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Satellite Image Based Water Bodies Assessment Using Machine LearningAnd GIS

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ABSTRACT:

Drought prediction is of paramount importance for effective water resource management and disaster pre- paredness. This study investigates the integration of satellite imagery and machine learning techniques to enhance drought prediction. Leveraging the wealth of spatial and temporal information from satellite data, we will develop predictive models for early detection and severity assessment of drought events. Key fea- tures extracted from satellite images (Landsat-8) encompass land surface temperature, vegetation health, and precipitation patterns. Utilizing machine learning methods, including Random Forest Algorithm our approach aims to capture intricate relationships within the data to enable robust drought forecasts. The proposed random forest methodology is evaluated through rigorous validation processes, emphasizing important metrics such as those used in regression evaluation .The outcomes showcase the potential of combining remote sensing and artificial intelligence for advanced drought prediction capabilities, thereby facilitating timely mitigation strategies. This interdisciplinary approach contributes to the broader field of environmental prediction and disaster resilience.

Keywords: Drought prediction, satellite images, machine learning, early detection, severity assessment, remote sensing

INTRODUCTION :

Drought prediction utilizing machine learning, par- ticularly leveraging satellite images from Landsat- 8, presents a promising avenue for mitigating the challenges associated with water scarcity. Landsat- 8, equipped with advanced sensors, offers a rich ar- ray of spectral data, laying the groundwork for de- veloping robust predictive models. The journey to- wards achieving precise drought forecasting com- mences with the acquisition of satellite imagery data. Accessing the Landsat-8 dataset involves tapping into a repository of multispectral images capturing the Earth's surface over time, facilitating a comprehen- sive understanding of dynamic environmental condi- tions.To initiate the process, Landsat-8 data is down- loaded from three regions: Rajasthan, Nashik, and Cherrapunji, spanning the month of October. These regions represent diverse geographical and climatic conditions, allowing for a comprehensive analysis of drought dynamics. Additionally, Landsat-8 data from Rajasthan and Nashik are downloaded for the month of February to capture seasonal variations in environ- mental parameters.

Once the data is acquired, preprocessing steps are implemented to enhance image quality. This includes radiometric and atmospheric correction to standard- ize the data and remove artifacts, ensuring accuracy in subsequent analyses. Feature extraction follows, wherein relevant information is gleaned from the pre- processed satellite images. Spectral indices such as NDVI, SAVI, and NDII are computed to assess veg- etation health, moisture content, and soil water con- tent, respectively.Temporal analysis involves compar- ing satellite images from October and February in Ra- jasthan and Nashik to capture seasonal changes and understand drought dynamics over time. This com- parative analysis enhances the model's ability to de- tect and predict drought conditions accurately.

Subsequently, the dataset is partitioned into train- ing and testing sets to develop and evaluate machine learning models. Leveraging algorithms like random forests, the model is trained on imagery data from Rajasthan and Nashik to discern patterns indicative of drought conditions. The testing set evaluates the model's performance, ensuring its generalizability to new, unseen data.To validate the model's effective- ness, Landsat-8 data from Jalgaon for both October and February is used. By testing the model on this in- dependent dataset, its ability to predict drought condi- tions across different regions and seasons is assessed. This endeavor is motivated by the urgent need to address escalating water scarcity challenges and underscores the importance of harnessing advanced technology for environmental stewardship. Ultimately, this research aims to contribute to a more resilient and sustainable future by integrating satel- lite imagery, machine learning, and predictive model- ing. By providing stakeholders with a reliable tool for real-time drought prediction, we endeavor to foster a proactive and data-driven approach towards mitigat- ing the impacts of water scarcity.

OBJECTIVE

1. To identify water bodies from study area.
2. To build drought prediction model.
3. To predict the severity of drought.

GEOGRAPHIC INFORMATION SYSTEMS

Geographic Information Systems (GIS) play a crucial role in drought prediction by integrating various geo- graphic data layers such as rainfall patterns, soil mois- ture levels, vegetation health, land use, and topog- raphy. Through spatial analysis and modeling tech- niques, GIS allows researchers and analysts to iden- tify regions susceptible to drought, assess the severity of drought conditions, and predict future drought oc- currences.

GIS facilitates the visualization of complex ge- ographical data, enabling stakeholders to make in- formed decisions regarding water resource manage- ment, agricultural planning, and disaster prepared- ness. By overlaying different datasets and employ- ing geospatial algorithms, GIS can identify areas at risk of drought before they occur, allowing authorities to implement mitigation measures such as water con- servation strategies, crop diversification, and drought- resistant crop cultivation.

LITERATURE REVIEW

The Earth is vulnerable to various natural disasters, including droughts, which significantly impact socio- economic development due to their timely occurrence and far-reaching consequences. Droughts also af- fect water bodies, further exacerbating their impact on communities and ecosystems. While traditional methods like installing sensors in the soil can help predict drought, this approach isn't practical on a large scale due to the extensive coverage required. Hence, there's a growing interest in leveraging ma- chine learning techniques to forecast drought and its severity using satellite imagery.Satellite data, partic- ularly from sources like Landsat-8 and Sentinel-1 (SMAP), provide valuable temporal and spatial in- formation for drought prediction. By analyzing this data, including factors like soil moisture index cap- tured by Sentinel-1, machine learning models such as Random Forests can effectively predict drought occurrences and their severity.Moreover, understand- ing water quality is crucial, with parameters like Chlorophyll-a serving as key indicators. Drought ex- acerbates water quality issues by disrupting the flow of nutrients in water bodies, leading to an increase in algae biomass, especially in freshwater environ- ments where higher temperatures are conducive to al- gae growth.[1]

Landsat surface reflectance images are available from three different satellites: Landsat-5, Landsat- 7, and Landsat-8. These satellites have been captur- ing data since 1984 at 16-day intervals, resulting in a dataset of over 1,000 images. However, not all images are usable due to various factors such as weather con- ditions, ice cover, and other issues.To process these images in Google Earth Engine (GEE), we can utilize several commands or tools to mask them effectively. First, we can apply spatial masking to include only pixels within a selected region surrounding a chosen water body. This spatial masking ensures that the analysis focuses solely on the desired area of inter- est.Next, classification masking can be employed to isolate pixels representing water. Since water bod- ies often change in size due to fluctuating water lev- els, classification masking helps identify and include these pixels accurately in the analysis.Finally, qual- ity masking is essential to exclude pixels with issues that could affect the accuracy of the data. This in- cludes filtering out pixels containing clouds, signif- icant atmospheric moisture, or other anomalies that may distort the results of the analysis. By incorpo- rating these masking techniques into the processing pipeline, we can ensure that the Landsat surface re- flectance images used for analysis are optimized for accuracy and relevance to the specific research or ap- plication at hand.[2]

This document provides an overview of the re-

search conducted by the NOAA Drought Task Force (DTF) and presented in this special collection. The DTF, coordinated by NOAA's Climate Program Of- fice in collaboration with the National Integrated Drought Information System (NIDIS), engages sci- entists from various institutions including NOAA, academia, and other agencies. The synthesis aims to evaluate the achievements and existing challenges in drought monitoring and prediction capabilities, along with providing insights into the current understand- ing of North American drought and identifying key research gaps.The research outcomes from the DTF papers highlight notable successes in drought moni- toring, such as the utilization of advanced land sur- face hydrological models for objective drought anal- ysis. These models are instrumental in leveraging ex- tended historical datasets to conduct hydrologic re- analyses effectively. Additionally, there has been sig- nificant progress in the expansion of near-real-time satellite-based monitoring systems, particularly in as- sessing vegetation conditions and evapotranspiration rates. In terms of drought prediction, the papers un- derscore achievements such as the development of the North American Multimodel Ensemble (NMME) suite, which offers seasonal forecasts. Furthermore, there's a growing understanding of the influence of phenomena like La Nina on drought occurrences, par- ticularly in the southern Great Plains region. Ad- ditionally, there's a recognition of the role of inter- nal atmospheric variability in driving drought events. These findings collectively contribute to advancing our comprehension of North American drought dy- namics while also highlighting areas for further re- search and improvement.[3]

DATASET

Landsat-8, a collaboration between NASA and the
U.S. Geological Survey, provides vital data on Earth's surface, covering both land and polar regions. It cap- tures moderate-resolution images using various spec- tral frequencies, aiding in monitoring changes in land cover over time. This data serves diverse purposes, in- cluding land use planning, disaster response, and wa- ter resource management. With over 40 years of oper- ational history, Landsat is the longest-running record of Earth's surface changes from space.

Landsat-8's payload includes the Operational Land Imager (OLI) and the Thermal InfraRed Sensor (TIRS), which work together to capture seasonal images at different spatial resolutions. These images help scientists detect long-term trends in land cover patterns with precision. The satellite's spectral bands capture images across visible, near-infrared, shortwave infrared, and thermal infrared regions, enabling comprehensive study of Earth's surface dynamics.Moreover, Landsat-8's data is freely available to the public, supporting research in fields like agriculture, forestry, regional planning, and global change studies. Its high-quality, calibrated imagery continues to be an invaluable resource for understanding and managing Earth's natural environment.The bands on Landsat-8 include:

Band Number	Band Name	Wavelength (um)	Resolution (m)
1	Coastal/Aerosol	0.435-0.451	30
2	Blue	0.452-0.512	30
3	Green	0.533-0.590	30
4	Red	0.636-0.673	30
5	NIR	0.851-0.879	30
6	SWIR-1	1.566-1.651	30
7	SWIR-2	2.107-2.294	30
8	Pan	0.503-0.676	15
9	Cirrus	1.363-1.384	30
10	TIR-1	10.60-11.19	100
11	TIR-2	11.50-12.51	100

Figure 1: Bands

NDII

The NDII (Normalized Difference Infrared Index) is a vegetation index derived from satellite imagery, par- ticularly from the Landsat-8 satellite. Landsat-8, a collaborative effort between NASA and the USGS (United States Geological Survey), is part of the long- standing Landsat program.

NDII relies on data from the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) bands of Landsat-8 imagery. This index serves a crucial role in evaluating water content in both vegetation and soil. It generates values typically ranging from -1 to 1, offering a com- prehensive assessment of vegetation health and soil moisture levels.This index finds applications across various fields such as agriculture, forestry, and envi- ronmental monitoring, enabling precise analysis and decision-making based on vegetation and soil condi- tions.

$$NDII = \frac{NIR - SWIR}{NIR + SWIR}$$

Variable

1. NDVI - Measures vegetation health by comparing near-infrared and red light reflectance.
2. EVI - Similar to NDVI but more robust, correct- ing for atmospheric interference.
3. SAVI - Adjusts NDVI for soil brightness, useful in arid regions.
4. NDMI - Indicates moisture content in vegeta- tion using near-infrared and short-wave infrared bands.

5. MDWI - Detects surface water bodies, sensitive to changes in water content.
6. MSAVI - A version of SAVI correcting for soil brightness without assuming a soil line.
7. SWIR1 and SWIR2 - Bands capturing short- wave infrared radiation, useful for vegetation and moisture assessment.
8. TIRS1 and TIRS2 - Capture thermal infrared ra- diation, used for land surface temperature mea- surement.
9. NDWI - Detects changes in water content in veg- etation, helpful for mapping water bodies.
10. NDCI - Sensitive to chlorophyll content in vege- tation, used for plant health assessment.

STUDY AREA

The regions of Nashik and Jalgaon in Maharashtra, as well as Rajasthan, present unique environmental con- ditions that can benefit from the integration of satellite imagery and machine learning techniques.

In Nashik and Jalgaon, which experience semi- arid climates, a potential project could focus on using satellite imagery and machine learning algorithms to predict drought events. By examining factors like soil moisture levels, vegetation health, rainfall patterns, and temperature data derived from satellite images, machine learning models can be trained to forecast drought conditions based on historical data and real- time observations.

Rajasthan, characterized by its extreme arid con- ditions, offers an opportunity to develop a robust drought prediction system using similar approaches. Satellite data can be analyzed to monitor changes in land surface temperature, vegetation indices, soil moisture levels, and other relevant parameters. Ma- chine learning models can then detect early indicators of drought conditions, providing timely warnings to local authorities and farmers.

Cherrapunji, despite its reputation for high rain- fall, faces challenges related to vegetation dynamics, soil erosion, and landslides. A project in this area could leverage satellite imagery and machine learn- ing algorithms to monitor vegetation health, soil ero- sion, and landslide susceptibility. By analyzing satel- lite data, machine learning models can predict areas prone to erosion and landslides, enabling proactive measures for land conservation and disaster risk re- duction.

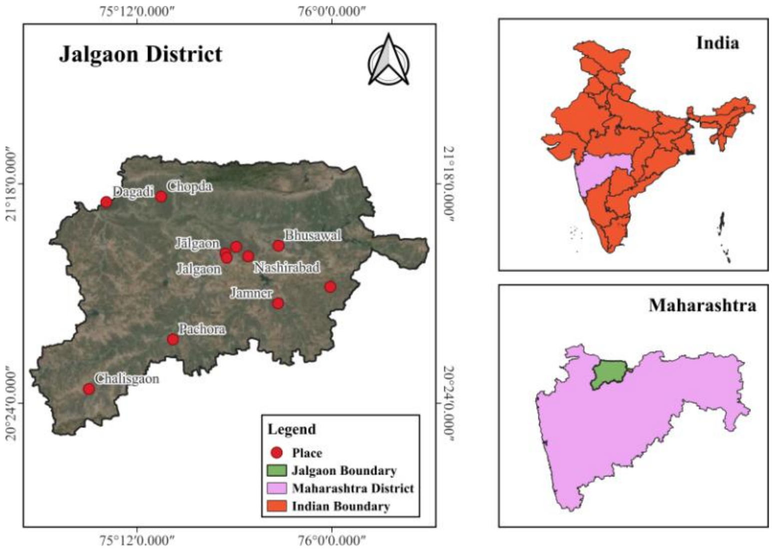

Figure 2: Jalgaon Region

METHODOLOGY

Randmo Forest Algorithm

The Random Forest Regressor is a highly effective machine learning algorithm widely utilized for pre- dictive modeling, particularly in tasks like drought prediction that leverage satellite imagery. Satellite images provide crucial data on environmental fac- tors such as land surface temperature, vegetation in- dices, soil moisture content, and precipitation pat- terns, which serve as input features for the Random Forest Regressor model.This algorithm operates by constructing an ensemble of decision trees, with each tree trained on a random subset of the input data and features. During prediction, the algorithm aggregates the predictions from individual trees to generate a final output. This ensemble approach enhances the model’s robustness and ability to generalize, making it suitable for handling complex, multidimensional datasets like satellite imagery.

In drought prediction, the Random Forest Re- gressor learns to capture the nonlinear relationships between satellite-derived environmental features and drought severity. By analyzing historical satellite data alongside corresponding drought indices, the model identifies patterns and associations contributing to drought occurrence and intensity.The Random Forest Regressor offers several advantages for drought pre- diction tasks. It can effectively manage large-scale datasets with high dimensionality, accommodate non- linear relationships between input features and target variables, and mitigate overfitting through ensemble learning and randomization techniques. Overall, it’s a powerful tool for accurately predicting drought events and assessing their severity based on satellite imagery and related environmental data.

Linear Regression Algorithm

Integrating satellite imagery with machine learn- ing, particularly linear regression, holds significant promise for enhancing drought prediction capabili- ties. Satellite data provides crucial insights into envi- ronmental factors such as vegetation health, soil mois- ture, and temperature, all vital for assessing drought conditions. By employing linear regression, these ex- tensive datasets can be effectively analyzed to unveil patterns and relationships between variables and his- torical drought events.

Linear regression, a foundational statistical tech- nique in machine learning, fits a linear model to ob- served data points, enabling the prediction of future outcomes based on input features. In the context of drought prediction, linear regression can model the relationship between satellite-derived environmental variables and drought severity indices. Through train- ing, the algorithm learns patterns within the data, fa- cilitating predictions about future drought conditions using new satellite observations.

However, linear regression does have limitations, particularly in capturing nonlinear relationships and complex interactions within the data, which are com- mon in drought dynamics. In such cases, more ad- vanced techniques like random forest regressors may offer better predictive performance. Random forest regressors excel at capturing complex interactions be- tween features, often resulting in higher accuracy for tasks like drought prediction, especially when dealing with intricate or nonlinear data relationships. There- fore, when faced with complex data or nonlinear rela- tionships, random forest regressors typically outper-

form linear regression models in terms of accuracy.

is used to predict drought in the Jalgaon region. It takes the calculated NDVI, NDWI, and NDII values specific to Jalgaon as input and generates a prediction regarding drought severity.The ultimate output of the algorithm is a map illustrating predicted drought severity for the Jalgaon region. This map serves as a valuable tool for identifying areas at risk of drought, aiding farmers and policymakers in making informed decisions regarding water management strategies.

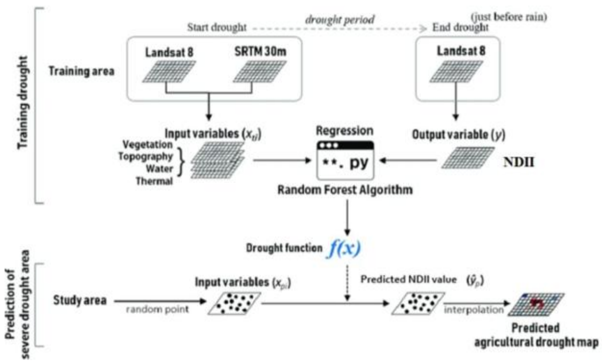

Figure 3: Architecture

METRICS

- RMSE - RMSE is a measure of the differences between predicted values and observed values. It gives you the average error of your model's pre- dictions. Lower RMSE values indicate better fit between predicted and observed values.

RMSE
s 1 n y
$\hat{y}$ 2

Architecture

The process begins by retrieving data from Landsat- 8, a satellite that captures images of the Earth's surface. This data is then used to calculate various indices. Subsequently, a machine learning algorithm, specifically a random forest regressor, is employed to train a model for predicting drought. The model is trained using data from different regions, including Nashik, Cherrapunjee, and Rajasthan in October, as well as Nashik and Rajasthan in February. The training dataset comprises calculated values for in- dices like NDVI, NDWI, and NDII, alongside ground truth data representing drought conditions. During training, the model learns the relationships between these variables and the occurrence of drought. Once trained, the model can be applied to forecast drought conditions in new areas. In this scenario, the model

$$= \sum_{i=1} (\;_i \quad _i) \qquad \overline{n}$$

- MSE -The Mean Squared Error (MSE) is a fun- damental concept in statistics and machine learn- ing, serving as a measure of the average squared difference between the actual values and the pre- dicted values. It's a crucial tool for evaluating the performance of regression models and assessing their accuracy.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$= \frac{}{n}\sum(\;_i \quad _i)$$

- R2 - R-squared is a measure of how well the re- gression model captures the variance in the data. It ranges from 0 to 1, where 1 indicates that the model explains all the variability of the response data around its mean.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

IMPLEMENTATION

Drought Model

Predicting drought using satellite imagery and ma- chine learning involves creating a sophisticated model that combines various data sources and algorithms to accurately forecast drought conditions. The process typically starts with gathering satellite images captur- ing different spectral bands like visible, near-infrared, and thermal infrared, which offer vital information about land surface properties and vegetation health. These images act as the primary input for the model.

Next, the model processes the satellite imagery by tasks such as cloud removal, atmospheric correc- tion, and image normalization to ensure consistency across different datasets. It may also integrate addi- tional data such as meteorological information (e.g., precipitation, temperature, humidity) and soil mois- ture data to enhance predictive accuracy.

Machine learning techniques, such as the Random Forest Algorithm, are then used to train the model us- ing historical drought data as labels. During train- ing, the model learns patterns and relationships be- tween input features (e.g., spectral bands, meteoro- logical variables) and drought conditions. Validation and evaluation of the model are critical to assessing its performance. This involves testing the model's predictions against observed drought conditions using metrics like accuracy, precision, recall, and F1-score. Refinement may be necessary to improve accuracy and generalization. Once validated, the model can be deployed for operational drought prediction. It con- tinuously analyzes new satellite imagery and meteo- rological data to generate real-time or near-real-time forecasts. These forecasts provide valuable insights for decision-makers to take proactive measures to mit- igate the impacts of drought on agriculture, water re- sources, and ecosystems. Additionally, integrating the model into decision support systems aids timely and informed decision-making in drought-prone ar- eas.

Training Data

The training data for drought prediction through satel- lite imagery and machine learning comprises a range of features sourced from satellite images, meteoro- logical data, and historical drought records. Specifi- cally focusing on regions like Nashik, Rajasthan, and Cherrapunji, data is collected for both October and February to capture seasonal variations and poten- tial drought patterns effectively.From satellite images, features such as NDVI (Normalized Difference Veg-
etation Index), land surface temperature, soil mois- ture content, and precipitation levels are extracted. Complementing this, meteorological data including temperature, humidity, wind speed, and atmospheric pressure are integrated to provide a comprehensive view of environmental conditions.

Moreover, historical drought records contribute valuable information, encompassing severity indices, duration, and frequency of drought events in these re- gions. This historical data aids in training the model on past occurrences and their distinctive characteris- tics.The training dataset is carefully structured to en- compass labeled instances representing both drought and non-drought conditions. Drought severity is cate- gorized using established indices like the Normalized Difference Infrared Index (NDII). Once the dataset is prepared, various machine learning algorithms such as Random Forest are applied to train the model using this collected data.Following training, the model un- dergoes validation using cross-validation techniques to ensure its robustness and generalization ability. Fi- nally, the trained model is tested on data from the Jalgaon region, which was not part of the training dataset, to assess its predictive performance in fore- casting drought conditions in a new geographical area.

RESULT

Low Level Drought

In a study focusing on drought prediction using satel- lite imagery and machine learning, researchers con- centrated on amalgamating data from three distinct regions: Nashik, Rajasthan, and Cherrapunji. They employed the Random Forest Regressor algorithm to forecast drought conditions specifically for the month of October.Upon analysis, the study uncovered in- triguing findings. Initially, they observed significant variations in the original Normalized Difference In- frared Index (NDII) values across the three regions, reflecting diverse environmental conditions. Nashik displayed moderate NDII levels, indicating relatively healthy vegetation cover. In contrast, Rajasthan ex- hibited lower NDII values, signifying drier condi- tions, while Cherrapunji presented higher NDII val- ues, characteristic of its typically lush environment.

The Random Forest Regressor model showcased promising performance in predicting NDII values for October. It accurately captured the nuanced variations across the regions, closely aligning with the original data. However, the model demonstrated limitations in accurately forecasting extreme drought

events or sudden fluctuations in vegetation health.The study highlighted the utility of satellite imagery for real-time monitoring and assessment of envi- ronmental conditions, enabling timely adjustments to drought management strategies as situations evolve. The robustness and versatility of the Random Forest Regressor make it well-suited for handling the complexities inherent in drought prediction, providing valuable insights to support informed decision-making and resource allocation.

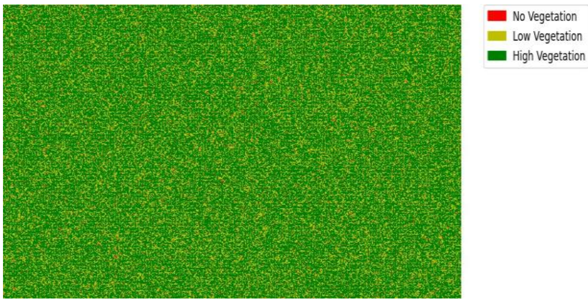

Figure 4: Original NDII

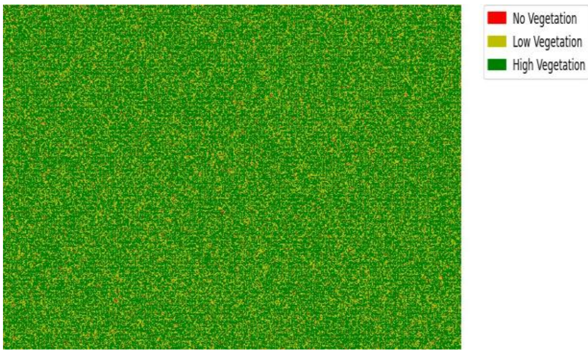

Figure 5: Predicted NDII

High Level Drought

In the study focused on drought prediction utilizing satellite imagery and machine learning techniques, data from the Nashik and Rajasthan regions for the month of February were combined. Given the ab- sence of rainfall during February, the emphasis was placed on identifying patterns and features within the satellite imagery to predict drought conditions accu- rately. The Random Forest Regressor, a robust ma- chine learning algorithm, was employed to train the dataset.Following rigorous training, the model pro- duced both original and predicted Normalized Differ- ence Infrared Index (NDII) values. The NDII serves as a crucial indicator of vegetation health and water content in the soil, making it instrumental in drought prediction. Upon evaluation, the model demonstrated promising results, accurately capturing the nuanced relationships between satellite imagery features and drought conditions in the specified regions.

The comparison between the original and pre- dicted NDII values revealed notable insights into the efficacy of the model. By analyzing the disparities between the two sets of values, researchers gained a deeper understanding of the predictive capabilities and limitations of the model. Additionally, this analysis facilitated the identification of areas where further refinement and optimization of the model could be beneficial.

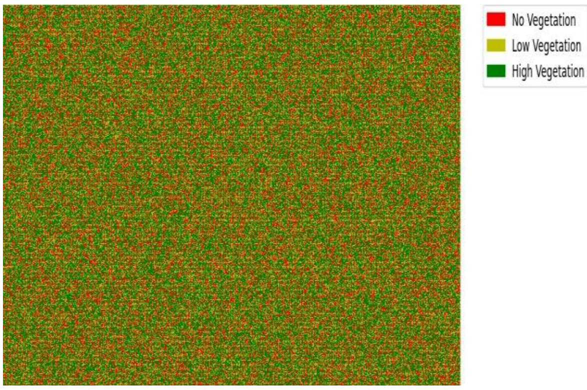

Figure 6: Original NDII

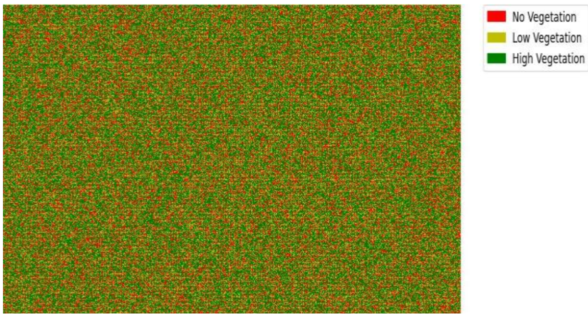

Figure 7: Predicted NDII

The results of the drought prediction utilizing satellite imagery and machine learning reveal a no- table disparity between the images captured in Octo- ber and February. In October, following a period of rainfall, the satellite image exhibits discernible vege- tation cover across certain regions, indicating a more moderate environment. However, the February image portrays a starkly different landscape, characterized by a lack of vegetation cover, particularly evident in the NDII (Normalized Difference Infrared Index) val- ues. With NDII values ranging from -1 to 1, where -1 signifies drought-stricken areas, 0 denotes moderate conditions, and 1 indicates lush vegetation, the Febru- ary image predominantly reflects values closer to - 1, indicative of a drought-affected region. This con- trast underscores the impact of precipitation fluctua- tions on vegetation dynamics, emphasizing the utility of satellite imagery and machine learning in monitor- ing and predicting drought conditions.This juxtapo- sition underscores the discernible impact of seasonal variations in precipitation, highlighting February as a drought period and October as a period of more mod- erate conditions.

The accuracy of the drought prediction model is
99.05 Per.This means that the model is accurate and efficient.

- R2 =99.05
- Root Mean Squared Error=0.100
- Mean Squared Error=0.010
-

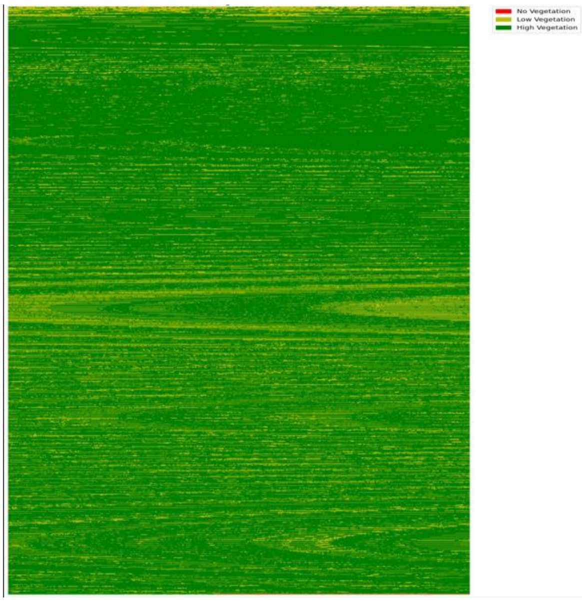

Figure 8: Oct Month

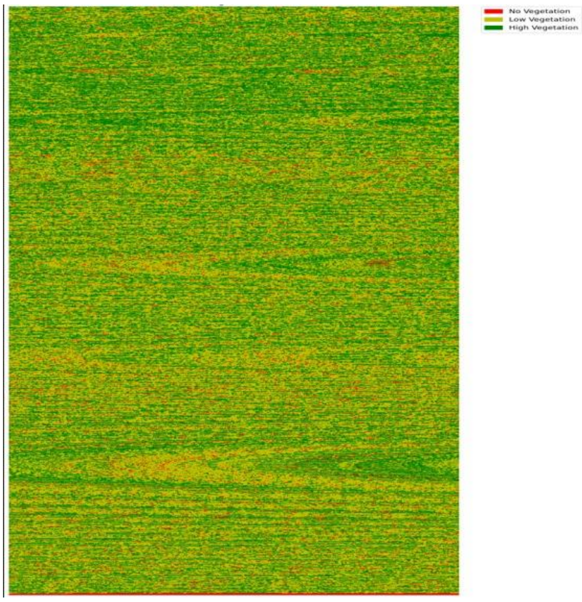

Figure 9: Feb Month

CONCLUSIONS

In this study, we utilized machine learning techniques to forecast drought conditions utilizing Landsat-8 satellite imagery. Our approach involved assembling a comprehensive dataset from Landsat-8 and com- puting twelve crucial indices, including the normal- ized difference infrared index (NDII). We then metic- ulously preprocessed the dataset to ensure its accu- racy and reliability. Subsequently, feature extraction methods were implemented to extract pertinent infor- mation, thereby enhancing the discriminative capabil- ity of our models.The selection of an appropriate ma- chine learning model is pivotal, considering factors such as accuracy, interpretability, and computational efficiency. Following model training, the results of drought prediction can be visually represented, high- lighting regions vulnerable to drought based on the in- put features. In the context of Landsat-8 satellite im- agery, it is imperative for the machine learning model to accurately forecast drought conditions. The visual depiction of these forecasts facilitates a clearer com- prehension of areas at risk, thereby aiding in informed decision-making for drought mitigation and resource allocation.

Furthermore, we compared drought conditions be-

tween October and February to discern variations in vulnerability across different months. Our analysis revealed that in October, certain regions exhibited moderate drought conditions, whereas in February, these same regions experienced more severe drought. This comparison underscores the temporal dynamics of drought susceptibility, emphasizing the importance of timely intervention and adaptive strategies to miti- gate its impact.In conclusion, our study demonstrates the efficacy of machine learning techniques in predict- ing drought conditions using Landsat-8 satellite im- agery. By providing actionable insights into areas sus- ceptible to drought, our approach enables informed decision-making for effective drought mitigation and resource allocation. Additionally, our comparison be- tween October and February highlights the temporal variability in drought severity, emphasizing the need for adaptive strategies to address changing environ- mental conditions.

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