MCSD 6215
MASTER PROJECT 1 PRESENTATION

UTM
UNIVERSITI TEKNOLOGI MALAYSIA

TEMPORAL ANALYSIS OF CLIMATIC-FOREST FIRE CORRELATION IN PENINSULAR MALAYSIA USING ARIMA AND MACHINE LEARNING

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FACULTY OF COMPUTING,
UNIVERSITI TEKNOLOGI MALAYSIA

PRESENTATION CONTENTS

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UTM UNIVERSITI TEKNOLOGI MALAYSIA

INTRODUCTION

INTRODUCTION

PROBLEM BACKGROUND AND STATEMENT

PROBLEM BACKGROUND

Climatic - Forest Fire Field

- Global
  - Forest fires severely **affect biodiversity**, human **health**, and **economic** stability. (Celis et al., 2023; Gajendiran et al., 2024)
  - **Climate change exacerbates fire risks**. (Burton* et al., 2023; Celis et al., 2023)
- Malaysia
  - **Fire risks increase during dry seasons** due to climatic anomalies like El Niño events. (Darween Rozehan Shah, 2023); Chew et al., 2023 ; (Azuar & Mardhiah, 2024; Abdullah, n.d.)
  - **Insufficient mitigation measures** hinder effective fire management. (Abdullah, n.d.)

Sabah fire cases spike in extreme hot weather

Published on: Sat. Feb 24. 2024

By Ben Tan

Tuesday, 17 Oct 2023 10:36 PM MYT

JOHOR BARU, Oct 17 — The Johor Fire and Rescue Department has successfully extinguished a fire

KUANTAN: A forest fire at three locations in Pahang since the end of March is finally easing after about two weeks of firefighting, with the Pahang fire and rescue department's operations now focused on Rompin.

Friday, 23 Feb 2024 10:08 PM MYT

KOTA KINABALU, Feb 23 — Extreme hot weather and drought, and deliberate burn open up new areas are among the main causes of the increase in forest, plantation,

Cases of bushfires in Sabah increased by over 600% from January to February 2024

By STEPHANIE LEE

SABAH & SARAWAK

Saturday, 02 Mar 2024

4:23 PM MYT

Reports of forest fires up

Published on: Monday, March 04, 2024

By: Sohan Das

961 forest and bush fires in Sabah

By Olivia Miwil - March 13, 2024 @ 11:44pm

Thursday, 04 Apr 2024 8:22 PM MYT

KOTA BARU, April 4 — The Kelantan Fire and Rescue Department recorded 577 fire cases in the first three months of this year, compared to 257 cases during the same period last year.

INTRODUCTION

PROBLEM STATEMENT

Climatic - Forest Fire Analysis

- **Lack of Localised Research** (Chew et al., 2022a)
  - **Rare research** on **climate change impact** on forest fire but other factors (Chew et al., 2023, 2024)
  - Mostly review on the effect but **limited** in analyzing **historical and future trends** (Tang, 2019)

hinder understanding of climatic influence on forest fire patterns caused ineffective fire management strategies

INTRODUCTION

RESEARCH MAPPING

	Research Gap	Problem Statements	Research Questions	Research Objectives
1	Regional Context Specificity: Most studies focus on global or broader Southeast Asian contexts, with limited attention given to forest fire dynamics specific to Peninsular Malaysia.	Lack of localized research hinder the understanding of recent trends in forest fire incidences causing ineffective forest fire management strategies. (Chew et al., 2022a)	What are the patterns of forest fire incidences in Peninsular Malaysia over the past five years?	To study forest fire patterns and climatic features in existing studies.
2	Temporal Analysis Limitations: Absence of long-term datasets and comprehensive temporal analyses restricts understanding of interannual variability, decadal trends, and seasonal fire dynamics in Peninsular Malaysia.	Local research mostly determine the factors and effects of the forest fire, but limited research on analyzing the temporal patterns of forest fire occurrences which involve historical and future trends, making it difficult to allocate resources and implement preventive measures effectively. (Tang, 2019)	Which months or seasons do forest fires most frequently occur in Peninsular Malaysia, and what are the relationships between these occurrences and the associated climatic factors?	To analyze the temporal characteristics of forest fire occurrences and their relationship with climatic variables.
3	Predictive Modelling Gaps: Few studies integrate advanced statistical and machine learning techniques with climatic variables to develop predictive models tailored to Peninsular Malaysia's unique climatic and geographical conditions.	Rare local research on how climatic factors interact to influence forest fire occurrences, obstruct the development of targeted mitigation strategies. (Chew et al., 2023, 2024)	How can climatic variables be used to predict the likelihood of forest fire occurrences in Peninsular Malaysia?	To develop a model that predicts the forest fires occurrence based on climate factors using machine learning methods.

INTRODUCTION

RESEARCH SCOPE

Scope

1. The study will utilize the dataset from previous study where the **dataset** is obtained from **Global Remote Sensing Data from Google Earth Engine (GEE).**
2. The study will focus on **temporal analysis** to identify trends and patterns over time, particularly in the context of climatic influences on forest fire occurrences.
3. The analysis will cover **at least 5 years** to capture long-term trends and patterns.
4. Key climatic variables such as **temperature, humidity and wind speed** will be examined for their influence on forest fire patterns.
5. The study will focus exclusively on **Peninsular Malaysia**, excluding East Malaysia due to different climatic and ecological conditions.
6. The research will use **historical data that is currently obtainable**, although it may have some constraints regarding precision and comprehensiveness.
7. **Statistical and Machine Learning Models** will be used for data analysis and model development.

LITERATURE REVIEW

LITERATURE REVIEW

THEORETICAL FRAMEWORK

Theoretical Framework

Climate Change Theory

Explores the relationship between climate change and its effects on environmental processes, such as in this study, the forest fire patterns.

Examines how climatic variables such as temperature, precipitation, and droughts exacerbate forest fire risks in Peninsular Malaysia.

Fire Ecology

Studies the interactions between fire, ecosystems, and the environment, emphasizing how fire shapes ecological dynamics.

Highlights the interplay between climatic factors and fire behavior, supporting the development of mitigation strategies.

LITERATURE REVIEW

FOREST FIRE PATTERNS
IN PENINSULAR MALAYSIA (OBJ 1)

Forest Fire Patterns in Peninsular Malaysia

- **Influence of Human Activities**
  - Major contributor to forest fires includes **open burning** and **agricultural practices** (Pradhan et al., 2007; S. M. Razali, 2010)
  - **Human activities** are often **associated with climatic factors**, amplifying fire risks (Smith et al., 2018; Musri et al., 2020; Sali et al., 2021)
- **Climatic Events Driving Forest Fires**
  - **El Niño-Southern Oscillation (ENSO)**
    - 1997–1998 and 2015–2016, caused significant forest and peatland fires in regions like Pahang and Selangor due to reduced precipitation and increased temperatures.
(Chew et al., 2022a; Li et al., 2023; Sloan et al., 2017)
  - **Droughts**
    - Prolonged dry periods lower water tables, making peatland areas highly flammable.
(S. M. Razali, 2010)
- **Forest Types Prone to Fires**
  - **Peat Swamp Forests**
    - Most vulnerable to fires during droughts due to flammable organic soil.
(S. M. Razali, 2010)
  - **Inland Forests**
    - Can also be affected by fire events during prolonged dry conditions or due to human-induced activities.
(Pradhan et al., 2007; S. M. Razali, 2010)
- **Topographical Influence**
  - **Slope and Elevation**
    - Topographical factors, such as steeper slopes, affect fire spread.
(Pradhan et al., 2007; S. M. Razali, 2010)

LITERATURE REVIEW

CLIMATIC FEATURES IN PENINSULAR MALAYSIA (OBJ 1)

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Previous studies on factors of forest fire in Peninsular Malaysia

Year of Publication	Research Locations	Year of Studies	Forest Fire Factors	Burnt areas (ha) / hotspots	References
2002	Peninsular Malaysia	1991-2001	**Human Factors** (Open Burning, Cigarette, Campers and Hunters, Agriculture), **Natural Phenomena** (Lightning in Dry Seasons, Friction from Branches, Heat From Stones, Methane Gas from Anaerobic Process)	Terengganu (1790 ha), Pahang (629 ha), Kelantan (573 ha), Selangor (528 ha), Perak (479 ha), Johor (59 ha), Kedah (42 ha), Negeri Sembilan (33 ha), Perlis (10 ha)	(Abdullah, Ibrahim, & Abdul Rahim, 2002)
2004	Pahang	1997	**Human Activities**, **Topographic** (Slope, Aspect, Elevation)	1600 ha peat swamp forest in 1997	(Setiawan et al., 2004)
2005	Peninsular Malaysia	2002	**Dry Conditions** During February and March, **Human Activities**	Selangor (543 ha)	(M. Mahmud, 2005)
2006	Selangor	Jun-99	**Topographic** (Slope, Aspect, Elevation), **Climatic Factors** (Temperature, Humidity), **Fuel**, **Human Activities**	-	(Patah et al., n.d.)
2006	Peninsular Malaysia	2000-2003	**Climatic Factors** (Low Humidity)	-	(Peng et al., 2006)
2007	Pahang	1998	**Human Activities,** **Topographic** (Elevation, Slope, Aspect)	-	(Razali, 2010)
2007	Selangor	2000-2005	**Fuel**, **Topographic** (Slope, Aspect), **Soil**, **Human Activities**	-	(Pradhan et al., 2007)
2008	Kelantan & Selangor	1990-1995	**Soil Moisture** By KDBI	-	(Ainuddin & Ampun, 2008)
2009	Pahang	1995-1999	**Climatic Factors** (Dry Seasons), **Human Activities**	-	(A. Mahmud et al., 2009)
2009	Peninsular Malaysia	1992-2009	**Climatic Factors** (Prolonged Spell Without Rain, Low Humidity), **Human Activities**	> 256600 ha	(Pradhan, 2009)
2010	Pahang	1998-1999	**Human Activities**, Fuel, Topography, **Climatic Factors** (Seasonal Changes, Dry Period By El Niño – Lower Water Table)	2480.95 ha	(Razali, 2010)
2010	Selangor	2001-2002	**Climatic Factors** (Long Drought caused by El Niño)	-	(Ainuddin & Goh, 2010)
2010	Selangor	2000-2004	**Human Activities,** **Climatic Factors** (Dry Spells JAN-MAR & JUN-AUG)	4143 ha in 1991-2002	(Bin Suliman et al., 2010)
2011	Peninsular Malaysia	-	**Human Activities,** **Snapped Electric Cables,** **Natural Phenomena** (Lightning, Spontaneous Combustion)	-	(Ismail, P. et al., 2011)
2014	Selangor	-	**Human Activities,** **Climatic Factors** (Dry Weather caused by Southwest Monsoon (MAY - SEP) and Wind)	3283 ha potential	(Suliman et al., 2014)
2014	Klang	2000-2007	**Climatic Factors** (Seasonal, Weather, Southwest Monsoon JUN-SEP)	-	(Sahani et al., 2014)
2016	Pahang	2014	**Climatic Factors** (Land Surface Temperature, Brightness Temperature), **Human Activities**	-	(Jamaruppin et al., 2016)
2018	Pahang & Selangor	2015 & 2016	**Climatic Factors** (El Niño Conditions, Mean Annual Rainfall, Mean Maximum Temperature) **Human Activities**	-	(Smith et al., 2018)
2020	Selangor	2010-2016	**Climatic Factors** (Prolonged Dry and Hot Period), **Human Activities**	Peninsular Malaysia (5347.19 ha) in 2010-2016, Selangor (1000ha)	(Musri et al., 2020)
2021	Selangor	JAN-MAR 2020	Prolonged Dry Seasons, Agriculture, Human Activities	-	(Sali et al., 2021)
2022	Pahang	2001-2021	**Climatic Factors** (Hot and Dry Seasons FEB-APR)	2005 (7,564 hotspots), 2014 (9,327 hotspots), 2019 (7,278 hotspots).	(Chew et al., 2022b)
2023	Selangor	JAN – MAR 2020	**Climatic Factors** (Temperature, Humidity, Wind, Rainfall), **Soil** (Groundwater Level, Soil Temperature, Soil Humidity), **Others** (Atmospheric Pressure, Solar Radiation)	307 ha	(Li et al., 2023)
2023	Pahang	Mar-21	**Climatic Factors** (High Temperature, Low Precipitation, Wind)	307 ha	(Chew et al., 2023)

Power BI

Climatic Features Associate with Forest Fire in Peninsular Malaysia

Monsoon

Two primary monsoons:
- Southwest Monsoon (April–September).
- Northeast Monsoon (October–March).

World Bank Group & Asian Development Bank

Precipitation Deficits

Decreased rainfall during ENSO years significantly **reduces soil moisture, increasing fire** severity.
(Li et al., 2023)

Dry / Drought

Lowering water tables in peatlands increases flammability.
(S. M. Razali, 2010)

related

Rainfall

(Smith et al., 2018)

Temperature

Average annual temperature: 23°C–32°C.
World Bank Group & Asian Development Bank

Historical temperature increases: 0.14°C–0.25°C per decade (1970–2013).
World Bank Group & Asian Development Bank

Higher temperatures during ENSO years amplify fire risks.
(Chew et al., 2022a; Li et al., 2023; Sloan et al., 2017)

Humidity

Low humidity during dry periods and ENSO events exacerbate fire severity.
(Chew et al., 2023)

Wind

Higher wind speeds aid the spread of forest fires.
(Chew et al., 2023)

LITERATURE REVIEW

DATA AND METHODS COMPARISON

Compare data sources, techniques used across previous research

Previous Studies for Temporal and Prediction Analysis on Climatic-Forest Fire in Tropical Region Utilised Remote Sensing Data

Data Sources	Climatic Factors	Temporal Analysis Techniques	Prediction Techniques	Evaluation Method	References
Remote Sensing (ATSR Algorithm 1:, MODIS - MOD14CHM); NCEP; CFSv2	ENSO, SSTs	FAI, Empirical Model Clusters, Getis-Ord Gi Statistic	Empirical Models, Optimal Lead Time	R^2, AIC, RSS, δ, r;	(Shen et al., 2019)
Remote Sensing (MODIS - MCD64A1, MOD11A1; LANDSAT); Climatic	Precipitation, SR, Temperature, RH	Hotspot Analysis Tool, Getis-Ord Gi Statistic, IDW	Geospatial Techniques, Correlation Analysis	Accuracy Assessment, Statistical Analysis	(Kumari & Pandey, 2020)
Remote Sensing (GFED4s, HadISST); ERA-Interim Reanalysis; GPCP	El Niño, Anthropogenic, Precipitation	PEA, AGCM, Empirical Functions	Large Ensemble Simulations (by MIROC5 AGCM), Empirical Relationships	Cumulative Probability Functions, Resampling Techniques, Comparison with Observations	(Shiogama et al., 2020)
Remote Sensing (GFED); ERA-Interim Reanalysis	Precipitation, Windspeed, Temperature, RH	K-Means & FCM Clustering,	Clustering Methods, Correlation Analysis	Silhouette Index	(Hidayati et al., 2020)
Remote Sensing (MODIS - MCD14DL, MCD64A1; VIIRS - VNP14IMGTDL)	Temperature, Rainfall, Drought	ARIMA Model; SARIMA Model	SARIMA Model, Box–Jenkins Methodology	Ljung–Box Test, Residual Analysis, Cross-Validation, Forecast Errors (RMSE, MAE, MASE)	(Kouassi et al., 2020)
Remote Sensing (MODIS - MCD14ML; VIIRS - VNP14_IMG; CHIRPS); Peatland Hydrological Unit Map; GFC	Precipitation, El Niño, Drought	Exploratory Method, Statistical Method, Log-Level Regression Models, Ordinary Linear Regression Models	Log-Level Regression Models, Prioritization Exercise	Validation Against Rain Gauge Observations, Comparison with TMPA Data, Cross-Validation, Fire Radiative Power (FRP)	(Santika et al., 2020)
Remote Sensing (Landsat 7 Images); Topographic Background; Forest Cover; Meteorological	Temperature, RH, Wind Speed and Direction; Precipitation	MCA, AHP, GIS Technology	Forest Fire Risk Map, Early Warning System	Regression, Correlation, CR	(Van Hoang et al., 2020)
Remote Sensing (OTD/LIS); NASA GISS; HadISST; ECMWF ERA5 Reanalysis; MERRA-2	LHF, SST, CAPE, Wind Shear, SAT, AOD, SHF, SH	MLR, Forward Stepwise Selection, VIF	MLR Model, Quantitative Estimation	Correlation, Trend, Explained Variance, Statistical Significance	(Qie et al., 2021)
Remote Sensing (MODIS - MCD64A1; Landsat 7; Sentinel 2); TerraClimate; NASA SRTM Digital Elevation	Precipitation, Temperature, Rainfall Seasonality	NBR, Fourier Filtering, Linear Interpolation and Smoothing, Savitzky-Golay Filter	MLR, Random Forest Models	Kruskal-Wallis Test, Dunn Test with Bonferroni Correction, Spearman Correlation Test, R^2, Permutation Importance	(Hartung et al., 2021)
Remote Sensing (MODIS - MCD64A1; FIRMS); IBGE; Mapbiomas; USGS; INMET	Evapotranspiration, Rainfall, Temperature, RH, Wind Speed	FR, ROC, AUC	FSI, P-R	ROC, AUC, Correlation Analysis	(De Santana et al., 2021)
Remote Sensing (MODIS - GFA, MCD12Q1 Collection 5.1); TerraClimate; GHM; Forest Structure	Precipitation, Temperature, Soil Moisture, Drought	Linear Mixed-Effect Models, MARS	MARS Model, PDPs	Post-Hoc Analysis, RSS, ROC Curve and AUC	(Singh & Zhu, 2021)
Remote Sensing (FRAP); Climate Teleconnections, SPEI, SAW	ENSO, AMO, PDO, Drought, SAWs	RDA, SEA, Multigroup Comparison Tests, Wavelet Coherence Analysis	RDA, SEA, Multigroup Comparison Tests, and Wavelet Coherence Analysis	ANOVA Permutation Test, Bootstrapped Confidence Intervals, Kruskal-Wallis Test and Dunn's Test with Bonferroni Correction, Wavelet Coherence Analysis	(Cardil et al., 2021)
Remote Sensing (MODIS; ERA5); GFED4	TP, PA, DS, ETO, DR	EOF based on SVD, Maximal Correlation based on ACE, Pearson, Spearman, and Chatterjee's Xi Correlations	EOF Based on SVD, ACE Algorithm, Pearson, Spearman, and Chatterjee's Xi Correlations	SCF Value, Average Error Value, Dependency and Correlation Analysis	(Nurdiati, Sopaheluwakan, Septiawan, et al., 2022)
Remote Sensing (MODIS; ERA5); GFED;	ENSO, IOD, Precipitation	SVD, EOF, HCM	SVD and EOF, HCM, DTW and Euclidean Distance	Variance Explained by SVD, Pearson Correlation, DTW and Euclidean Distance	(Nurdiati, Bukhari, et al., 2022)
Remote Sensing (MODIS - MCD64A1; ERA5)	VPD, TMMX, PET, CWD, TWS	PRM, Local Likelihood Fitting, AIC, R^2, Bivariate Distributions	PRM, Local Likelihood Fitting, CMIP6 Simulations, Bias-Correction Methods	AIC, R^2, Empirical Estimates of Fire Risk, Confidence Intervals	(Ribeiro et al., 2022)
Remote Sensing (CMORPH ; MODIS)	Dry Spells, Precipitation, ENSO, IOD, MJO	Copula-Based Joint Distribution, Quadrant Analysis, SVD	Copula-Based Models, Conditional Survival Probability, Tail Distribution Analysis	AIC, Spearman's Rho, Conditional Survival Distribution	(Nurdiati, Sopaheluwakan, & Septiawan, 2022)
Remote Sensing (MODIS; FIRMS)	Hot, Dry Seasons	GEE, GEE Code Editor (JavaScript)	Spatial Analysis, GEE Platform	Comparison with Historical Data, Interactive Charts	(Chew et al., 2022b)
Remote Sensing (MODIS)	Temperature, RH, Wind Speed, Precipitation, MNI	Descriptive Statistics, Logistic Regression, Chi-Squared Analysis, Power Law Distribution	MAXENT Models, Permutation Importance	AUC, Marginal Response Curves, Jackknife Measures of Variable Importance	(Trang et al., 2022)
Remote Sensing (MODIS); IMD; SRTM	Temperature, Dry Days	ARIMA, ACF, PACF, Cumulative Periodogram, Portmanteau (L-Jung Box) Test	ARIMA Models, Frequency Ratio Method	Model Validation: observing the significance level of residuals, Comparison with Test Data, R^2	(Kale et al., 2022)
Remote Sensing (MODIS; CHIRPS); SRTM	Precipitation, SPI, KBDI	ML Algorithms (RF, SVM, MAXENT, BRT), Ensemble Model, Statistical Downscaling	MLMs (RF, SVM, MAXENT, BRT), PCA	AUC, TSS, Sørensen similarity indices	(Prasetyo et al., 2022)
Remote Sensing (LAPAN; MODIS; ERA5)	Precipitation, Dry Spells, ENSO, IOD	PMA, Bayesian Linear Regression, Cross Validation	PMA, BLM	Cross Validation, R^2, RMSE	(Ardiyani et al., 2023)
Remote Sensing (MODIS; Sentinel-2 MSI; FIRMS; SRTM; WorldClim 2.1; Copernicus Climate Change Service; Open Street Map; SEDAC)	Temperature, Precipitation, Wind Speed, Soil Moisture	Emerging Hot Spot, Space Time Cube, NetCDF	MCDM, Weighted Overlay Analysis	Validation with Ground Data, Comparison with Actual Fire Occurrences	(Dhar et al., 2023)
Remote Sensing (VIIRS; SNPP; Sentinel-2 level 1C; SRTM; DEM; CHELSA V2.1 ; Sentinel-2; Landsat 8)	Temperature, Precipitation, Wind Speed, VPD, RH	Multi-collinearity Analysis, Cross-Validation, BlockCV Package	MLMs (ANN, RF, GLM, MAXENT, MARS, GBM), Ensemble Model	AUC, ROC, TSS, CBI, Accuracy	(Babu et al., 2023)
Remote Sensing (TerraClimate; MODIS - MCD64A1)	Temperature, Precipitation, Wind Speed	GEE, TerraClimate, Graphical Analysis	MLMs, GEE	Comparison with Historical Data, Graphical Analysis	(Chew et al., 2023)
Remote Sensing (MODIS - MOD44B, MCD14DL); WorldClim2	MAP, SI	GAMs, Binomial GAMs, Quasipoisson GAMs, AIC-Based Model Selection	GAMs, GLMs, Marginal Effect Plots	Model Fit Diagnostics, AIC, Comparison with MODIS Data, Choropleth Maps	(Williamson et al., 2024)
Remote Sensing (MODIS - MCD14DL); WorldClim	Temperature, Precipitation	BNB, NB, Simulation Studies, RMSE, MASE, Bias	BNB, NB, MCMC Sampling Algorithm	RMSE, MASE, bias, Prediction Intervals, Comparison with Actual Data	(Orero et al., 2024)
Remote Sensing (MODIS; CHIRPS; SRTM); FIRECC51; SoilGrids	MAP, Dry Season Precipitation Metrics, MCWD	GLMs, Stratified Random Sampling, Pseudo-R^2	GLMs, Standardization of Predictor Variables, Bilinear Interpolation	Model Fit Diagnostics: Pseudo-R^2, Confidence Intervals, Comparison with Other Regions	(Valencia et al., 2024)
Remote Sensing (MODIS - MCD64A, MCD12Q1.061; TerraClimate; CHIRPS); NASADEM	KBDI, Soil Moisture, Temperature, Wind Speed, PDSI, NDVI, Precipitation, AET, DEF, PET, RO, SRAD, SWE, VAP, VPD	GEE, GEE Python API and Geemap, Bilinear Interpolation, Morphological Operations	MLMs, Statistical Analysis	Model Performance Metrics, Validation with Historical Data, Graphical Analysis	(Chew et al., 2024)

With **most complete climatic features** (Chew et al., 2024), Utilised the dataset for current study

Both ARIMA (Kouassi et al., 2020; Kale et al., 2022) & NBR (Hartung et al., 2021) using time series, but **ARIMA** (Kouassi et al., 2020) **is more relevant to current study**

2 major types of forest fire occurrence prediction: SARIMA, MLMs (most). The accuracy : **Ensemble MLMs** (0.89) (Babu et al., 2023) > MLMs > BNB > BLM. **MXD & GLM** perform better among others

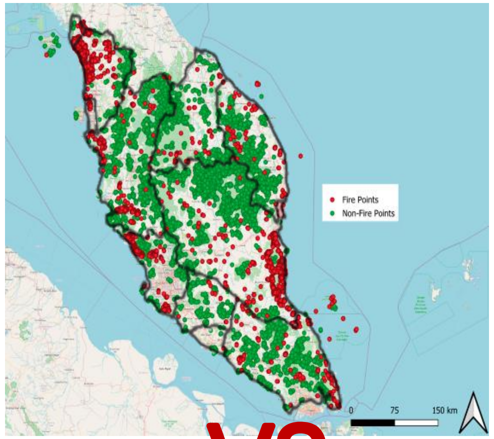
Use **ARIMA** (Kouassi et al., 2020) and **Ensemble MLMs** (Babu et al., 2023) related evaluation methods.

Aspect	Most Relevant Previous Studies	Current Research	Research Gap
Data	Use part of climatic data (**yearly**) obtained from **Remote Sensing** dataset from Google Earth Engine (**GEE**) (Chew et al., 2024)	Use **full** dataset (daily) from previous study (Chew et al., 2024)	Not fully utilised the available dataset.
Time Series Analysis Techniques	**ARIMA** (Kouassi et al., 2020) without involve climatic features *use open-source software R	**ARIMA** (Kouassi et al., 2020) Involving climatic features * use Python	Application of climatic features for improved time series analysis accuracy.
Prediction Techniques	**MLMs** (ANN, GBM, GLM, MARs, MXD, RF), **Ensemble MLMs** (Babu et al., 2023) * use open-source software R	Ensemble MLMs (**MXD & GLM**) from best MLM performance from (Babu et al., 2023) * use Python	Application of best MLMs in ensemble MLMs for improved prediction accuracy.
Evaluation Methods	**ARIMA** (Kouassi et al., 2020) : Ljung–Box test, residual analysis, and cross-validation (RMSE, MAE, MASE) * use open-source software R	**ARIMA** (Kouassi et al., 2020) : residual analysis, and cross-validation (RMSE, MAE, MASE) * use Python	--
	MLMs (Babu et al., 2023) : ROC-AUC, TSS, CBI, Accuracy * use open-source software R	**MLMs** (Babu et al., 2023) : ROC-AUC, TSS, CBI, Accuracy * use Python	

LITERATURE REVIEW

STUDY AREA COMPARISON

Forest Fire Hotspot Regions in Peninsular Malaysia (Chew et al., 2024)



VS

Forest Fire Hotspot in Peninsular Malaysia (by state)

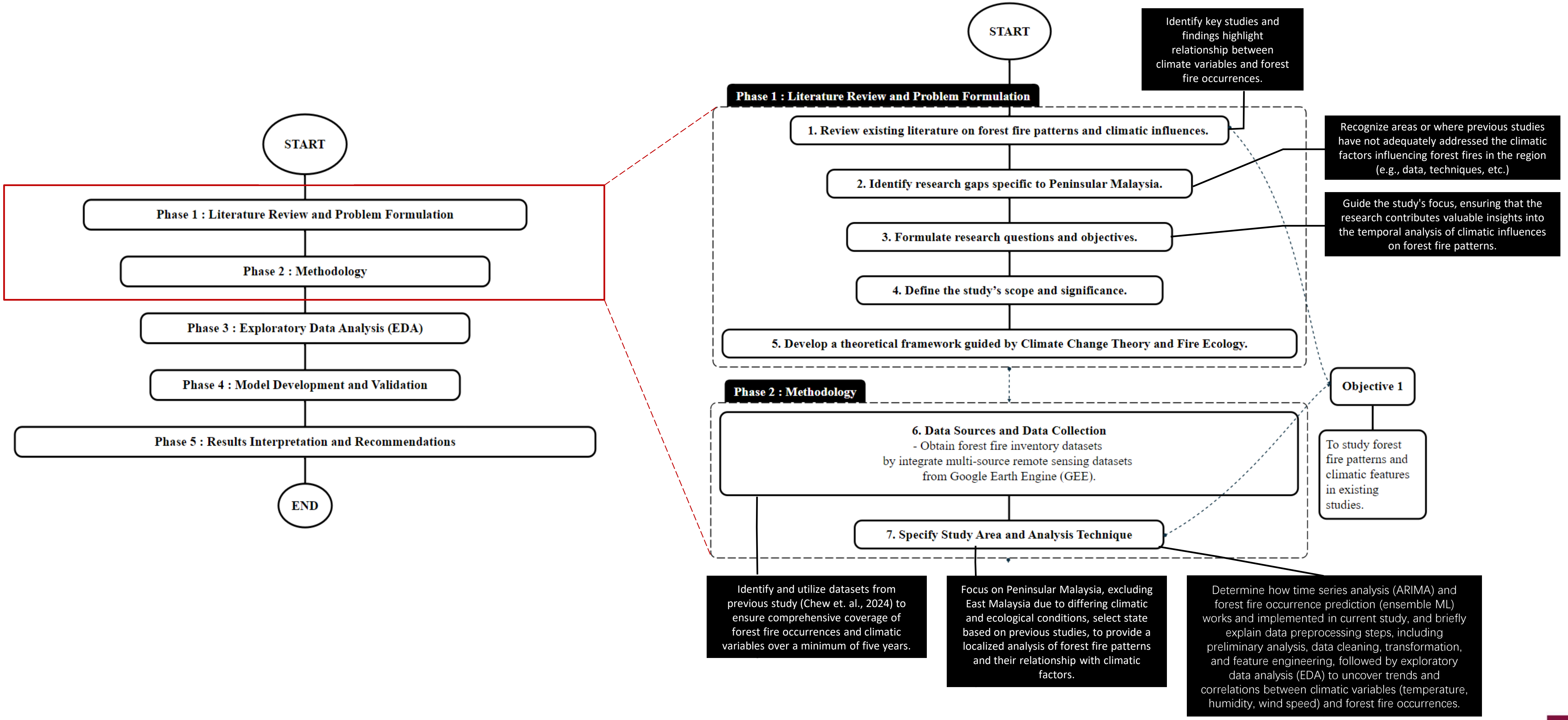
Forest Fire Hotspot	Year of Studies	Burnt areas (ha) / hotspots	References	Number of Studies
Selangor	1990-1995	-	(Ainuddin & Ampun, 2008)	12
	1991-2001	528 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	
	1999	-	(Patah et al., n.d.)	
	2000-2004	4143 ha (1991-2002)	(Bin Suliman et al., 2010)	
	2000-2005	-	(Pradhan et al., 2007)	
	2001-2002	-	(Ainuddin & Goh, 2010)	
	2002	543 ha	(M. Mahmud, 2005)	
	2010-2016	1000ha	(Musri et al., 2020)	
	2015 & 2016	-	(Smith et al., 2018)	
	-	3283 ha	(Suliman et al., 2014)	
	2020	-	(Sali et al., 2021)	
	2020	307 ha	(Li et al., 2023)	
Pahang	1991-2001	629 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	9
	1995-1999	-	(A. Mahmud et al., 2009)	
	1997	1600 ha	(Setiawan et al., 2004)	
	1998	-	(Razali, 2010)	
	1998-1999	2480.95 ha	(Razali, 2010)	
	2001-2021	7,564 hotspots (2005), 9,327 hotspots (2014), 7,278 hotspots (2019).	(Chew et al., 2022b)	
	2014	-	(Jamaruppin et al., 2016)	
	2015 & 2016	-	(Smith et al., 2018)	
	2021	307 ha	(Chew et al., 2023)	
Kelantan	1990-1995	-	(Ainuddin & Ampun, 2008)	2
	1991-2001	573 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	
Terengganu	1991-2001	1790 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	1
Perak	1991-2001	479 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	1
Johor	1991-2001	59 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	1
Kedah	1991-2001	42 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	1
Negeri Sembilan	1991-2001	33 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	1
Perlis	1991-2001	10 ha	(Abdullah, Ibrahim, & Abdul Rahim, 2002)	1
Klang	2000-2007	-	(Sahani et al., 2014)	1

Previous Studies		Current Research	Research Gap
Chew et al., 2024	Kedah, Pahang, Selangor, Perak, Johor, Terengganu, Kelantan, Negeri Sembilan, Perlis, Pulau Pinang and Melaka.	Kedah, Pahang, Selangor, Perak, Johor, Terengganu and Kelantan.	Prioritise study area with highest frequency based on hotspot region to ensure a robust analysis of fire patterns and drivers.
Other Researchers	Selangor, Pahang, Kelantan, Terengganu, Perak, Johor, Kedah, Negeri Sembilan, Perlis and Klang.		

RESEARCH METHODOLOGY

RESEARCH METHODOLOGY

RESEARCH FRAMEWORK (MP1 - PHASE 1, 2, 3)



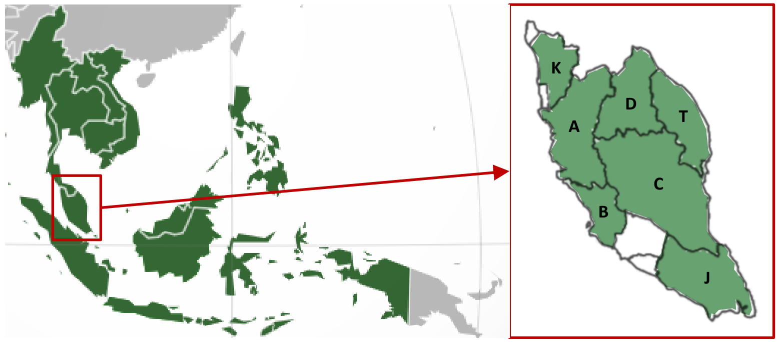
RESEARCH METHODOLOGY

PHASE 2 : DATASET & STUDY AREA

Example of Key Features Information (Chew et al., 2024)

Feature Name	Description	Feature Name	Description
system:index	System-generated from MCD64A1	current_aet_annual	Actual Evapotranspiration
longitude	Longitude Coordinate of Fire Points	current_def_annual	Climate Water Deficit
latitude	Latitude Coordinate of Fire Points	current_pdsi_annual	Palmer Drought Severity Index
fire	Fire Occurrence (binary class)	current_pet_annual	Reference Evapotranspiration
date	Date from Administrative Boundaries refer to the Shape	current_pr_annual	Precipitation Accumulation
ADM1_PCODE	Administrative level 1 code	current_ro_annual	Runoff
ADM2_PCODE	Administrative level 2 code	current_soil_annual	Soil Moisture
Shape_Leng	Shape Length (from MCD64A1)	current_srad_annual	Downward Surface Shortwave Radiation
ADM0_EN	Country Name	current_swe_annual	Snow Water Equivalent
ADM1_EN	Administrative level 1 name	current_tmmn_annual	Minimum Temperature
ADM2_EN	Administrative level 2 name	current_tmmx_annual	Maximum Temperature
validOn	Validation Date from Administrative Boundaries refer to the Shape	current_vap_annual	Vapor Pressure
Shape_Area	Shape Area (from MCD64A1)	current_vpd_annual	Vapor Pressure Deficit
ADM0_PCODE	Country code	current_vs_annual	Wind Speed at 10 m
BurnDate	Date in 0–365 (from MCD64A1)	current_EVI_annual	Enhanced Vegetation Index
year	Year of Fire Observation	current_NDVI_annual	Normalized Difference Vegetation Index
month	Month of Fire Observation	current_LST_annual	Land Surface Temperature
day	Day of Fire Observation	current_KBDI_annual	Keetch-Byram Drought Index
current0101_hii_annual	Human Impact Index	current0101_LC_Type2_annual	Land Cover Classification of UMD (Numeric)
current0101_average_annual_nighttime	Nighttime Brightness	current0101_LC_Type2_annual_classname	Land Cover Classification of UMD (Class Name)

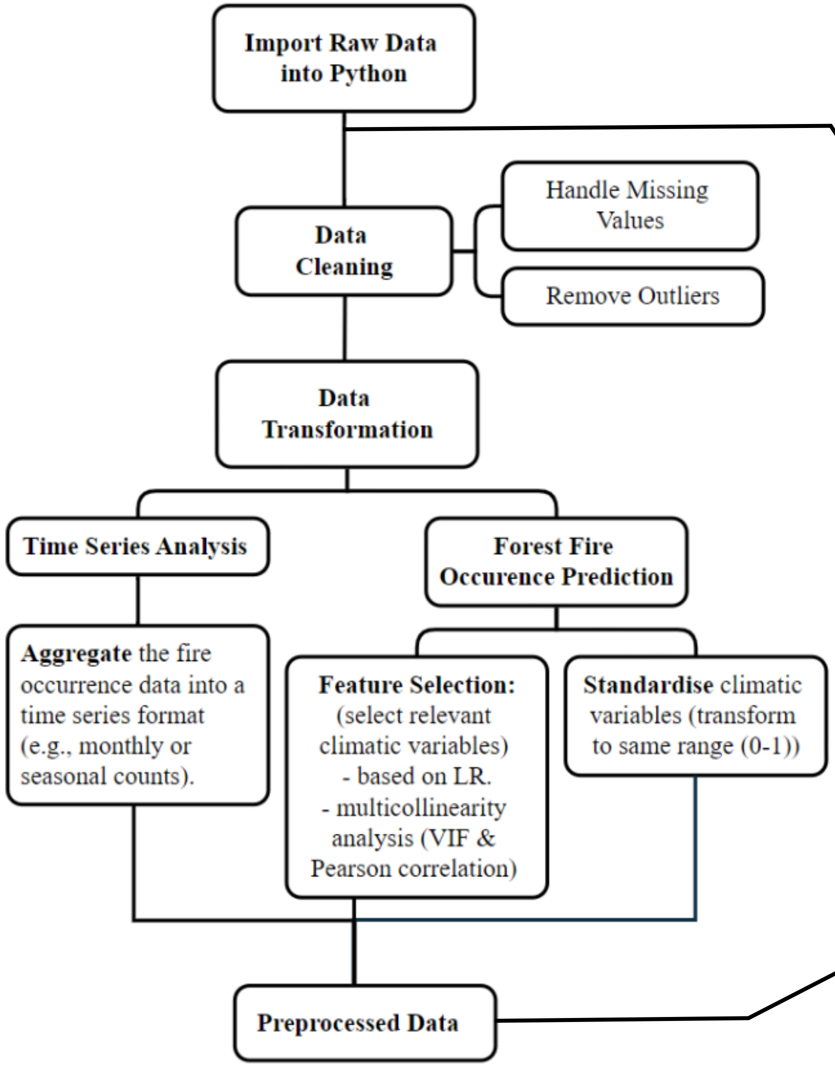
Data Info	Description	
Data Sources	Forest Fire Inventory datasets generated from the Framework created by Chew et al. (2024), from Google Earth Engine (GEE) leverage multi-source remote sensing.	
Size	82.89 million (2001 to 2023)	11279 rows : forest fire occurrence (daily)
		7294 columns : climate variables (monthly, annual and seasonal)
Fire Factors (Features)	Total : 26	climate variables (18)
		land cover variables (2)
		topography variables (3)
		social economic/anthropogenic factors (3)
	Utilize : 21	climate variables (18)
		land cover variables (1)
		topography variables (0)
		social economic/anthropogenic factors (2)



	State (Licence Plate Prefix)
Study Area Info	Kedah (K), Pahang (C), Selangor (B), Perak (A), Johor (J), Terengganu (T) and Kelantan (D).

RESEARCH METHODOLOGY

PHASE 2 : ANALYSIS TECHNIQUES AND TOOLS : DATA PREPROCESSING FOR EDA



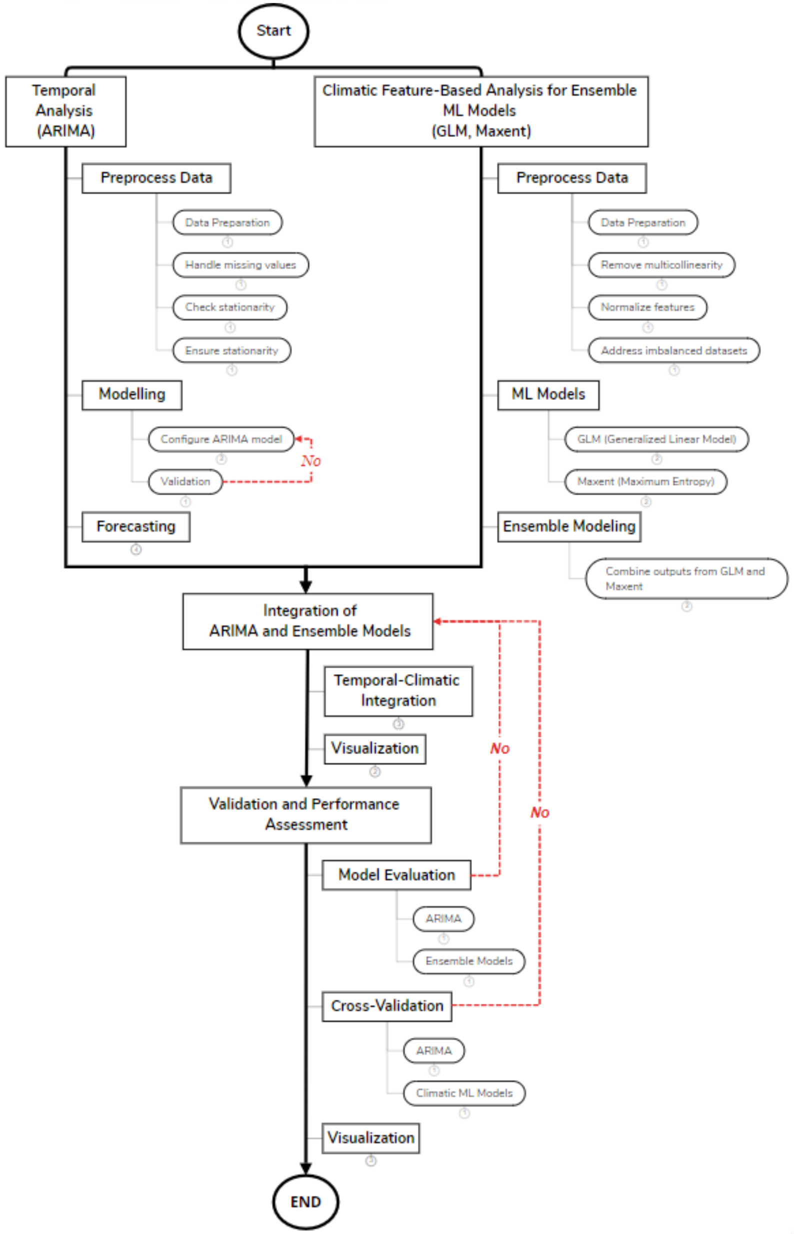
* Python is utilized for all the processes

Preliminary Analysis : Step before data cleaning to discover data information.

Exploratory Data Analysis (EDA) : Preprocess data is used to uncover trends and correlations between climatic variables and forest fire occurrences.

RESEARCH METHODOLOGY

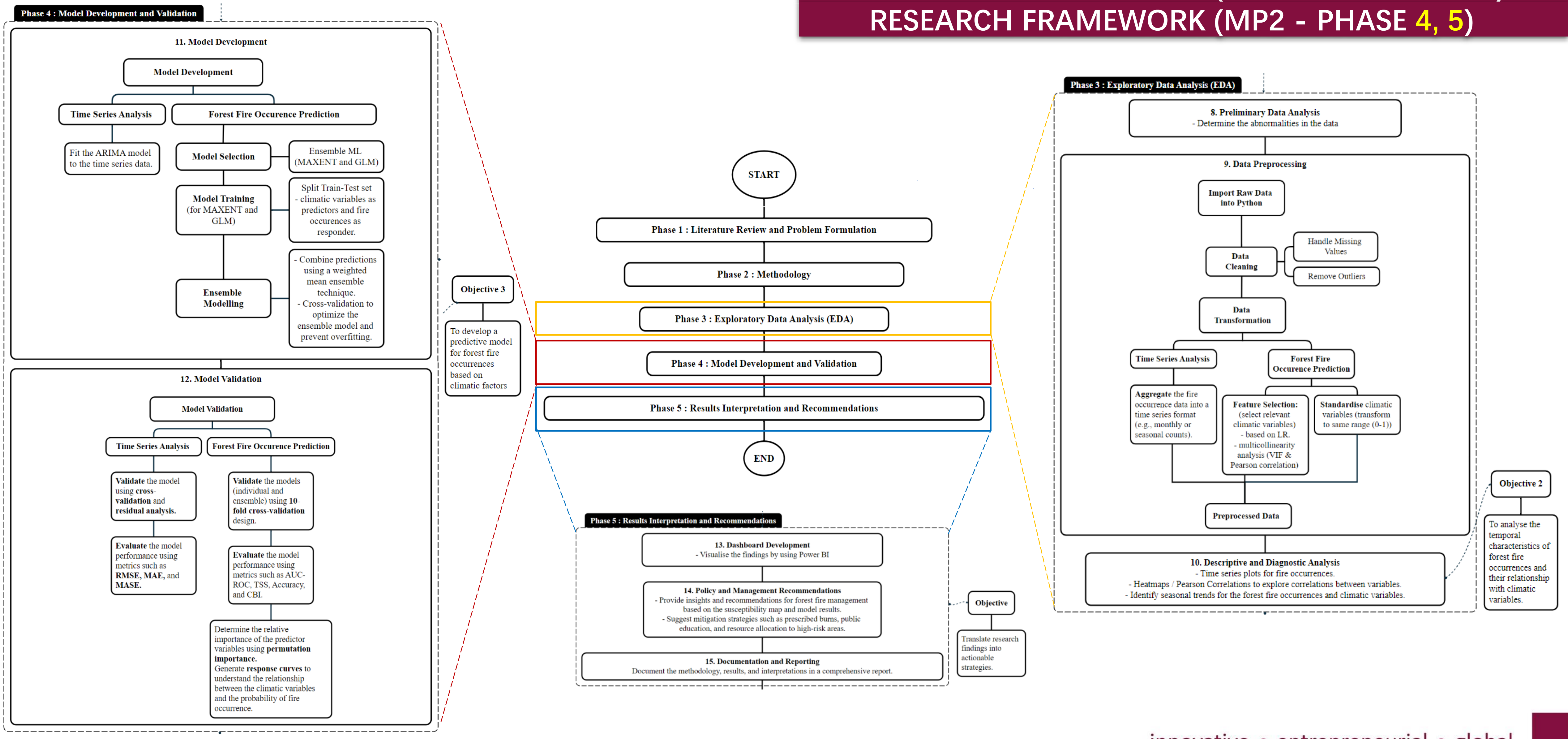
PHASE 2 : ANALYSIS TECHNIQUES AND TOOLS : MODELLING WORKFLOW



Aspect	Time Series Analysis		Prediction	
Model Overview	**ARIMA** combines **Autoregressive (AR)**, **Moving Average (MA)**, and **Integration (I)** terms for stationarity. - **Autoregressive (AR) :** Captures dependency on past values. - **Moving Average (MA) :** Models dependency on past errors. - **Integration (I)** : Ensures stationarity by differencing. Seasonal ARIMA (**SARIMA**) incorporates seasonality with additional seasonal AR and MA terms.		Predicts forest fire occurrence probability using **MLTs** and **ensemble ML**: - Generalized Linear Model (**GLM**), - Maximum Entropy (**MAXENT**) - Ensemble ML (**GLM, MAXENT**)	
Equation	**ARIMA** (p, d, q)	**SARIMA** (p, d, q) (P, D, Q)s	**GLM**	**MAXENT**
	$Y_t^d = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots \beta_p Y_{t-p} + e_t + \phi_1 e_{t-1} + \phi_2 e_{t-2} + \dots \phi_q e_{t-q}$ Predicted Y_t = Intercept (I) + Lagged Values (AR : p) + Lagged Errors (MA : q) **where:** Y_t : Value of the time series at time t β : Coefficients of the AR terms ϕ : Coefficients of the MA terms e_t : Error term (white noise) d : Order of differencing applied to Y_t to make the series stationary	$\phi(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D y_t = \delta + \theta(B)\Theta_Q(B^s)\varepsilon_t$ **where:** $\phi(B)$ and $\theta(B)$: Ordinary autoregressive and moving average component $\Theta_Q(B^s)$ and $\Phi_P(B^s)$: Seasonal autoregressive and moving average component $(1-B)^d(1-B^s)^D$: Ordinary and Seasonal difference component of order d and D. ε_t : Gaussian white noise	$P = \frac{\exp(\sum \alpha Y)}{1 + \exp(\sum \alpha Y)}$ **where:** P : Possibility of fire occurrence as 1 and non-occurrence as 0 Y : Effective factors α : Fractional regression constant - Uses multiple regression models to establish connections between effective and conditional factors of fire occurrence. - Sensitive to variable significance and uses specific distributions for dependent covariates. (e.g., fire occurrence as binary: 1 for occurrence, 0 for non-occurrence).	$H(\hat{\pi}) = -\sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x)$ **where:** $\hat{\pi}$: The probability distribution $\ln$: Natural logarithm - Higher entropy indicates less constrained choices. - Employs **L1-regularization (lasso)** to simplify models and prevent overfitting.
Testing	**Stationarity Test :** Tested using **Augmented Dickey-Fuller (ADF)** and **KPSS tests**, with transformations (e.g., **Box-Cox**) applied to stabilize variance.		**Multi-Collinearity Analysis :** Variables with **VIF > 10**, **TOL < 0.1**, or **correlation coefficient > 0.7 were excluded**.	
Framework	Stage 1: Identification: - Use **ACF** and **PACF plots** to determine AR, MA, and differencing orders. Stage 2: Estimation: - Estimate parameters using maximum likelihood and select models using **Akaike Information Criterion (AIC).** Stage 3: Diagnostic Checking: - Analyze **residuals for randomness** and evaluate **model accuracy**.		**Ensemble** - Combine **GLM** and **MAXENT** using **weighted mean ensemble technique**. - **Response curves** generated for the best-performing models.	
Evaluation	- Used metrics like Root Mean Square Error (**RMSE**), Mean Absolute Error (**MAE**), and Mean Absolute Percentage Error (**MAPE**). - Cross-validation was performed to ensure robustness.		- Cross-Validation: **10-fold CV** with **70%** data for **training** and **30%** for **validation**. - Metrics: **AUC, TSS, CBI**, and **accuracy**.	
Data Transformation	- Logarithmic transformation $Y = log(X+1)$ was applied to normalize values.			
Tools	Python			

RESEARCH METHODOLOGY

RESEARCH FRAMEWORK (MP1 - PHASE 1, 2, 3)
RESEARCH FRAMEWORK (MP2 - PHASE 4, 5)



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INITIAL FINDINGS

INITIAL FINDINGS

EXPLORATORY DATA ANALYSIS (EDA) python

Preliminary Analysis Finding	Preprocessing Taken	Exploratory Data Analysis

ADM2_REF	ADM2ALT2EN
0.0	0.0
NaN	NaN
NaN	NaN
NaN	NaN

Missing Value / Null Values

```
# Condition: if the difference between mean and median >= 1
if abs(mean - median) >= 1:
    ff_df[col].fillna(median, inplace=True)
else:
    ff_df[col].fillna(mean, inplace=True)
```

Imputation: if |mean-median| >= 1, filled with median, else mean

	Missing Values	Percentage (%)
200101_aet	0	0.0
200101_def	0	0.0
200101_pdsi	0	0.0
200101_pet	0	0.0
200101_pr	0	0.0

Shape_Leng	Shape_Area
11279.000000	11279.000000
2.511669	0.224141
1.159037	0.183749
0.268241	0.005021

system:index
1_2001_09_01_00000000000000000071_0
1_2001_09_01_00000000000000000071_1

11279 rows × 7349 columns

Redundancy Data (Spatial Data / Metadata Information)

```
# column to remove (but keep ADM1_EN, year, month, day, fire)
#useless_cols = ['current0101_LC_Type2_annual_classname', 'ADM2_REF', 'ADM2ALT2EN', 'ADM2ALT1EN']
useless_cols = ['system:index', 'esa_class_values', 'esa_class_name', 'elevation', 'slope', 'aspect', 'hillshade',
                'Unnamed: 0', 'longitude', 'latitude', 'date', 'ADM1_PCODE', 'ADM2_PCODE','Shape_Leng', 'ADM0_EN',
                'ADM1_EN', 'validOn', 'Shape_Area', 'ADM0_PCODE', 'BurnDate','current0101_LC_Type2_annual_classname',
                'ADM2_REF', 'ADM2ALT2EN', 'ADM2ALT1EN']

# Remove the columns
for col in useless_cols:
    if col in ff_df.columns:  # Check if column exists before attempting to drop it
        ff_df.drop(columns=[col], inplace=True)
ff_df
```

Remove

[11279 rows x 7303 columns]

200101_aet	200101_def	200101_pdsi	200101_pet	200101_pr
11277.000000	11277.000000	11277.000000	11277.000000	11277.000000
90.300727	1.572608	3.066276	91.873938	392.987940
10.524221	4.454644	1.806563	12.766335	205.113426
55.000000	0.000000	-2.080000	55.000000	69.000000
83.600000	0.000000	1.710000	83.600000	277.000000
90.800000	0.000000	3.360000	90.800000	352.000000
96.600000	0.000000	4.250000	96.600000	551.000000
121.600000	20.700000	6.160000	121.600000	1025.000000

Variability In Data Scales

```
# need to avoid normalize fire, year, month data
# apply Min-Max normalization on used_price (numerical) to scale it between 0 and 1.

from sklearn.preprocessing import MinMaxScaler

# Columns to exclude from normalization
exclude_columns = ['fire', 'year', 'month', 'day']

# Identify numerical columns to normalize, excluding specified columns
normalized_columns = [col for col in ff_df.select_dtypes(include=['float64', 'int64']).columns if col not in exclude_columns]

# Min-Max Normalization
scaler = MinMaxScaler()
ff_df[normalized_columns] = scaler.fit_transform(ff_df[normalized_columns])
```

Min-Max Normalization (scale to [0,1])

200101_aet	200101_def	200101_pdsi	200101_pet	200101_pr
0.493994	0.0	0.359223	0.493994	0.612971
0.493994	0.0	0.359223	0.493994	0.612971
0.495495	0.0	0.353155	0.495495	0.618201
0.495495	0.0	0.353155	0.495495	0.618201
0.486486	0.0	0.608010	0.486486	0.410042
...	...	...	...	...
0.330330	0.0	0.379854	0.330330	0.534519
0.474474	0.0	0.444175	0.474474	0.608787
0.301802	0.0	0.626214	0.301802	0.265690
0.438438	0.0	0.799757	0.438438	0.271967
0.456456	0.0	0.177184	0.456456	0.696653

year	month	day
11279.000000	11279.000000	11279.000000
2016.432485	7.862665	22.580814
7.633719	4.509456	10.453132
2001.000000	1.000000	1.000000

Year, Month, Day Column

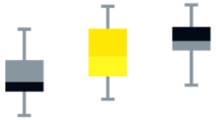
```
# Ensure 'year', 'month', and 'day' columns are numeric
ff_df['year'] = pd.to_numeric(ff_df['year'], errors='coerce')
ff_df['month'] = pd.to_numeric(ff_df['month'], errors='coerce')
ff_df['day'] = pd.to_numeric(ff_df['day'], errors='coerce')

# Create a 'date' column by concatenating year, month, and day
ff_df['date'] = pd.to_datetime(ff_df[['year', 'month', 'day']], errors='coerce')
```

Feature Creation by concatenating into a new column: ‘date’

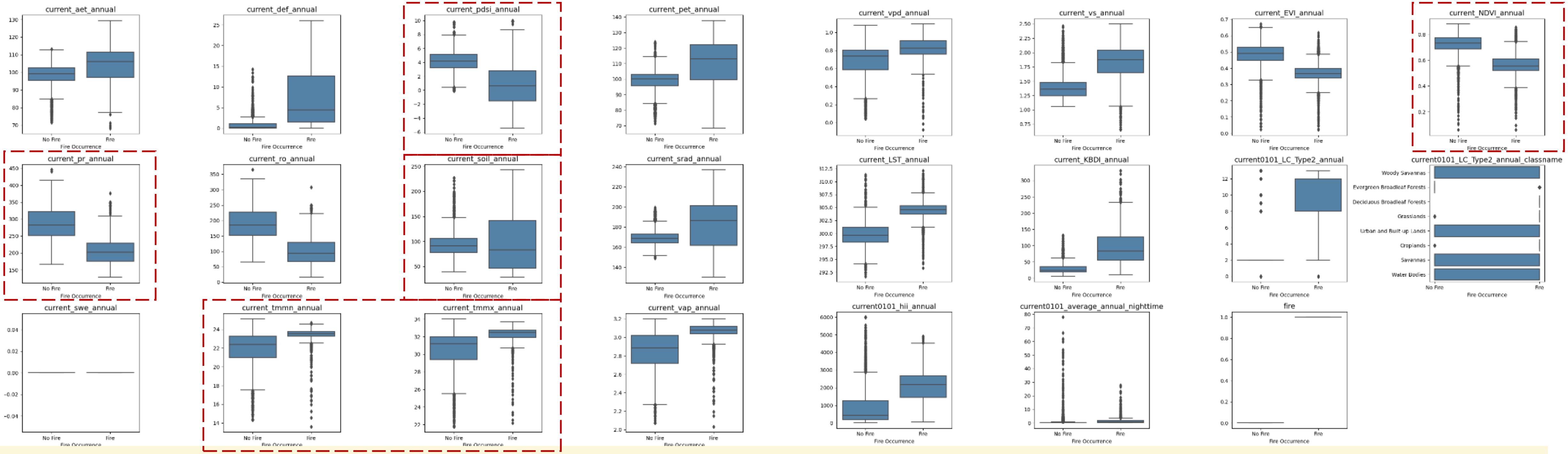
year	month	day	date
2001	9	27	2001-09-27
2001	9	13	2001-09-13

INITIAL FINDINGS

VISUALIZATIONS : DESCRIPTIVE AND DIAGNOSTIC ANALYSES



Box Plots: Illustrating the distribution and range of climatic variables during fire and non-fire periods.

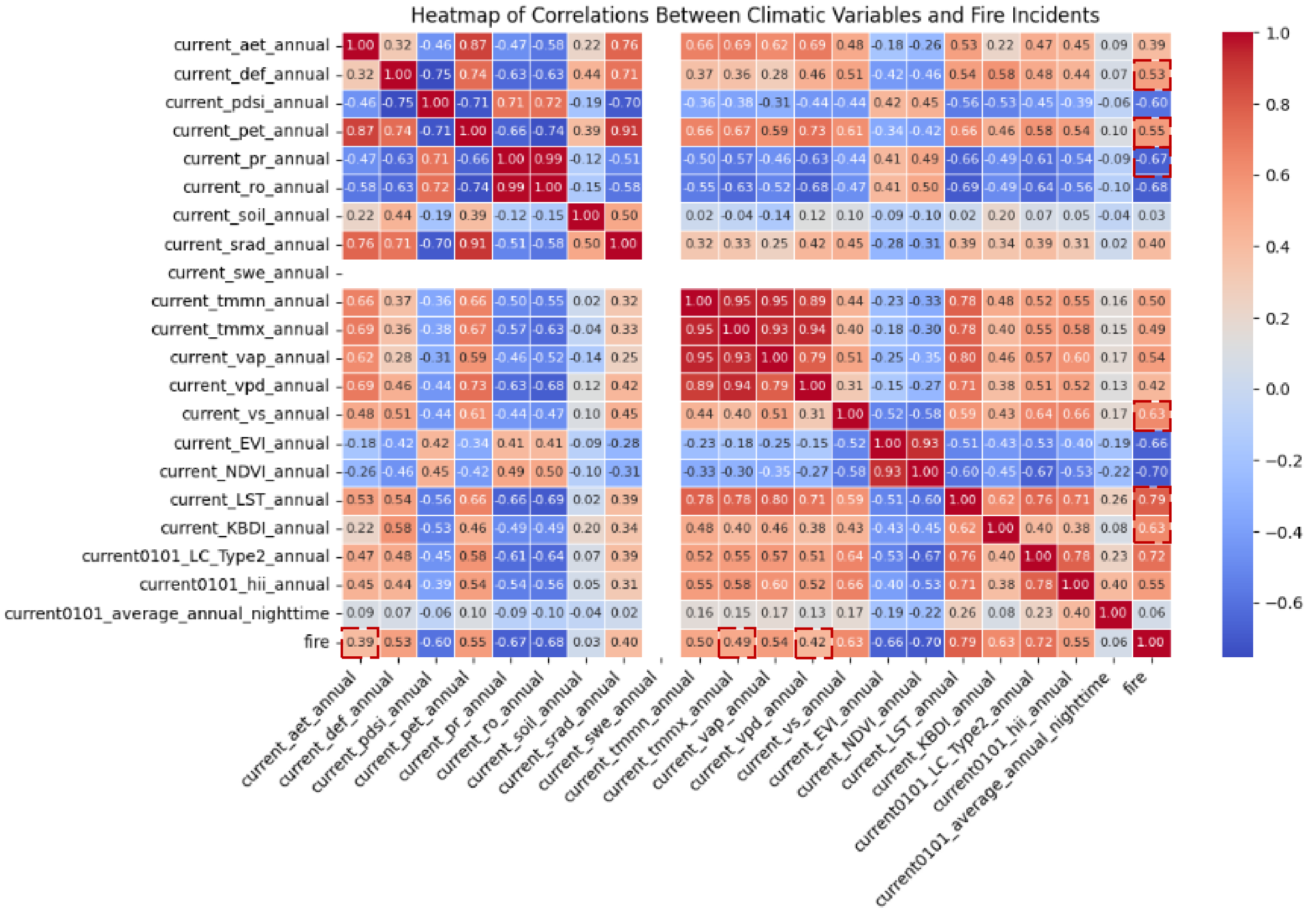


- **min temperature** and **max temperature** show **higher median** values during fire occurrences: elevated temperatures contribute to fire.
- **precipitation** exhibits **lower median** values for fire occurrences : reduced precipitation contribute to fires.
- **soil moisture** and **PDSI** show **wider interquartile ranges** during fire events, indicating more variability which reflect the influence of extreme dryness or water deficit during fire-prone periods.
- **NDVI** have **lower medians** during fire occurrences, possibly signaling reduced vegetation health or cover in fire-prone regions.

INITIAL FINDINGS

VISUALIZATIONS : DESCRIPTIVE AND DIAGNOSTIC ANALYSES

Heatmaps: Showing the correlation between different climatic variables and fire incidents.

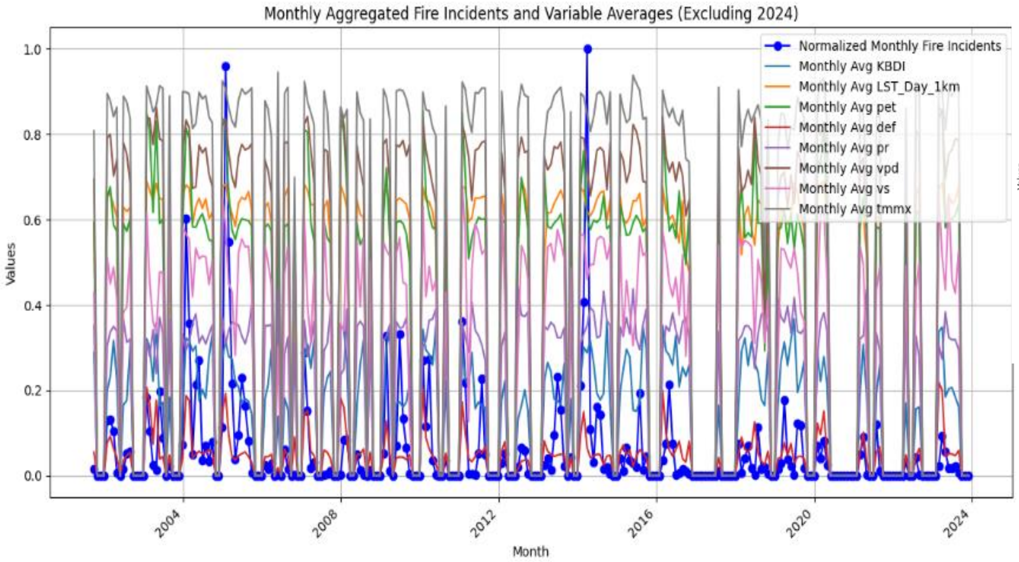


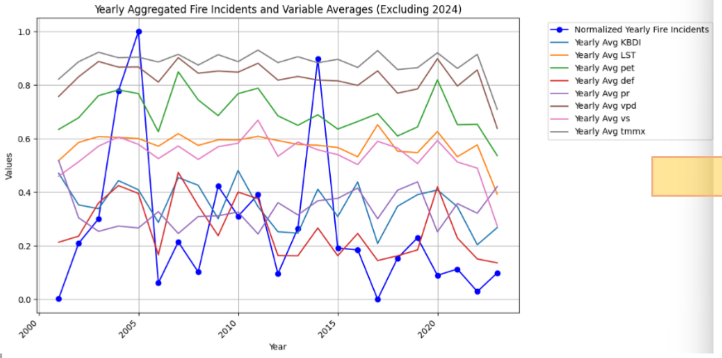
- **LST** (0.79), **KBDI** (0.63), **Wind Speed at 10 m** (0.63), **Reference Evapotranspiration** (0.55), **Climate Water Deficit** (0.53), show **strong** correlation, suitable consider as temperature-related predictor.
- **Precipitation Accumulation** (-0.67), prove reduce precipitation increase fire risk.
- **Max Temperature** (0.49), **Vapor Pressure Deficit** (0.42) show **moderate** correlation and Actual Evapotranspiration (0.39) show **weak** correlation .

INITIAL FINDINGS

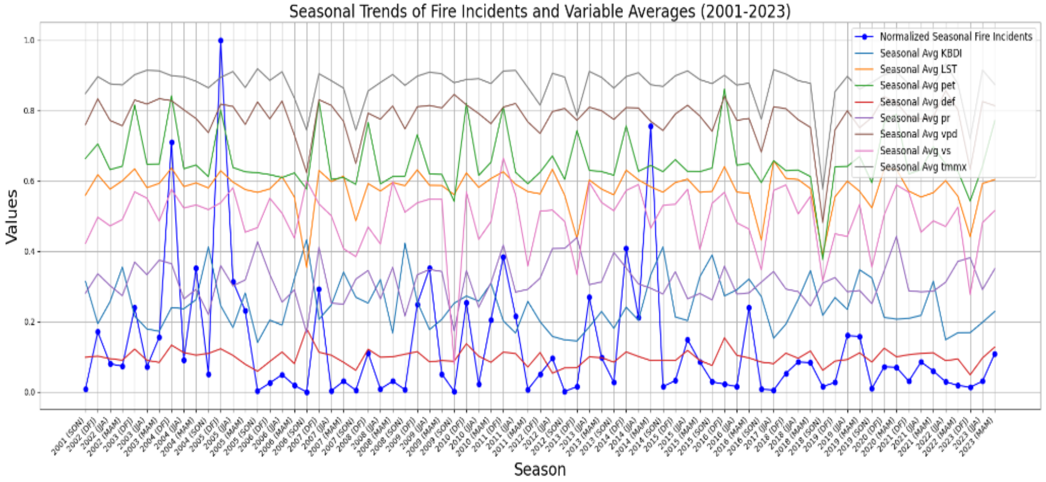
VISUALIZATIONS : DESCRIPTIVE AND DIAGNOSTIC ANALYSES

Time Series Plots: Displaying the temporal patterns of forest fire occurrences and climatic variables.





- **Monthly** and **Yearly** aggregate result : Fire incident spike in **2005** & **2014** with elevated **LST**, **KBDI**, **VPD** & low **precipitation**.



- **Seasonal** aggregation result : Fire increased during **spring** (MAM) and **summer** (JJA)

INITIAL FINDINGS

INITIAL FINDINGS, EXPECTED OUTCOMES, FUTURE WORK

Aspect	Initial Findings	Expected Outcomes	Future Work
Dataset Overview	Dataset contains 11,279 rows and 7,349 columns with time-series data from 2001 to 2023.	Identification of relevant variables and improved dataset quality through preprocessing.	Optimize dataset structure for efficient analysis during model development.
Climatic Variable Patterns	Higher temperatures, wind speed and reduced precipitation during fire events.	Better understanding of how climatic variability influences fire risk.	Perform deeper analysis using ML (GLM & MAXENT) on the role of climatic variables in predicting fire occurrences.
Data Normalization	Key variables (e.g., precipitation, temperature) exhibit wide ranges, requiring normalization.	Scaled and normalized dataset for consistent and accurate analysis.	Explore advanced scaling methods (Min Max Scaler or Standard Scaler) to improve the effectiveness of MLMs.
Correlations Identified	Strong positive correlation between LST, KBDI, and fire incidents; negative correlation with precipitation (PR).	Quantified relationships between climatic variables and fire occurrences.	Develop correlation-based predictive features (Multi-Collinearity Analysis) to enhance model accuracy.
Seasonal Patterns	Increased fire activity in spring and summer, particularly in years with extreme drought conditions (e.g., 2005, 2014).	Clear identification of seasonal trends and high-risk periods for fire incidents.	Perform seasonal decomposition and anomaly detection through ARIMA to better capture extreme events and seasonal variations.
Visualization Insights	Boxplots and time-series plots highlight correlations and spikes in fire incidents during extreme drought years.	Comprehensive visual representation of patterns and trends in the dataset.	Incorporate interactive visualizations to enhance interpretability.
Predictive Modelling Potential	Strong associations between key climatic variables and fire occurrences suggest feasibility of accurate predictions.	Development of robust predictive models for fire occurrence.	Implement ML models (GLM & MAXENT) to predict fire incidents based on climatic variables.

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APPENDIX

MP1 GANTT CHART

MP1 GANTT CHART

2024/2025																			
Task	Description	B-W1 19/09 - 05/10	W1 06/10 - 12/10	W2 13/10 - 19/10	W3 20/10 - 26/10	W4 27/10 - 02/11	W5 03/11 - 09/11	W6 10/11 - 16/11	W7 17/11 - 23/11	W8 24/11 - 30/11	W9 01/12 - 07/12	W10 08/12 - 14/12	W11 15/12 - 21/12	W12 22/12 - 28/12	W13 29/12 - 04/01	W14 05/01 - 11/01	W15 12/01 - 18/01	W16 19/01 - 25/01	W17 26/01 - 01/02
1	**Project Kick Start**																		
1.1	Proposal Preparation																		
1.2	Proposal Submission																		
2	**Literature Review & Problem Formulation**																		
2.1	Review Existing Literature on Forest Fire Patterns and Climatic Influences.																		
2.2	Identify research gaps specific to Peninsular Malaysia.																		
2.3	Formulate Research Questions and Objectives.																		
2.4	Define The Study's Scope and Significance.																		
2.5	Develop A Theoretical Framework Guided by Climate Change Theory and Fire Ecology.																		
3	**Methodology**																		
3.1	Data Sources and Data Collection																		
3.2	Specify Study Area and Analysis Technique																		
4	**Exploratory Data analysis (EDA) / Initial Results**																		
4.1	Preliminary Data Analysis																		
4.2	Data Preprocessing																		
4.3	Descriptive and Diagnostic Analysis																		
5	**Documentation and Submission**																		
5.1	Report Preparation																		
5.2	Turnitin and Turnitin Form																		
5.3	Evaluation Form																		
5.4	Submission																		
5.5	Presentation Slides Preparation																		
5.6	Presentation																		
5.7	Report Admendment																		

APPENDIX

MP2 GANTT CHART PLANNING

MP2 GANTT CHART PLANNING

		2024/2025																
Task	Description	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15	W16	W17
6	**Model Development and Validation**																	
6.1	Model Development - Time Series Analysis (**ARIMA**)																	
6.2	Model Development - Forest Fire Occurrence Prediction (**Enhance ML** - GLM & MAXENT)																	
6.3	Model Validation																	
7	**Results Interpretation and Recommendations**																	
7.1	Dashboard Development																	
7.2	Policy and Management Recommendations																	
8	**Documentation and Submission**																	
8.1	Report Preparation																	
8.2	Turnitin																	
8.3	Submission																	
8.4	Presentation Slides Preparation																	
8.5	Presentation																	