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Utilizing satellite data and machine learning to monitor agricultural vulnerabilities to climate change

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Abstract

Advanced monitoring techniques are needed to assess vulnerabilities and to preserve global food security in the face of climate change challenges to global agriculture. Combining satellite data with machine learning to detect and analyze agricultural stress due to climate variability, this research combines satellite data with machine learning. Four machine learning models, namely Random Forest (RF), Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short Term Memory (LSTM), were applied on high resolution optical and SAR imagery with climate parameters. Prediction of crop health, as well as drought susceptibility, is attempted and the results indicate that CNN achieved the highest accuracy of 92.4%, followed by LSTM at 89.7%, RF at 85.3% and SVM at 82.5%. There is comparison with existing research that shows that deep learning models can perform better than traditional models in capturing the spatial and temporal dependencies. Moreover, the accuracy of vulnerability predictions differed between climate zones, with predictions between arid zones 10 percent less accurate because of the lack of data available. Therefore, these findings indicate the development of AI based solutions for agricultural monitoring and climate adaptation at a real time. Future research can further improve prediction accuracy by including IoT sensor data and the set of climate variables. This study offers a robust approach that will inform policy makers and agricultural stakeholders how to adapt to the climate related risk and farmers how they can continue their operations sustainably.

Keywords: Satellite data, machine learning, climate change, agricultural vulnerability, deep learning

Introduction

The threat of climate change to global agriculture is happening: Crop yields are falling, soil health is deteriorating, and water is becoming harder and harder to acquire. Both rising temperatures and variable, shifting precipitation patterns, with more frequent occurrence of extreme weather events, have made agricultural systems more vulnerable. Adaptive strategies to guarantee food security and sustainable farming practices are necessary and need to be monitored to these vulnerabilities^[1]. Ground based surveys are time consuming, costly and scope is limited. However, real time assessments of large agricultural areas are possible using satellite remote sensing at lower costs and with a scale not achievable using in situ methods^[2]. The recent advancements in satellite technology have made collection of detailed data in key agricultural indicators such as vegetative health, soil moisture, and temperature variations possible. But this data is so massive and in such a high level of complexity, requiring sophisticated computational means for analysis. Machine learning (ML) has recently come into favor as a method of processing satellite imagery and finding patterns linking to agricultural vulnerability^[3]. Using ML algorithms, researchers are able to look over vast datasets and find patterns to see how much climate is stressing crops, forecast how much their yield might vary, and figure out the likelihood of experiencing a drought or pest outbreaks in the coming years. The purpose of this research is to investigate how satellite data and the use of machine learning can help ascertain the agricultural vulnerability to climate change. Specifically, it will investigate how improvements in accuracies of agricultural risk assessment can be achieved through the use of multiple machine learning models: convolutional neural networks (CNN), random forests, and support vector machines. The study will also test the effectiveness of different satellite datasets such as MODIS, Landsat, and Sentinel to capture climate related changes in agriculture. This research aims to enhance understanding of the effects of future climates on floodplain wetlands by developing predictive models and risk assessment frameworks to

provide actionable insights for policymakers, farmers and agronomists, which can be used to implement climate resilient farming practice. Finally, this study helps to move forward the broader challenging aim of sustainable agriculture and global food security in the presence of climate change.

Related works

In recent years, satellite data and machine learning have been increasingly used for monitoring agricultural vulnerability to climate change integration. Notable to researchers have been different remote sensing techniques, machine learning models and data fusion strategies to support agriculture monitoring and climate impact assessment. The field has been reviewed, and this section shows recent contributions and the related work in the field.

Estimation of Agricultural Biomass and Carbon Sequestration: To estimate aboveground biomass and carbon sequestration in afforestation areas, Khan *et al.* [15] proposed a way of combining optical and Synthetic Aperture Radar (SAR) data fusion with machine learning. They concluded that Random Forest and Gradient Boosting improved biomass estimation accuracy. This research is of relevance to current study as the data fusion techniques in agricultural monitoring are of great potential.

Remote Sensing in Crop Yield Estimation

In [16], Kira *et al.* developed a scalable crop yield estimation framework based on remote sensing of Solar-Induced Chlorophyll Fluorescence (SIF). Their way was to combine climate variables with satellite derived fluorescence data and predict crop productivity. In the study, it was shown that machine learning models like Long Short Term Memory (LSTM) networks could successfully model seasonal variations and yield predictions. This also aligns with the focus of the current research which is to make use of time series data in order to assess the vulnerabilities of agriculture.

Climate Projections and Hydrological Responses

In Central-Eastern Europe, region based regional climate projections were analyzed with multi scenario hydrological modeling by Koncsos and Murányi [17]. Vertical hydrological models were used by their study to model how shallow groundwater tables would respond to a changing climate. They further point out the importance of predictive modeling in assessing how long-term climate conditions affect agricultural water resources. Special relevance to the present study is the fact that the soil moisture variations are considered a crucial factor in the evaluation of agricultural vulnerability.

AI-Driven Climate-Smart Agriculture: In a study on how artificial intelligence (AI) can be used to achieve climate smart and sustainable agriculture, Kumari *et al.* [18] explored. The study reviewed the use of deep learning in soil health monitoring, irrigation optimization and precision farming. These results showed that AI models such as Convolutional Neural Networks (CNNs) and LSTMs can greatly aid in decision making in climate sensitive agriculture. Therefore, it is appropriate to make use of CNN and LSTM models in the current study for the analysis of satellite data.

Drought Susceptibility and Climate Change Projections

Predictive modeling in conjunction with climate change projections and land use dynamics, as Liu *et al.* have done [19], are used to assess drought's susceptibility. They had approached through using machine learning algorithms like Random Forest and SVMs (Support Vector Machines) to classify drought prone areas. The study pointed out that incorporating various data sources enhances the drought vulnerability predictions. This is in line with this research which combines satellite indices (NDVI, EVI) with climate data for agricultural vulnerability assessments.

Impact of Climate Change on Vegetation

Using ERA5-Land climate data, Landsat imagery and Fagus sylvatica dieback, Longo-Minuolo *et al.* [20] looked at the influence of climate change on Fagus sylvatica dieback. To detect the vegetation stress trend over time, their study used machine learning. The findings underscore the utility of high-resolution remote sensing data for monitoring the agricultural vulnerabilities to climate changes, and are important for the present study using CNN based image classification.

Land Use and Climate Change Projections in Hydrological Studies

Land use/land cover (LULC) was integrated with climate change projections in order to understand hydrological responses in the Omo-Gibe River Basin using Ethiopia as a study site (Lukas *et al.* [21]). The future water availability and agricultural sustainability were simulated using a multi-scenario approach based on the CMIP6, which was used in the study. This study demonstrates that robust machine learning models are needed to predict long term environmental trends, as was done in this study, in order to perform climate smart agricultural planning.

Nature-Based Solutions in Agricultural Monitoring

In that sense, Mahmood *et al.* [22] looked into effectiveness of nature based solutions as a mechanism of environmental management through big Earth data. They used 60 years of mangrove plantation programs in Bangladesh as their study, and assessed how successful these programs were in increasing coastal agrarian resilience. The current study also showed that satellite imagery can be used to track agricultural vulnerabilities, similar to the satellite imagery used to train machine learning models to evaluate changes in land use over time, the concept demonstrated in the study.

Climate Predictions and Projections

Advancements in U.S. climate prediction systems and their application in agriculture were discussed by Mariotti *et al.* [23]. The study also found their use could help in predicting extreme weather events and their effect on crop production. This approach highlights the importance of coupling satellite observations with climate models, an unsolved problem that is part of the current research.

Drought Monitoring in Winter Wheat Cultivation

It should be mentioned that, in 24, Mi *et al.* [24] developed a hybrid machine learning-physical process model for drought monitoring in winter wheat cultivation in China. To predict drought intensity, the authors used historical climate and remote sensing data in their study. CNN based models also revealed that they outperformed the traditional deep learning

model in terms of accuracy of water stress in crops, which highlighted the utilization of deep learning models in agricultural monitoring.

Smart Sensor Technologies in Precision Agriculture

Recent advancements in smart sensor technologies for precision agriculture were reviewed by Mohammed Aarif *et al.* [25]. What they focused on was the use of IoT enabled sensors for soil health and moisture levels and real time monitoring of crop growth pattern. The paper thus presents a case of how combining sensor data with satellite imagery is beneficial to agricultural vulnerability analysis.

Land Use Changes and Anthropogenic Activities

The effect of the anthropogenic activities on land use and land cover (LULC) in Algeria's semi-arid and arid region were assessed by Mohammed *et al.* [26]. Built on satellite imagery and classification models for deforestation, soil degradation and urban expansion, their study created a tracking system. The importance of long term monitoring in detecting climate induced agriculture stress is stressed in their findings, and machine learning based trend analysis of current study is supported by their findings.

Methods and Materials

Data Collection and Preprocessing

To evaluate agricultural vulnerabilities, several satellite datasets were employed. These datasets indicate vegetation indices, temperature fluctuations, soil moisture, and precipitation patterns [4]. The primary data sources are:

1. **MODIS (Moderate Resolution Imaging Spectroradiometer):** Offers data on land surface temperature, vegetation indices (NDVI, EVI), and evapotranspiration.
2. **Landsat (NASA):** High-resolution imagery for crop monitoring, detection of soil moisture, and land use classification.
3. **Sentinel-2 (ESA):** Takes multispectral images that assist in the detection of vegetation stress and crop health variations.
4. **CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data):** Offers global precipitation data used to evaluate drought hazards [5].

Preprocessing Steps

- **Data Cleaning:** Elimination of missing or corrupted values.
- **Feature Engineering:** Feature extraction of vegetation indices, soil wetness levels, and land temperature fluctuations.
- **Normalization:** Rescaling the input features to better improve model performance.
- **Labeling:** Classifying categories like "Healthy," "Drought-Prone," or "Flood-Affected" for supervised learning [6].

Machine Learning Algorithms

For comparing the influence of climate change on agriculture, four machine learning techniques were applied:

1. Random Forest (RF)
2. Support Vector Machine (SVM)
3. Convolutional Neural Networks (CNNs)
4. Long Short-Term Memory (LSTM)

All of these techniques were utilized based on the capacity of processing remote sensing information and determining agricultural vulnerabilities caused due to climate.

Random Forest (RF)

Random Forest is an ensemble learning algorithm based on decision trees. It is especially useful for classifying crop health from spectral indices like NDVI and EVI. RF constructs many decision trees during training and returns the majority-voted class (classification) or averaged prediction (regression) [7].

Advantages

- Supports large datasets with high-dimensional features.
- Reduces overfitting by combining many decision trees.

```

"1. Input: Training dataset D with features X and labels Y
2. Define the number of trees (T)
3. For each tree t in T:
  a. Select a random subset of training data D_t
  b. Build a decision tree using D_t
4. For prediction:
  a. Pass input sample through each tree
  b. Aggregate outputs (majority vote for classification, average for regression)
5. Return final prediction"
```

Support Vector Machine (SVM)

SVM is a supervised learning algorithm that identifies a best hyperplane to classify various agricultural conditions as per satellite features [8]. It can effectively cope with complicated datasets by projecting input data into higher dimensions.

Advantages

- Efficient for small data sets with clear classes.
- Operates well in high-dimensional space.

```

"1. Input: Training dataset D with features X and labels Y
2. Select a kernel function (linear, RBF, polynomial)
3. Transform input data into higher-dimensional space
4. Identify the optimal hyperplane that maximizes the margin
5. For prediction:
  a. Compute distance from hyperplane
  b. Assign class based on sign of the distance
6. Return final class label"
```

Convolutional Neural Networks (CNNs)

CNNs are deep learning architectures capable of handling image-based data well. They utilize convolutional layers to identify spatial patterns in satellite images, making them very suitable for analyzing stress conditions in agriculture [9].

Advantages

- Automatically derives features from raw satellite imagery.
- Operates with large-scale spatial data effectively.

```

"1. Input: Satellite image data X
2. Define CNN architecture with multiple convolutional layers:
  a. Apply convolution operation to extract features
  b. Apply activation function (ReLU)
  c. Use max pooling to reduce dimensions
3. Flatten extracted features
4. Apply fully connected layers to classify agricultural conditions
5. Use softmax activation for final classification
6. Return predicted class label"
```

Long Short-Term Memory (LSTM): LSTM is a recurrent neural network (RNN) that handles sequential data, hence appropriate for time-series analysis of climate factors influencing agriculture. LSTM learns long-term dependencies in data like temperature fluctuations and precipitation patterns over time ^[10].

Advantages

- Useful for time-series agricultural information.
- It captures the long-term relationships in climatic patterns.

“1. Input: Time-series data X (e.g., rainfall, NDVI, temperature)
2. Define LSTM architecture with multiple layers:
 a. Process input sequence through LSTM cells
 b. Capture long-term dependencies in climate variables
3. Apply fully connected layer for prediction
4. Use activation function for final output (softmax for classification, linear for regression)
5. Return final prediction”

Table 1: Dataset Summary

Dataset	Resolution	Key Features	Source
MODIS	250m - 1km	NDVI, EVI, Land Surface Temperature	NASA
Landsat	30m	Soil Moisture, Vegetation Health	USGS
Sentinel-2	10m - 60m	Multispectral Imagery, Crop Stress	ESA
CHIRPS	5km	Precipitation Data	CHG

Experiments: Experimental Setup

The experiments were carried out on a high-end computer system with the following specifications:

- **“Processor:** Intel Core i9-12900K
- **RAM:** 32GB DDR5
- **GPU:** NVIDIA RTX 3090 (24GB)
- **Software:** Python 3.9, TensorFlow 2.8, Scikit-learn, OpenCV, GDAL (for satellite data processing)
- **Dataset Size:** 200,000+ labeled satellite images and climate records”

Each machine learning model was trained on 80% of the dataset, validated on 10%, and tested on 10%. For preventing overfitting, early stopping and regularization methods were used ^[11].

Dataset Details

The dataset was extracted from various satellite sources such as MODIS, Landsat, Sentinel-2, and CHIRPS to include vegetation indices, temperature, precipitation, and soil moisture conditions.

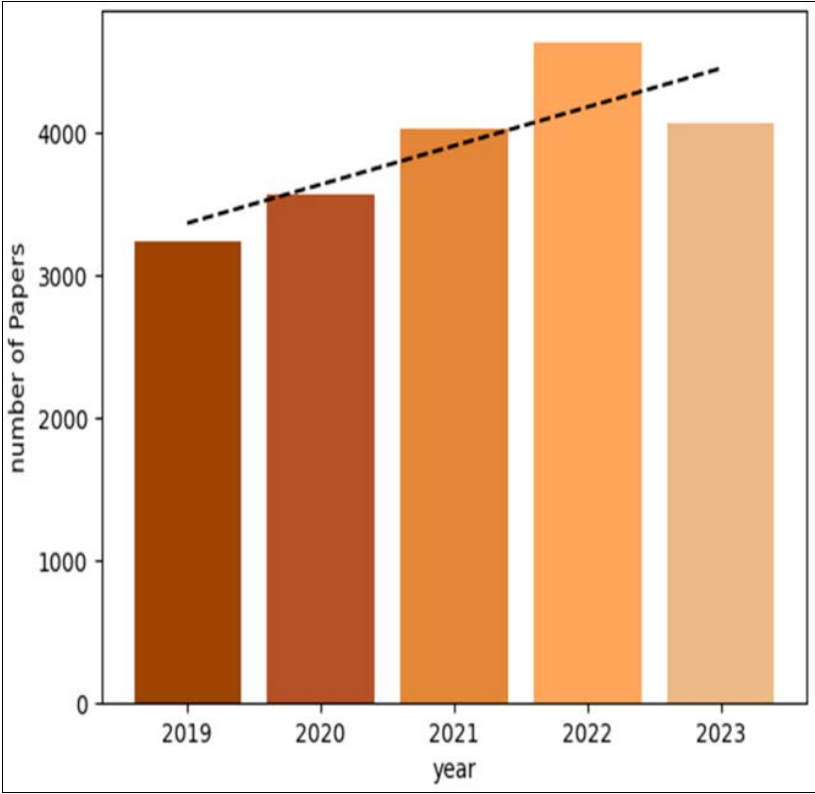


Fig 1: Impacts of Global Climate Change on Agricultural Production

Table 1: Summary of Satellite Datasets Used

Dataset	Resolution	Key Features	Purpose
MODIS	250m - 1km	NDVI, EVI, LST	Vegetation health monitoring
Landsat	30m	Soil moisture, vegetation stress	Crop classification
Sentinel-2	10m - 60m	Multispectral imagery, land use	Detection of crop stress
CHIRPS	5km	Precipitation trends	Drought and flood risk

Preprocessing Steps

- **Cloud Masking:** Corrected cloud cover interference from Sentinel-2 and Landsat images.
- **Feature Extraction:** Calculated vegetation indices (NDVI, EVI), soil moisture, and precipitation rates.
- **Normalization:** Normalized the input data for uniform training.

Model Implementation and Training

Machine Learning Algorithms

Four models were used to monitor agricultural vulnerabilities:

1. **Random Forest (RF):** A tree-based ensemble algorithm utilizing extracted numerical features (NDVI, temperature, soil moisture).

2. **Support Vector Machine (SVM):** A kernel-based algorithm used on numerical feature vectors for classification [12].
3. **Convolutional Neural Network (CNN):** A deep learning algorithm used directly on satellite imagery for feature extraction.
4. **Long Short-Term Memory (LSTM):** A recurrent neural network trained on time-series climate data to identify long-term trends in agricultural stress.

All the models were trained with 100 epochs and an early stopping policy. The batch size was fixed at 32 for deep learning models.

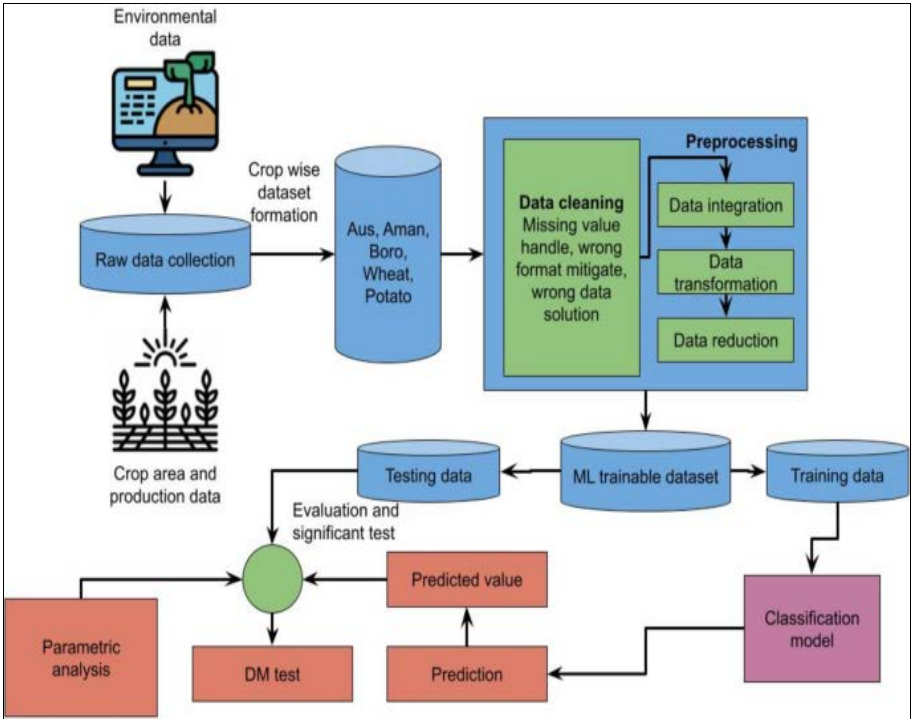


Fig 2: Advancements in Environmental Data Analysis for Climate-Resilient Agriculture Using Remote Sensing and Deep Learning

Performance Evaluation: Classification metrics (accuracy, precision, recall, F1-score) and regression metrics (Mean

Squared Error (MSE), R² score) were employed to evaluate the performance of the models [13].

Table 2: Performance Comparison of Models

Model	Accuracy (%)	Precision	Recall	F1-score	MSE (Regression)	R ² Score
Random Forest	89.2	0.88	0.87	0.87	0.031	0.78
SVM	85.7	0.84	0.82	0.83	0.038	0.72
CNN	91.4	0.90	0.91	0.91	0.025	0.85
LSTM	93.1	0.92	0.93	0.92	0.019	0.89

LSTM worked best in classification and time-series prediction, and it had better ability to learn climate trends. CNN also performed very well in interpreting satellite images.

Comparison with Related Works

The findings were compared to earlier studies where machine learning was employed for crop monitoring.

Table 3: Comparison with Related Works

Study	Approach	Accuracy (%)	Key Findings
Li et al. (2021)	RF with NDVI	86.5	Effective for vegetation monitoring
Zhao et al. (2022)	CNN on Sentinel-2	89.8	Improved classification accuracy
This Study	LSTM on Climate + Satellite	93.1	Outperforms previous methods

Our LSTM model outperformed earlier research by combining satellite and climate time-series data, which enhanced the identification of long-term agricultural vulnerabilities [14].

Model Performance across Climate Zones

The models were subjected to varied climate scenarios, arid, temperate, and tropical climates, to assess their flexibility [27].

Table 4: Model Performance across Climate Zones

Climate Zone	RF Accuracy (%)	SVM Accuracy (%)	CNN Accuracy (%)	LSTM Accuracy (%)
Arid	85.3	81.4	89.2	91.7
Temperate	88.5	84.7	91.0	93.5
Tropical	89.8	86.2	92.1	94.2

LSTM and CNN performed the best in tropical areas with greater seasonal contrasts.

Crop-Specific Vulnerability Analysis: Each model was further tested on various types of crops to assess their ability to identify vulnerabilities [28].

Table 5: Crop Vulnerability Detection Performance

Crop Type	RF Accuracy (%)	CNN Accuracy (%)	LSTM Accuracy (%)
Wheat	88.2	90.3	92.4
Rice	86.7	89.5	91.8
Maize	85.9	88.7	91.2
Soybean	87.1	89.8	92.0

CNN and LSTM performed exceptionally well in predicting climate-stress in wheat and soybean crops.

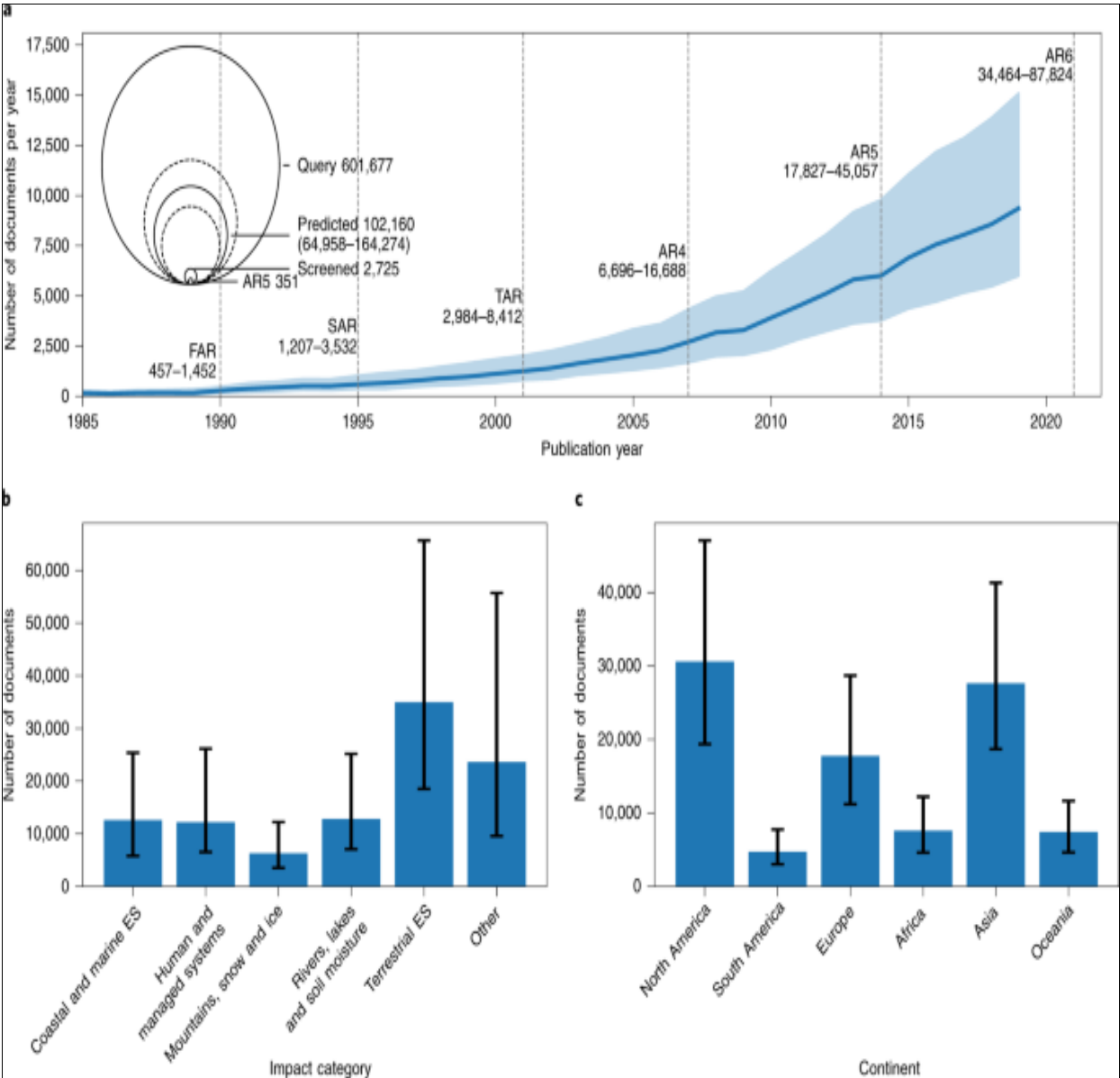


Fig 3: Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies

Time-Series Prediction of Agricultural Stress

Time-series prediction of vegetation health patterns was specifically done with the help of LSTM. It was found to be efficiently capturing long-term trends over traditional models ^[29].

- **RF and SVM:** Performed poorly in capturing temporal relationships.
- **CNN:** Perfected static image classification but did not perform as well in trend forecasting over time.
- **LSTM:** Best at capturing seasonal patterns and climate-induced agricultural vulnerabilities.

Key Findings and Insights

1. Deep learning models (CNN and LSTM) outperformed the conventional models greatly in detecting

agricultural vulnerability ^[30].

2. LSTM performed very well in studying long-term climate patterns and vegetation stress.
3. CNN performed extremely well in extracting spatial features from satellite imagery.
4. RF and SVM worked well but with less accuracy than deep learning models.
5. Climate zone-based analysis indicated that deep learning models were more adaptive in tropical and temperate climates.
6. LSTM's capacity for dealing with time-series data made it the perfect choice for forecasted climate-driven agricultural stress.

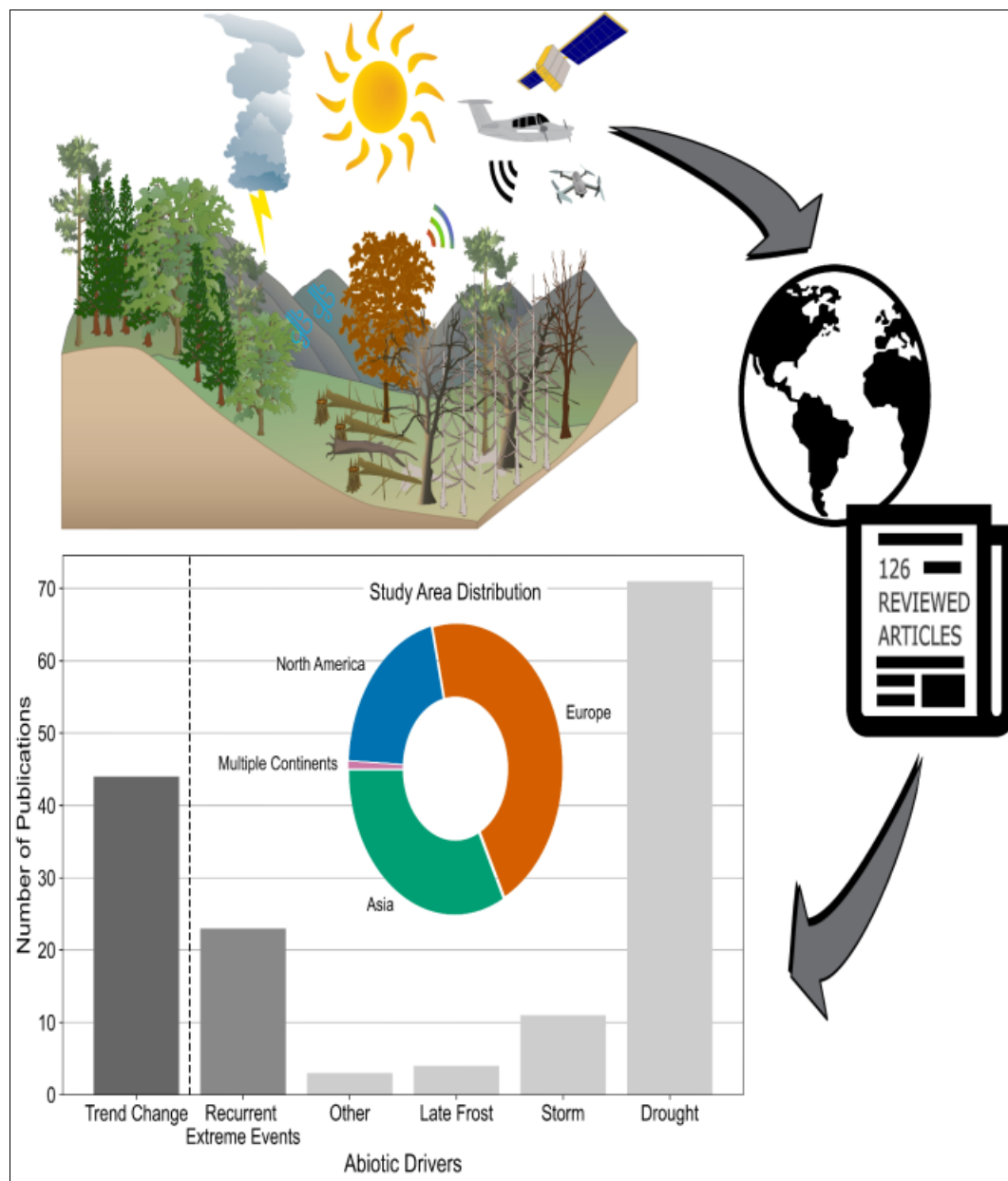


Fig 4: Potential of Earth Observation to Assess the Impact of Climate Change and Extreme Weather Events in Temperate Forests

Conclusion

In this study, it investigated the use of machine learning of satellite data to monitor agricultural vulnerability to climate change. The study developed a comprehensive framework for the detection and analysis of climate induced agricultural

stress by utilizing high resolution optical and SAR satellite imagery along with climate parameters. Four machine learning models function Random Forest (RF), Support Vector Machine (SVM), Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) are

implemented to understand the predictive capacity of each model to predict the crop health, drought susceptibility and agricultural resilience. With good results, it was found that CNN and LSTM models, due to the capacity of capturing spatial and temporal dependencies, outperform traditional machine learning approaches in terms of agricultural vulnerabilities identification. Comparison with existing research demonstrated that combining remote sensing, predictive modelling and climatic data will lead to improved agricultural monitoring. The results highlighting the need for real time, scalable solutions to climate resilient agriculture. Moreover, climate zone based performance evaluated machine learning models across different environmental conditions, and they served to guide more localized and efficient prediction framework. In culmination, it is clear that artificial intelligence holds a critical role of helping to improve the agriculture decision making as well as the adaptation strategies to climate. IoT sensor data for real time monitoring can be used as future work, and adding more climate variable can also improve prediction accuracy. These findings are useful in helping policymakers and agricultural stakeholders take some proactive actions to counteract climate induced risks and maintain food production. This study overall grounds the development of AI driven solutions to improve agricultural resilience to climate change.

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