Long-Term Climate Change based Locust Infestation Prediction System

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***Abstract*— Locust are one of the most destructive agricultural pests in the world. The impact of climatic factors on locust infestation is well documented, these insights hence climate change is expected to radically change historic patterns. In fact, it is anticipated that climate change will increase locust habitat range by up to 25%. It is essential to control locust infestations early to prevent the formation of large-scale locust swarms. Currently, there is a gap in long-term locust prediction using climatic data which this paper fills. This paper has built a pipeline harnessing data from locust field surveys, TerraClimate and World IUCN Habitat Map to prepare the model's training and testing dataset. After testing multiple ML models, an Extreme Gradient Boosting Model was identified as the most accurate model. It has been optimized using the Bayesian Hyper-parameter tuning. The model has achieved 78% accuracy, AUC of 87.7%, AP of 89%, Brier score of 0.14 and a healthy distribution of predicted probabilities indicating its potential to collaborate with human experts and develop holistic locust threat maps considering the Socio-Economic Shared Pathways and Climate Change Projections from TerraClimate and Copernicus Climate Services. Using this model the impact of climate change on food supply chains and agricultural costs can be better estimated, supporting greater green financing from all sectors.**

Keywords—locusts, predictive modelling, climate change, food security, artificial intelligence, Extreme Gradient Boosting

I. Introduction

There are over 10,000 grasshopper species worldwide distributed throughout tropical, temperate grasslands and desert regions. Out of these species only 18-21 species are locusts, capable of swarming [1]. Locusts are one of the most destructive agricultural pests in the world and they threaten 10% of the global food supply [2]. A locust swarm consumes enough food to feed 35,000 people daily. In India, locust upsurges have been linked to 12% decline in national wheat production and resulted in an estimated US $3 billion worth of financial losses [3]. In the more vulnerable region of East Africa crop production losses due to locust infestations have been estimated between 42% to 69% or around 160,000 tons a day. To control a locust swarm toxic insecticide including fipronil, deltamethrin or chlorpyrifos are used which causes significant soil and water pollution reducing agricultural productivity [4]. Locust infestations also lead to major socio-economic repercussions like declining literacy, reduced household income and increased infant mortality [5], [6].

When locusts form large swarms, they become extremely difficult to control due to their pesticide resistance and general resilience [7]. To prevent the threat of locust swarms, it is essential for locust management to become proactive. Hence, accurate detailed prediction of locust hotspots is key so that the locusts can be controlled pre-swarming itself by using anti-solitarizing agents like bio-pesticide neem oil [8], [9].

II. Literature Review

A. Locust Swarming Biology

Locusts demonstrate population density dependent phase plasticity mediated by serotonin between the solitarious, transiens and gregarious phases [10]. Locusts normally exist in the solitarious phase where they avoid each other, however according to [11] when the population density increases to 75 locusts per square meter they transition into the gregarious phase where they are attracted to each other [12]. When locusts gregarize and form swarms there are multiple morphological and behavioral changes. For instance, their wingspan increases, their color changes and their taste mediated feedback is down regulated to include toxins in their diet as a defense against predators [13], [14].

Climatic factors like rainfall, soil humidity, temperature and vegetation development play a major role in locust breeding and population density patterns [15].

Excessive rains, followed by a period of drought, are strongly linked to the formation of gregarious locust swarms. Since, the excessive rains lead to high vegetative growth increasing the locust population and the subsequent drought leads to vegetative desiccation forcing the locust populations into regions where food is available [16]. To transition from a minor locust upsurge into a major locust plague, environmental conditions like temperature, wind and soil moisture must be suitable for egg laying and development [17].

Historical analyses reveal a strong correlation between locust swarms and extreme weather events like hurricanes, unseasonal rainfall and wet-dry climates [1], [18]. Locust habitats are projected to rise by 5-25% by the end of the 21st century and become more likely to occur simultaneously in different regions [19]. The impact of climate change through cyclone Pawan and the Indian Ocean Dipole was observable in the 2019-21 locust plague in an unprecedented locust swarm invasion into multiple agricultural Indian states [20], [21]

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B. Remote Sensing

Conventionally, manual surveys were undertaken to measure climatic variables. However, these surveys were impractical for faster frequency and global coverage. Hence, remote sensing satellite technologies are being implemented. Satellite based earth observation systems consist of geostationary and low-Earth orbiting satellites to measure meteorological data at high spatial resolution [22]. Satellites analyze the electromagnetic radiation emitted by the planet to derive meteorological variables.

There are multiple datasets that leverage satellites and derive climatic variables including TerraClimate, a dataset of resolution 4 km with monthly data on precipitation, wind speed, vapor pressure, solar radiation and temperature [23].

C. Machine Learning Models

Machine learning is the capacity of computational algorithms or models to learn from data, identify patterns and make decisions [24]. Common models used in classification tasks for structured datasets including Random Forest Classifier, Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM) and Light Gradient Boosting Machine (LGBM). XGBoost, LGBM and Random Forest algorithms are based on multiple decision trees and the model weighs output of multiple trees in ensemble to develop its final decision [25].
Research has started into developing AI based solutions to predict locust infestation sites. For instance [26] developed a Random Forest algorithm based on data from the ESA CCI SM v03.2. However, the model was only restricted to Mauritania and the SM satellite data could only measure soil moisture to 5cm while locusts lay their eggs at 10cm affecting model performance. Another effort was undertaken by [27] to develop LocustLens, however, this model had certain methodological concerns which may have influenced its reported accuracy score. For instance it created country-specific subsets for their K-NN classification method which could have caused a geographic bias and neglected multiple climatic factors. Hence scaling to new countries would be challenging for Locust Lens and the absence of climatic data may cause the model to underestimate the evolving impact of Climate Change. [28] Developed an effective forecast model with 77% success rate demonstrating that machine learning can be effectively leveraged and implemented within conventional survey operations. However, current modeling efforts have focused on short-term locust hotspot predictions, a significant research gap that this paper aims to fill.

III. METHODOLOGY

A. Data Preparation

To train the model, data regarding locust infestations and corresponding climatic conditions were collected. Data regarding locust infestations was collected from Kaggle, derived from the UNFAO locust hub. This dataset contained data from 25.2°W to 83.3°E – spanning large parts of through Europe, Asia and Africa. However, preliminary analysis revealed that it was completely imbalanced towards the locust infestation class. Therefore data was requested from the Government of India's Directorate of Plant Protection and Quarantine and Storage. The DPPQS provided historic locust survey data from 1985 to 2025. These surveys had a healthy balance of both the negative and positive classes. Hence further operations were conducted with this data.

Preliminary locust data exploration revealed that maximum locust data was recorded in 1988, 1989, 1993, 1994, 2003, 2004, 2005, 2019 and 2020 hence climatic data from these years were utilized. The data was obtained in a netCDF format hence they were converted into CSV formats to enable easy analysis. The TerraClimate data was filtered based on the geographical limitations on the available locust data to reduce compute speed.

To obtain data regarding vegetation, a global map of terrestrial habitat types was analyzed. This map categorized all terrestrial areas into 47 habitat types as classified by the IUCN at ~100m resolution [29]. The map categorized the habitats at level 1 providing broad information and level 2 which was more specific. This research paper analyzed the level 2 map with a sampling rate of 5000 pixel in chunks, and mapped the pixel color value to the map legend to create a dataframe labelling each region with the corresponding habitat class.

The climatic data, the locust infestation data and habitat data were merged and non-integer variables like habitat type were one-hot encoded. All missing data was dropped, hence yielding a dataset of size (158317x19). During the merge process precision of 0.01° latitude and 0.01° longitude was maintained. This corresponded to a precision of approximately 1.11 km [30].

B. Data Exploration and Augmentation

To understand the importance of each climatic variable on locust infestation the following visualization was plotted - kernel density estimates (KDE), violin plots and empirical cumulative distribution functions. A correlational heatmap was also plotted and features with low difference across the classes were dropped.
To filter out the outliers present in the dataset the Mahalanobis distances of points were calculated and plotted. The Mahalanobis distance is a statistical measure of the distance between a data point and the probability distribution and accounts for the correlations between multiple variables. Finding the presence of few big outliers an Isolation Forest algorithm – an unsupervised outlier detection method was used to filter out the outliers present.
The habitat data appended to the dataset as string was one-hot encoded into numerical data so that the model could understand it.

C. Model Design

Random Forest Classifier, Extreme Gradient Boosting, Light Gradient Boosting Machine, Support Vector Machine and Logistic Regression were experimented with. Each model was trained with the same datasets and default hyper-parameters.

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The effectiveness of the model was analyzed by calculating their precision and accuracy and plotting their confusion matrix and ROC curve. The features considered by each model were also plotted. A histogram of model confidence level was also generated.

D. Model Optimisation

The most accurate model was optimized by tuning the hyper-parameters: n-estimators, maximum depth of decision trees, learning rate, lambda regularization and alpha regularization. Regularization improves machine learning accuracy by preventing over fitting through the alpha and lambda variables. The lambda variable determines the strength of regularization while alpha determines the type of regularization. A randomized search was first conducted to provide a rough estimate of the ideal parameters, next a grid search and a Bayesian search were conducted to find the best hyper-parameters.

E. Generating Future Locust Threat Maps

Data from TerraClimate was used for their simulated conditions of 2015+2°C condition. The netCDF4 files were converted into excels and merged together into a single dataframe. This dataset was filtered within the Indian sub-continent to the latitudinal extent of 7°N to 38°N and longitudinal extent of 67°E to 98°E.

This data was then refined by dropping NaN values and integrating habitat data. This data was then fed into the model for predictions with probabilities. Predictions of locust infestation absences were negated, so that the low confidence negative classifications were also adequately communicated.

IV. Results & Discussion

A. Exploring the Dataset

The dataset is geographically spread across Northwest India which is most affected by locust swarms. It has 158,317 data points. It naturally has a positive class balance with a 52:48 split. Hence oversampling techniques like SMOTE were not necessary.

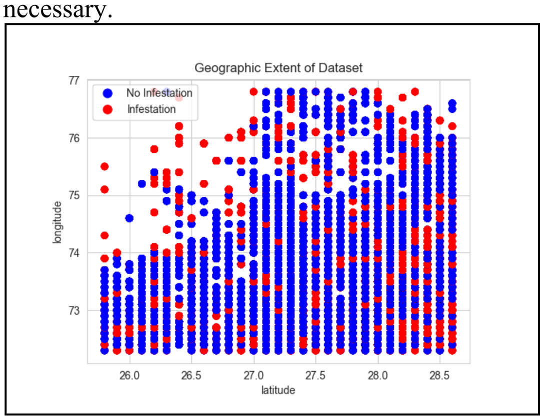

Fig. 1 Geographic Spread of Datapoints in Dataset

While checking for outliers inconsequential variables like Year, latitude and longitude were excluded. All datapoints with Mahalonobis Distance greater than 99% were considered to be outliers. These were filtered out using the Isolation Forest Algorithm.

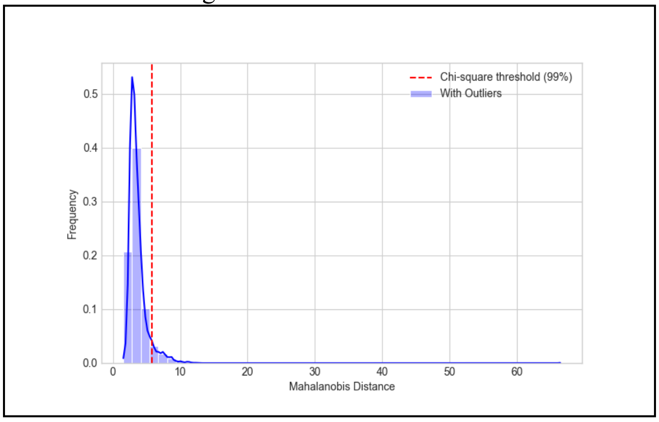

Fig. 2 Outliers in the Dataset

To better understand the climatic data present and how it related to locust infestations, violin plots and kernel density plots were made. On analyzing the plots it was revealed that largely across both categories – the climatic variables had the same range, however, there were density differences in values.

To better understand the variables having the maximum impact on the locust infestation a correlation heat-map was plotted. Some significant correlations were observed that shifted according to the presence of locust infestation. These variables were identified to be important for determining locust presence. These variables included the Palmer Drought Severity Index, Soil Moisture, minimum and maximum temperature, evapotranspiration rate and Climate Water Deficit. This aligns with literature which suggests that ambient moisture, drought stress and temperature conditions have a significant effect on locust breeding, migration and gregarization *citation*.

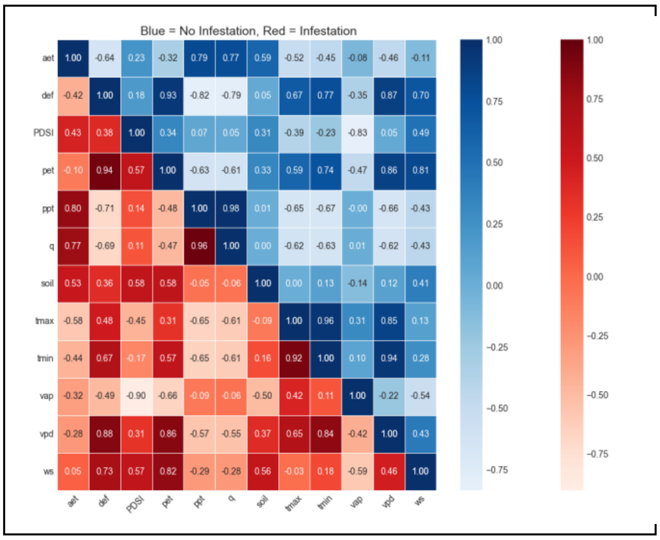

Fig. 3 Correlation Heat Map

B. Model Performance

XGBoost, LightGBM, Support Vector Machines and Random Forest Models were tested with the dataset. It was found that XGBoost and Random Forest showed comparable results for the metric of accuracy and

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outperformed the other models. Since XGBoost had a significantly faster compute time and lower memory overhead it was pragmatically selected as the model to be optimized.

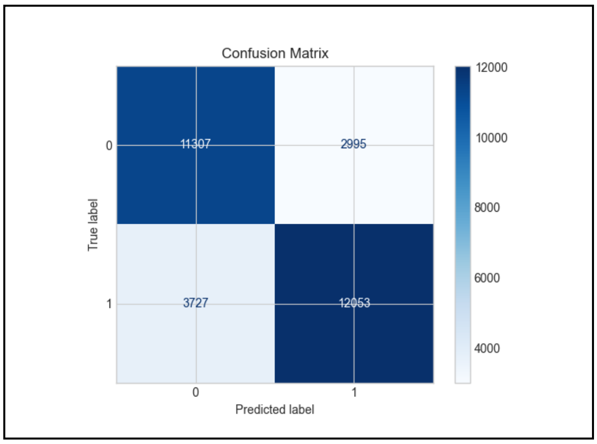

Fig. 4 XGBoost Confusion Matrix

The best hyper-parameters for XGBoost was found to be a learning rate of 0.0667, max depth of trees at 8 and 453 n-estimators. The optimized model achieved equal precision, recall and F1 scores at 78%. The model had a higher precision for detecting locust outbreaks at 80% and a high average precision of 89% highlighting its ability to correctly identify locust infestation sites. It also had a higher area under the curve of 87.7%, indicating good discriminative power between the two classes.

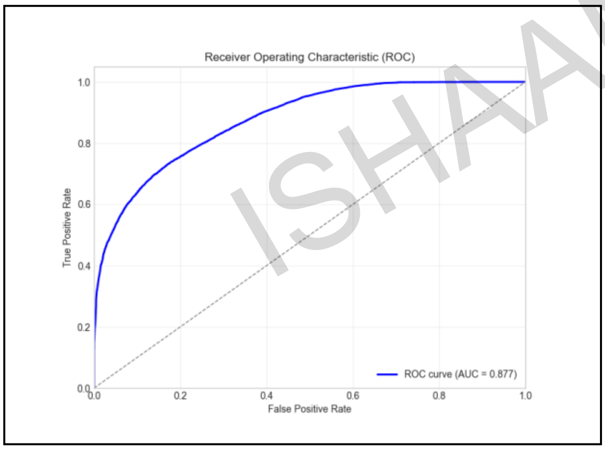

Fig. 5 ROC of XGBoost – much better than random predictions

It achieved a low Brier Score of 0.14 which is the mean squared error between the actual class and the predicted probability, indicating accurate probabilistic determinations

The model generated a broad range of probabilities for its prediction indicating that the model can be effectively harnessed as a collaborative tool as it is communicative to scientists to the level of its own confidence.

The feature importance obtained from the model support literature review since variables like vapor density, soil moisture, Palmer Drought Severity Index are highly weighted.

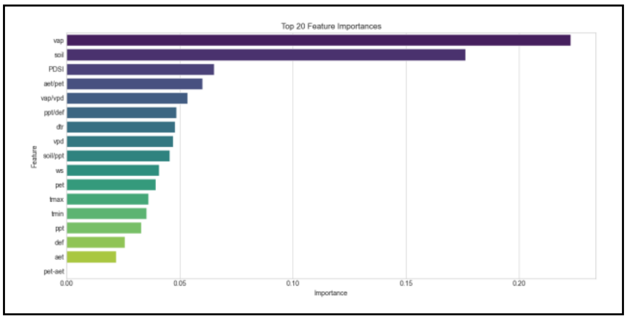

Fig. 6 Features most important to the Model

C. *Future Threat to India*

The model pipeline worked successfully as the threat levels of locust swarm were communicated visually through maps. The impacts of climate change are being simulated under multiple possible shared socio-economic pathways. The most optimistic climate pathways is SSP1 which assumes a gradual sustainable transition [31]. However, some researchers including [32] consider the SSP as too optimistic given trends towards conflicts and the enduring resilience of the fossil fuel sector. Estimates suggest that the SSP 2-4.5 are most realistic, these models project warming by 2.5°C to 3°C by 2100.

To validate the capacity of the predictive pipeline climatic data simulating the year 2015 under a +2°C future which under SSP2-4.5 is likely to be breached in the mid-2050s is tested.

India traditionally is not an active locust hotspot region, as it largely lies in the recession zone with only sporadic locust activity once every 8 years due to external locust migration [33]. However, in these predictions the Thar Desert Region, in Rajasthan, has become a major hotspot for locust infestations. The model also predicts more states in India to becoming suitable for locusts infestations including Punjab, Haryana, Madhya Pradesh Maharashtra and Gujarat. These predictions are supported by empirical observations as during the 2019-2021 locust plague, these states were also affected [34]. Additional vulnerabilities are highlighted in South and Eastern India in the states of Odisha, West Bengal, Tamil Nadu and Andhra Pradesh. This may be due to the fact that climate change is anticipated to increase the scale and frequency of tropical cyclones in these regions [14]. Literature has suggested that tropical cyclones promote favorable conditions by increasing air moisture and temperatures [35]. The expansion of locust infestations in India aligns with literature.

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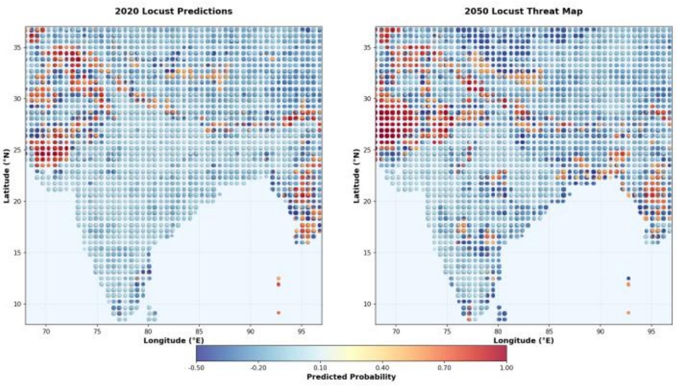

Fig. 7 Comparative Threat Assessment of India in the present and in the 2050s considering a +2ºC climate pathway

V. Conclusion

This model is geographically restricted to the Indian sub-continent – similar models can be developed for other geographical regions including MENA and Latin America recognizing the biological differences in these regions due to which locust infestations are correlated with different climatic relationships. The pipeline described in this paper can be scaled globally, as the UNFAO and national governments affected by locusts collect these datapoints.

While developing the model there were constraints on compute resources and data. Hence the accuracy currently achieved by the model – 78% is a baseline which will keep improving with the addition of more data. Most affected governments conduct regular surveys which yield both negative and positive results hence a government can leverage the pipeline developed in this paper to continuously add data to the model improving its performance for their specific geographic context.

The future projections data can also be leveraged from different sources. For instance, the Copernicus Climate Change Service which provides climatic data based off the SSPs till 2100 through the globally standardized Coupled Model Intercomparison Project. Hence governments can realistically evaluate the impacts of climate change on the critical agricultural sector.

This model can shape up national pest mitigation policies. With long-term warnings governments can take preventive steps through biological or mechanical means to prevent swarm formation rather than resorting to chemical pesticides. An edge device can also be developed to collect soil moisture and other environmental data while locust surveys are being collected. Governments can leverage existing communication channels like SMS to disseminate the model's insights among stakeholders like farmers and environmentalists.

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