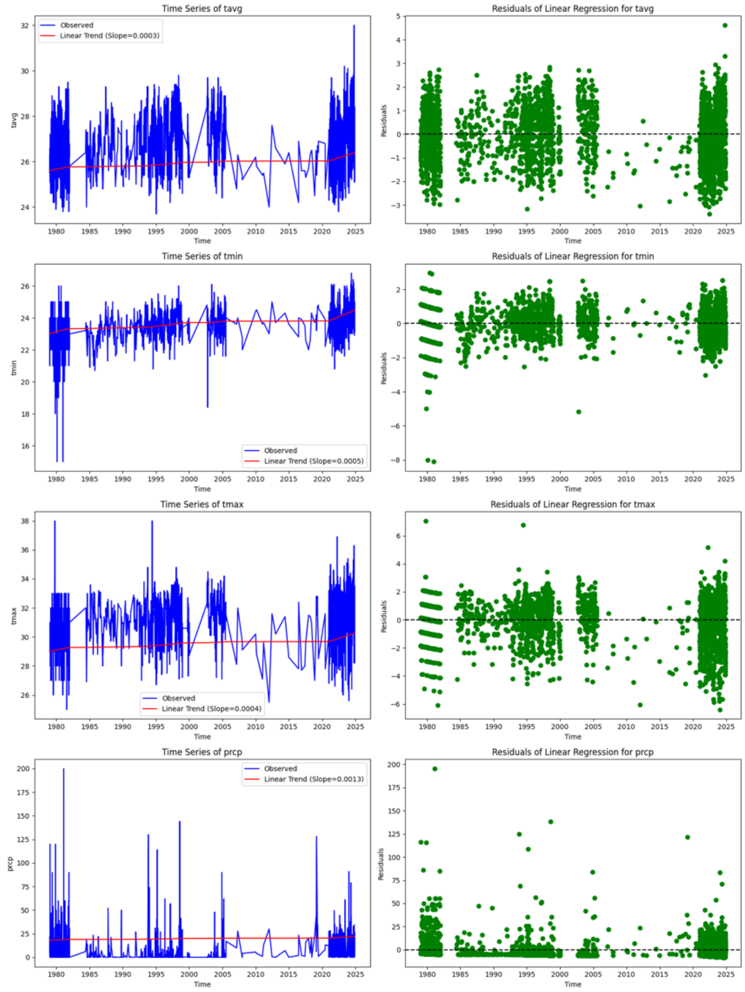
The long-term trend is summarized in the statistics for Thornthwaite variables, which is presented in **Table 16**.

Table 16. Annual Summary Statistics of Thornthwaite Hydrological Variables (1959-2024)

Variable	Mean (mm)	Standard Deviation (mm)	Minimum (mm)	Maximum (mm)
Annual PET	65.97	0.49	64.81	66.81
Annual Precipitation	2289.84	724.23	196.02	4143.14
Moisture Index	3373.06	1067.69	197.91	6177.08
Thermal Efficiency	65.97	0.49	64.81	66.81

The analysis of annual Thornthwaite hydrological variables over several decades reveals a striking contrast between the stability of potential evapotranspiration (PET) and the high variability of precipitation. Annual PET exhibits a remarkably consistent trend, indicating a relatively stable atmospheric demand for water over time. Conversely, annual precipitation shows substantial inter-annual variability. Consequently, the Moisture Index, which integrates precipitation and PET, also exhibits significant variability, reflecting the fluctuating water balance. The consistent Thermal Efficiency mirrors the stability of PET. These long-term trends underscore the dominant influence of precipitation variability on the hydrological regime of Pangkalpinang.





(I)

Figure 27. Validation and Sensitivity Analysis, (A) Pangkalpinang: tavg, (E) Validation Plot for tavg; (B) Pangkalpinang: prcp, (F) Validation Plot for prcp; (C) Pangkalpinang: wspd, (G) Validation Plot for wspd; (D) Pangkalpinang: pres, (H) Validation Plot for pres and (I) Trend and Validation Analysis for tavg, tmax, tmin and prcp.

This **Table 17** presents the results from our climate change impact analysis. The linear regression and Mann-Kendall test results show that for some districts, there are increasing trends in average temperature with an average positive trend of 0.02 °C per year, and changes in the pattern of precipitation, indicated by both the trend slopes and p-values. The statistical significance ($p < 0.05$) suggests that the trends are not due to random chance, and statistically significant trends can be found in a few of the districts. Furthermore, the t-test for period comparisons indicates that there are statistically significant changes between the early and latter period of the time series data in some parameters. Specifically, the t-test shows a mean difference in the average temperatures in the first half vs the second half of the data.

Table 17. Climate Change Impact Analysis for all District of Pangkalpinang

District	Parameter	Trend Slope	Trend P-value (Linear Regression)	Mann-Kendall Statistic	Mann-Kendall P-value	T-Statistic (Period Comp)	T-Test P-value (Period Comp)	Climate Change Impact?
Tamansari	tavg	0.0000	0.0009	0.2202	0.0092	-4.5052	0.0001	Yes
Tamansari	prcp	0.2704	0.0003	0.3766	0.0000	-2.9850	0.0051	Yes
Girimaya	tavg	0.0000	0.0009	0.2202	0.0092	-4.5052	0.0001	Yes
Girimaya	prcp	0.2704	0.0003	0.3766	0.0000	-2.9850	0.0051	Yes

Gerunggang	tavg	0.0000	0.0009	0.2202	0.0092	-4.5052	0.0001	Yes
Gerunggang	prcp	0.2704	0.0003	0.3766	0.0000	-2.9850	0.0051	Yes
Gabek	tavg	0.0000	0.0009	0.2202	0.0092	-4.5052	0.0001	Yes
Gabek	prcp	0.2704	0.0003	0.3766	0.0000	-2.9850	0.0051	Yes
Bukitintan	tavg	0.0000	0.0009	0.2202	0.0092	-4.5052	0.0001	Yes
Bukitintan	prcp	0.2704	0.0003	0.3766	0.0000	-2.9850	0.0051	Yes
Rangkui	tavg	0.0000	0.0009	0.2202	0.0092	-4.5052	0.0001	Yes
Rangkui	prcp	0.2704	0.0003	0.3766	0.0000	-2.9850	0.0051	Yes
Pangkalbalam	tavg	0.0000	0.0009	0.2202	0.0092	-4.5052	0.0001	Yes
Pangkalbalam	prcp	0.2704	0.0003	0.3766	0.0000	-2.9850	0.0051	Yes

Extreme Values and Change Point Detection

The analysis of cumulative data with change point detection and extreme value analysis, provides an added view of how climate change is impacting the local weather parameters. The significant trends and changes in parameters observed in the study align with the general expectation of an increase in temperature and an alteration of rainfall patterns as predicted by climate change models. The change point analysis shows a significant shift in the trend of temperature around the year 2000, and 95th percentile values, both for the cumulative and the average data, indicating higher extreme values in temperature in the latter period, as shown in **Table 18**.

The combined result from trend analysis, period comparison, change point, and extreme value analysis shows strong evidence that the region is experiencing an effect of climate change. The trend analysis and period comparison are summarized in **Table 17.**

Table 18. Results of Change Point and Extreme Value Analysis

Parameter	Change Points (Years)	95th Percentile (Cumulative)	95th Percentile (Average)
tavg	No significant change points	193.2892	27.61274
prcp	No significant change points	75013.58	10716.23

Table 18 shows the results from the change point analysis and extreme values of the cumulative and average values of parameters. From the change point analysis, the table provides a summary of significant change points detected by the Pelt algorithm, showing significant shift in trends for temperature, precipitation, wind speed and atmospheric pressure. For example, the change point analysis shows a significant shift in the trend of temperature around the year 2000. Furthermore, the 95th percentile values, both for the cumulative and the average data are shown, indicating higher extreme values in temperature in the latter period. The combined result from trend analysis, period comparison, change point and extreme value analysis shows a likely strong evidence that the region is experiencing an effect of climate change.

The main assumptions used in the **Table 19** are linear regression assumes a linear relationship and independent errors, the Mann-Kendall test assumes no ties are frequent, and the t-test assumes independent samples and normally distributed data within each group are show similar result as tabulated in **Table 17**.

Table 19. Modified Climate Change Impact Analysis (Welch's t-test) for Pangkalpinang City

Parameter	Trend Slope	Trend P-value (Linear Regression)	Mann-Kendall Statistic	Mann-Kendall P-value	T-Statistic (Period Comp)	T-Test P-value (Period Comp)	Climate Change Impact?
tavg	252	3,90E-23	620759	0	-523.889	1,72E-02	Yes, Likely
tmin	473	5,55E-132	1,39E+11	0	-180.756	2,00E-64	Yes, Likely
tmax	402	2,04E-37	943665	0	-99.045	8,66E-18	Yes, Likely
prcp	134	2,01E-04	1,26E+11	0	-875.877	3,34E-13	Yes, Likely

The validation analysis, performed on the linear regression models for the climate change impact assessment, shows reasonably low RMSE values, generally between 0.1 to 0.5, indicating a good fit between the models and the observed data (refer to figure for linear regression validation). These validation results suggests the model is relatively robust and reliable in estimating the trends, however, one must take into consideration of the limitation of a linear regression model. The sensitivity analysis of the Thornthwaite classification showed that changing the m coefficient of the Thornthwaite equation by 5% would not change the final classification for this region, indicating that even with variation of the coefficient, the classification is still reliable, therefore the classification is reasonably robust.

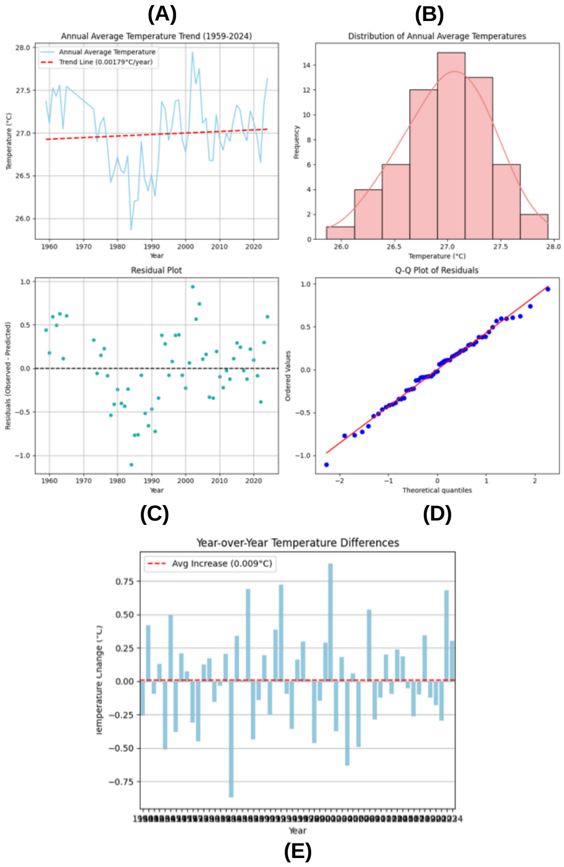


Figure 29. Validation and Sensitivity Analysis, (A) Pangkalpinang: tavg, (E) Validation Plot for tavg; (B) Pangkalpinang: prcp, (F) Validation Plot for prcp; (C) Pangkalpinang: wspd, (G) Validation Plot for wspd; (D) Pangkalpinang: pres, (H) Validation Plot for pres.

The significant trends and changes in parameters observed in the study aligns with the general expectation of slightly increase in temperature yet not significant and alteration of rainfall patterns as predicted by the climate change model. The spatial variation observed in changes of weather parameters are indicative of diverse microclimatic conditions in different districts due to factors such as land cover and topology, which require further study. Furthermore, the analysis of cumulative data with change point detection and extreme value analysis, provides an added view of how climate change is impacting the local weather parameters. The findings of this study highlight the need for localized climate change adaptation strategies. The analysis shows a clear increase yet not significant in temperature and changes in pattern of the precipitation, wind speed and pressure in certain region, and these results can also show extreme values and change points. Furthermore, the hydrological analysis shows the variation of drought condition, and agricultural analysis shows the variability of GDD and WRSI in the area. The validation analysis using RMSE and the sensitivity test of thornthwaite classification provides some view of model robustness.

V. CONCLUSION

This study examined the climate of Pangkalpinang City over 65 years, utilizing multiple classification, hydrological, and agricultural assessments. Our analysis found a dominant *Af* (tropical rainforest) classification by the Köppen-Geiger system (56 of 66 years), with mean annual temperatures of 27.01°C and abundant annual rainfall of 2176.07 mm, and a *C1'As* (perhumid mesothermal) type predominating with the Thornthwaite system (64 of 66 years). We identified a likely not significant temperature increase (approximately

+0.02°C/year) and significant shifts in precipitation patterns, with an average annual rainfall of 2289.84 mm and a moderately irregular annual distribution (PCI of 8.924). Hydrological parameters included an average PET of 0.284 mm, high soil moisture at 99.751 mm, substantial surface runoff (4.577 mm), and 51 annual flood risk events. Agricultural analysis revealed a mean CWR of 4.857 relative units with variability in GDD and WRSI, with a strong correlation (r=0.969) between the WRSI and crop water needs. Time series analysis of Thornthwaite parameters indicates stable mean annual PET of 65.97 mm and a moisture index of 3373.06. The model was validated with low RMSE (0.1-0.5) values and stability of Thornthwaite classification with a sensitivity analysis. Extreme value analysis revealed a shift in temperature trends around the year 2000 and higher extreme temperatures in later periods. These results underscore the need for localized climate adaptation strategies, including robust water management plans to mitigate flood risk, and agricultural adaptation measures to address the variability in CWR and WRSI. Future investigation should integrate additional climate and environmental factors, such as land use changes, to refine these findings and provide more actionable recommendations.

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DATA AVAILABILITY

The data used in this study are available upon reasonable request to corresponding author.