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AI-based Drought Forecasting for Parametric Insurance

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Abstract

In drought-prone African countries like Zimbabwe, the uptake of parametric insurance has been low due to the absence of localized models. Guided by the CRISP-DM model, the present study proposes an AI-based approach to drought prediction in parametric insurance. The study's paramount objectives are establishing trigger thresholds for drought events, assessing their significance, identifying the most effective machine learning models for drought modeling based on the Standardized Precipitation Index (SPI), and forecasting future drought occurrences and their magnitudes. Historical weather data, including temperature and rainfall, are utilized and a range of machine learning models - neural networks, random forest, and support vector machines are employed for drought prediction. The performance of these models is evaluated based on accuracy, reliability, and interpretability, with continuous refinement based on feedback from stakeholders. The significance of this research lies in promoting data-driven decisions, incentivizing preparedness, enabling risk transfer, facilitating rapid insurance payouts, and enhancing financial stability. With accurate drought predictions driving parametric insurance, policyholders can make well-informed choices, adopt proactive measures, transfer the risk of drought-related losses, receive swift insurance payouts, and improve their financial resilience during drought events.

Keywords
Climate change, Machine Learning (ML), Artificial Intelligence (AI), Parametric Insurance, Standardized Precipitation Index (SPI)

1. Introduction
In recent years, the fusion of artificial intelligence (AI) and environmental science has spurred innovative strategies to mitigate natural disasters. Droughts, in particular, pose significant challenges to agriculture, water management, and socio-economic stability. Traditional forecasting methods often lack precision and timeliness, hindering effective decision-making. However, AI technologies offer promising solutions by enhancing forecasting accuracy and offering

actionable insights. This paper presents a study on AI-based drought forecasting tailored for parametric insurance. Leveraging machine learning and big data analytics, the approach aims to bolster predictive capabilities, enabling more efficient risk assessment and management in the insurance sector.

The increasing frequency of extreme climate events due to climate change has resulted in significant economic and political implications, making climate change a universal concern in terms of risk management (Patnaik, 2022). According to the Global Centre on Adaptation, climate change acts as a risk multiplier, exacerbating vulnerabilities and intensifying the impact of extreme weather conditions. In Africa, approximately 20 million people are affected by climate change, with drought affecting 13 million individuals annually (GCA, 2023). Droughts have emerged as the primary weather hazard in Zimbabwe, contributing to food insecurity and power shortages (ReliefWeb, 2023).

Efforts to improve preparedness and mitigate the impact of drought include conservation agriculture, the promotion of drought-tolerant crops and short-season varieties, as well as the implementation of irrigation and water harvesting techniques (Nangombe, 2023). However, challenges such as poor service delivery, poverty, and corruption have hindered the effectiveness of these strategies (Makova et al., 2019). Parametric insurance, an often-neglected approach, has not been adequately explored in Zimbabwe's drought mitigation strategies. Nyagadza and Nyauswa (2019) investigated the applicability of parametric insurance in the country, revealing mixed opinions regarding its feasibility. The study also lacked quantitative evidence to support its findings. Artificial intelligence (AI) models offer advantages over traditional underwriting techniques, including comprehensive risk factors for accurate insurance pricing (IBM, 2023). AI has the potential to optimize pricing and underwriting for various insurance risks (Insurance Europe, 2023).

The lack of robust models that can accurately predict drought events remains a significant challenge in implementing effective parametric insurance schemes in sub-Saharan Africa, more so in Zimbabwe (Cesarini et al., 2023). Manyukwa (2023) argues that the lack of appropriate models in parametric insurance exposes both the insurer and the insured to positive and negative basis risk respectively due to the inadequacy of set premiums. This has caused domestic reinsurers to shun parametric insurance due to the lack of appropriate trigger thresholds and premium rates, exposing them to huge uncertainties and bankruptcy risk (Nyagadza and Nyauswa, 2019). Resultantly, at least 50% of the Zimbabwean population becomes food insecure every time a drought strikes, despite futile attempts to reserve grain harvests and implement climate-proof mechanisms such as the pfumvudza/intwasa program (Nyangadza and Nyangwa, 2019). This is lamentable considering the notable advances in data and technology that can be manipulated to predict droughts and increase confidence in parametric insurance accurately. Against this background, this paper applied machine-learning techniques to predict the occurrence and impact of drought triggers. The results provide a data-driven basis for determining fair premiums that will adequately cover the underlying drought triggers without bankrupting the insurer. Beyond the introduction, this paper is structured into further sections, that is: 2. Literature Review, 3. Methods, 4. Data collection, 5. Results and 6. Conclusions.

1.1 Objectives
The objectives of the paper are:

i) To model meteorological drought using machine learning algorithms
ii) To predict the occurrence of droughts in Zimbabwe.
iii) To evaluate the effectiveness of these models in reducing basis risk in parametric insurance.

2. Literature Review
2.1 Drought
Droughts typically involve prolonged periods of reduced precipitation that can span seasons or even a whole year. Natural disasters, including droughts, contribute to more than 22% of global economic damage (Bouaziz et al., 2023). Droughts manifest in different forms, such as meteorological, hydrological, agricultural, and socioeconomic droughts, adding to their complexity (Nandgude et al., 2023). Meteorological droughts, which result from prolonged rainfall deficits are the most critical and serve as the primary form from which other types of droughts emerge (Bouaziz et al., 2023). Accurate prediction of meteorological droughts is crucial for proactive preparation, minimizing drought effects, and enabling effective contingency planning. Early drought prediction is increasingly recognized as significant at both local and global levels (Nandgude et al., 2023). Selecting appropriate models that align with available data and having access to adequate computing resources are essential for accurate and reliable drought prediction, enabling timely interventions and proactive measures (Nandgude et al., 2023).

2.2 Related Works -Existing Drought Prediction Techniques

The study interrogated several drought prediction techniques being used across the globe with findings showing that traditional approaches are still popular in African communities and artificial intelligence is only being explored in Asian and Western countries.

2.2.1 Indigenous Knowledge Systems (IKS)

Households' perceptions of weather variability and climate risks are influenced by indigenous knowledge (Mashoko, 2019). In Zimbabwe, more than 50% of respondents rely on indigenous knowledge and local indicators derived from the natural ecosystem to anticipate cropping conditions and drought hazards (Mashoko, 2019). Restricted access to scientific weather forecasts and uncertainties has popularized the use of indigenous knowledge systems worldwide (Salite, 2019). Traditional prediction methods have increased confidence and reduced vulnerability to weather and climate change, but farmers face challenges due to unpredictable and severe drought events (Salite, 2019; Mashoko, 2019). Climate change, variability, and non-climatic factors affect the reliability of traditional indicators, with some plants and animals disappearing or behaving unusually (Salite, 2019; Mashoko, 2019). Their accuracy and reliability have been questioned due to challenges in predicting rainfall timing and quality necessitating adjustments in agricultural activities (Salite, 2019).

2.2.2 Stochastic Models

Stochastic models, like the Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA), are commonly used in drought forecasting (Affandy et al., 2023). ARIMA models analyze the relationship between previous and current values and are suitable for linear datasets like streamflow and precipitation (Nandgude et al., 2023). They offer a systematic search process for model identification and are effective in detecting serial autocorrelation (Rezaiy and Shabri, 2023). However, ARIMA assumes linearity and requires stationary data, which may not capture the non-linear dynamics of drought (Rezaiy and Shabri, 2023). SARIMA extends ARIMA by considering seasonality, making it useful for capturing and forecasting drought patterns with seasonal variations (Affandy et al., 2023). It has been successful in monitoring indicators like the Vegetation Temperature Condition Index (VTCI) and the Standardized Precipitation Index (SPI) (Nandgude et al., 2023). However, SARIMA models have limitations in fully encompassing the complexity of drought factors and spatial extent (Nandgude et al., 2023). Linear Regression models, like binary logistic regression, have been effective in using remote sensing variables for drought prediction (Cesarini et al., 2021). They can identify relevant variables and handle correlations (Schwarz et al., 2020). However, they may not capture spatial variability, and predicting drought's spatial distribution and extent accurately at a fine scale is challenging (Cesarini et al., 2021; Nandgude et al., 2023). Transferring models from one region to another can also affect their predictive quality (Schwarz et al., 2020).

2.2.3 Machine Learning Models

Machine learning models have gained prominence in drought forecasting due to their ability to detect complex patterns and relationships in data. These models use algorithms to learn from historical climate as well as hydrological data and make predictions about future drought conditions (Nandgude et al., 2023). They can handle large and diverse datasets, incorporating various environmental and climatic variables such as precipitation, temperature, soil moisture, and vegetation indices. Three machine-learning models commonly used in drought prediction are Artificial Neural Networks (ANN), Random Forest (RF) and Support Vector Machines (SVM). ANNs can learn complex patterns and handle multidimensional data, but they are often considered "black box" models with limited interpretability (Nandgude et al., 2023). Felsche and Ludwig (2021) applied multiple ensemble simulations to predict drought in Munich and Lisbon regions using the ANN model. The model achieved low accuracy on a 1-month time scale, ranging from 55% to 57%. They require a substantial amount of labeled training data to perform effectively. RF captures complex nonlinear relationships and interactions between features, but it may be susceptible to overfitting and can be less interpretable. Mokhtar et al. (2021) used the RF amongst other models to estimate SPEI values towards meteorological drought in China. The RF and XGB models were found to be practical for regional-scale estimation of SPEI, although their performance improved when used separately for each zone. Cesarini et al. (2021) compared machine-learning models such as SVM and Neural Networks (NN) to statistical models in assessing performance in drought and flood forecasting to enhance weather index insurance. The SVM and NN outperformed the statistical models especially in the context of drought with the study however, recommending the improvement of the NN's probability estimates. The SVM has shown high accuracy in drought prediction and outperforms other techniques in meteorological and hydrological scenarios (Nandgude et al., 2023). However, the reviewed studies focused primarily on Asian and Western regions, possibly due to the advanced economic and technological infrastructure in those areas**.**

2.2.4 Deep Learning Models

Deep learning models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Extreme Gradient Boosting (XGB), and Extreme Learning Machines (ELM) have been explored for drought prediction (Nandgude et al., 2023). CNNs are effective in capturing spatial and temporal patterns in high-dimensional data, like satellite imagery and meteorological information, without manual feature engineering. RNNs are well-suited for analyzing sequential data and can capture long-term dependencies, but they require extensive computational resources and data for training (Cesarini et al., 2021). LSTM networks, a type of RNN, selectively retain or discard information from previous time steps, making them suitable for handling time series data. XGB addresses overfitting and underfitting issues by combining predictions from weak learners, while ELMs are simpler and more efficient alternatives to traditional neural networks, but they have limitations in terms of interpretability and generalization to diverse regions. Thorough evaluation and validation processes are crucial for ensuring the reliability and accuracy of deep-learning models in drought prediction (Nandgude et al., 2023). Poor infrastructure and operational risk are significant factors in the use of these models, especially in developing countries.

2.3 Current state of parametric insurance

Largely adopted in developed countries, parametric insurance is a type of insurance that pays out a predetermined amount based on specific triggers, such as rainfall levels or crop yield indices, instead of compensating for actual losses (Johnson, 2021). In the context of drought, parametric insurance is crucial for managing financial risks associated with drought-related losses. It offers faster claims processing and timely payouts, enabling affected parties to respond promptly to drought events (Prokopchuk et al., 2020). Parametric insurance provides a safety net, mitigates financial risks and allows for customization based on regional characteristics and stakeholder needs (Cesarini et al., 2021). It also promotes proactive risk management and resilience-building practices. However, the challenge lies in convincing policyholders of the adequacy of the specific parameter-based coverage, known as basis risk, especially in developing countries (Johnson, 2021).

2.4 The Challenge- basis risk

Basis risk refers to the potential mismatch between the occurrence of an insured event and the trigger used for payouts in parametric insurance (Cesarini et al., 2021). In drought insurance, basis risk arises because the trigger, such as rainfall levels, may not precisely align with the actual losses suffered by the insured party. Factors contributing to basis risk include the variability and spatial heterogeneity of the insured event and inaccuracies in pricing models. This discrepancy can lead to the avoidance of parametric insurance products, particularly in regions with poor infrastructure for trigger determination and refinement (Nyagadza and Nyauswa, 2019).

2.5 Existing Drought parameters in the market

Drought parameters are essential for designing and implementing parametric insurance and drought monitoring systems. Various indicators are used to assess drought conditions, including the Crop Moisture Index (CMI) for agricultural drought, Palmer Drought Severity Index (PDSI) for overall moisture availability, Normalized Difference Vegetation Index (NDVI) for vegetation health, Standardized Precipitation Index (SPI) as a meteorological drought index, Standardized Precipitation Evapotranspiration Index (SPEI) for comprehensive drought measurement, Evaporative Stress Index (ESI) for flash droughts **and** moon phases and dew/fog patterns as additional indicators (Nandgude et al., 2023. Among these parameters, the World Meteorological Organization (WMO) for predicting meteorological droughts (Rezaiy and Shabri, 2023) recommends SPI.

2.6 The Gap

Parametric insurance relies on accurate triggers based on drought prediction models. However, the unreliability and inaccuracy of these models have led to a slow uptake of drought forecasts in Africa, causing stakeholders to resort to indigenous knowledge systems (IKS) for adaptation (Mujere et al., 2023). Even IKS has become increasingly unreliable, leading to crop losses (Salite, 2019). Traditional statistical models have lower predictive quality compared to machine learning models (Schwarz et al., 2020). In addition, generalized ML models from Western and Asian studies may not be suitable for drought-prone countries like Zimbabwe. Implementing localized machine-learning models is crucial for optimal predictions (Mokhtar et al., 2021). Insurers are hesitant to offer parametric insurance for drought due to the poor efficiency of existing models and undefined parameters (Nyagadza and Nyauswa, 2019). As such there is a need for accurate machine learning models tailored to specific climatic conditions to mitigate basis risk and enhance parametric schemes in a sub-tropical to arid African country like Zimbabwe.

3. Methods

Using artificial intelligence, the study employed the Cross-Industry Standard Process for Data Mining (CRISP-DM) model to predict drought occurrences and severity for parametric insurance. The process involved six stages:

1. Business Understanding: The study aimed to develop an AI model for predicting drought occurrences and severity to enable accurate pricing, selling, and valuation of parametric insurance. The dynamics of parametric insurance globally and specifically in Zimbabwe were assessed. Basis risk and other challenges associated with parametric insurance were identified and relevant stakeholders were identified: insurers, government, reinsurers, and farmers.

2. Data Understanding: Historical data on monthly precipitation and lowest and highest temperatures were gathered and analyzed. The data's format, quality, and completeness were assessed. The study ensured that the data covered at least 30 years of monthly precipitation as recommended by NASA (2020). The climate characteristics of different regions in Zimbabwe were considered. The dataset used was obtained from the Meteorological Services Department in Zimbabwe.

3. Data Preparation: The data was cleaned, normalized, and imputed to address missing values. Feature engineering was performed to extract relevant features for drought prediction- precipitation. Exploratory Data Analysis (EDA) techniques were used to identify trends and patterns in the data. Data cleaning, descriptive statistics, data visualization, and correlation analysis were conducted.

4. Modelling: Vector Machines (SVMs), RF (RF), and Artificial Neural Networks (ANNs) were used to model the prediction. These models were selected based on their accuracy and applicability to drought forecasting as proposed by the literature (Nandgude *et al.*, 2023). The data was split into training and testing datasets and the models were trained using historical data. Hyperparameter tuning and optimization were done to improve model performance. The World Meteorological Organisation (WMO) (Felche and Ludwig, 2021) used precipitation data to predict the Standardized Precipitation Index (SPI) as it is the recommended standard.

5. Evaluation: The models' performance was evaluated using cross-validation, evaluation metrics such as accuracy and RMSE, and external validation by domain experts. These evaluations assessed the models' reliability, generalisability, and usefulness in predicting drought conditions.

4. Results and Discussion

The results show the inherent effectiveness of machine learning models in predicting drought and eventually reducing basis risk in parametric insurance. The most appropriate model for each region in Zimbabwe was also established.

4.1 Numerical Results

4.1.1 Region 1

The results reveal that the region has not experienced drought across all lead times in the past 50 years. In addition, the machine learning models employed proved to achieve the highest accuracy on a 1-month lead-time with the RF being the most accurate scoring an accuracy of 73.98%. Whereas accuracy generally declines over longer lead times for the region, Support Vector Machines (SVM) scored a higher accuracy at longer lead times than the ANN and the RF. The ANN scored 0% accuracy at the 6- and 12-month timescales (Table 1).

Table 1. Region 1 predictions on 1-month lead-time

	Model	Accuracy Score	Precision	Recall	F1 Score
0	Random Forest	0.739837	0.724932	0.739837	0.729810
1	SVM	0.691057	0.665312	0.691057	0.673442
2	ANN	0.146341	0.119444	0.146341	0.127963

4..1.2 Region 2

The study, again, revealed that Region 2 hardly experienced drought in the past 50 years with a 1-month scale drought forecast showing that the RF is the most accurate in modeling the region's drought experience at 76.42%. The three models had similar predictive abilities on 3-month lead time, averaging around 20%. The accuracy uniformly declined over higher lead times (Table 2).

Table 2. Region 2 predictions on 1-month lead-time

	Model	Accuracy Score	Precision	Recall	F1 Score
0	Random Forest	0.764228	0.734417	0.764228	0.743902
1	SVM	0.731707	0.707995	0.731707	0.716028
2	ANN	0.349593	0.319603	0.349593	0.331315

4.1.3 Region 3

Again, the one-month time scale achieved the highest accuracy: RF scored 80.43% with this accuracy declining with each increase in the lead-time. This region experiences the average climatic conditions relative to all the other regions in the country (Table 3).

Table 3. Region 3 predictions on 1-month lead-time

	Model	Accuracy Score	Precision	Recall	F1 Score
0	Random Forest	0.804348	0.774909	0.804348	0.783514
1	SVM	0.722826	0.680707	0.722826	0.693297
2	ANN	0.364130	0.283168	0.364130	0.311901

4.1.4 Region 4

There was a general increase in the accuracies of the models with RF remaining the most accurate (Table 4).

Table 4. Region 4 predictions on 1-month lead-time

	Model	Accuracy Score	Precision	Recall	F1 Score
0	Random Forest	0.880435	0.866848	0.880435	0.871377
1	SVM	0.826087	0.799547	0.826087	0.809748
2	ANN	0.391304	0.361204	0.391304	0.375652

4.1.5 Region 5

This region by classification generally experiences extreme drought, with SPI values exceeding -2. Interestingly, whilst being the driest of them all, machine learning models achieved the highest accuracy values in this region overall (Table 5).

Table 5. Region 5 predictions on 1-month lead-time

	Model	Accuracy Score	Precision	Recall	F1 Score
0	Random Forest	0.894309	0.884824	0.894309	0.888347
1	SVM	0.821138	0.784553	0.821138	0.796477
2	ANN	0.276423	0.192535	0.276423	0.223916

4.2 Graphical Results

Figure 1 depicts the 5-year period drought predictions using the RF algorithm.

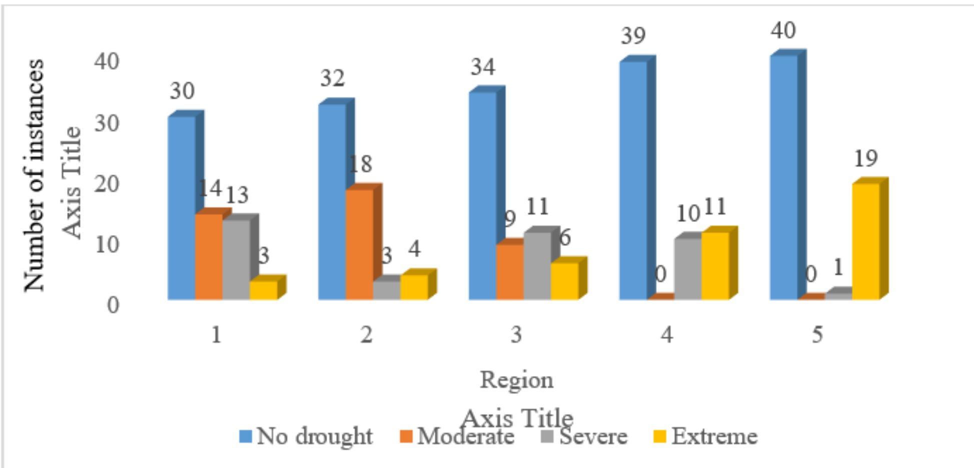

Figure 1. 5 Year drought prediction results

Projected using the RF, the regions are expected to experience increasing monthly drought instances from 2021 to 2025 across all regions. Region 5 is the most drought-resilient despite being susceptible to extreme droughts. Region 1 on the other hand is expected to suffer about 50% drought instances over the period, making it the most vulnerable. The risk exposure gradually decreases across the regions.

Further analysis validated the RF as the most accurate and consistent model in predicting droughts in the country. (Figure 2- Figure 11)

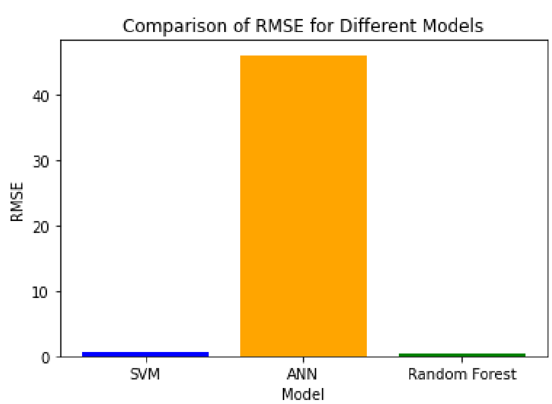

Figure 2. Region 1 RMSE computations. The RF has the lowest value of 0.4243.

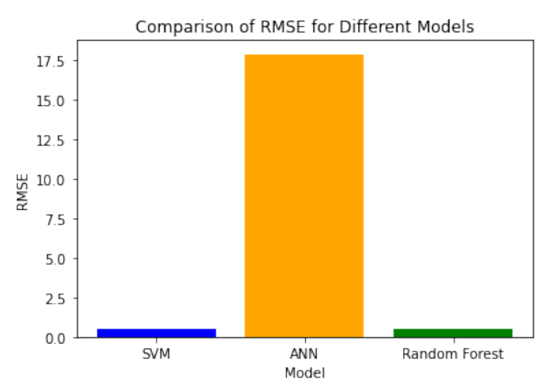

Figure 3. Region 2 RMSE computations. The RF had the lowest value of 0.51.

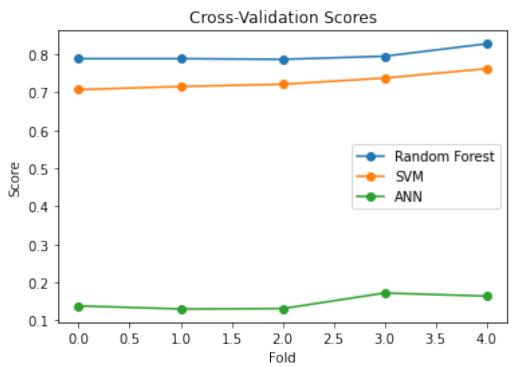

Figure 4. Region 1 Cross-validation scores. The RF had the highest values across all folds.

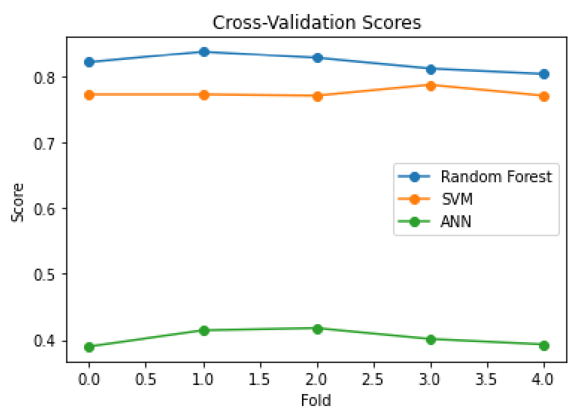

Figure 5. Region 2 Cross-validation scores. The RF had the highest values across all folds.

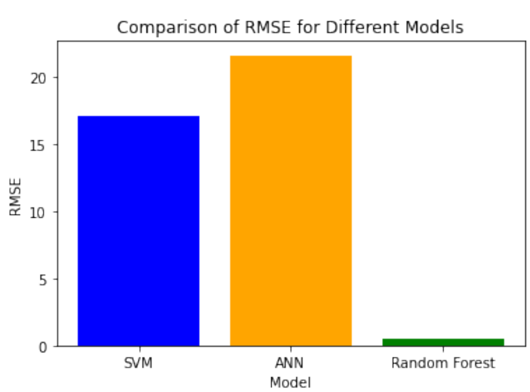

Figure 6. Region 3 RMSE computations. The RF had the lowest value of 0.5054.

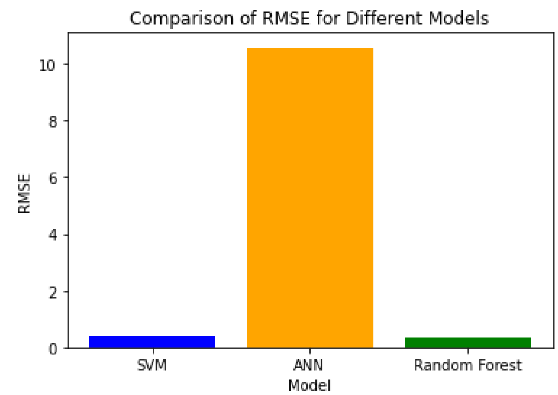

Figure 7. Region 4 RMSE computations. The RF had the lowest value of 0.3458.

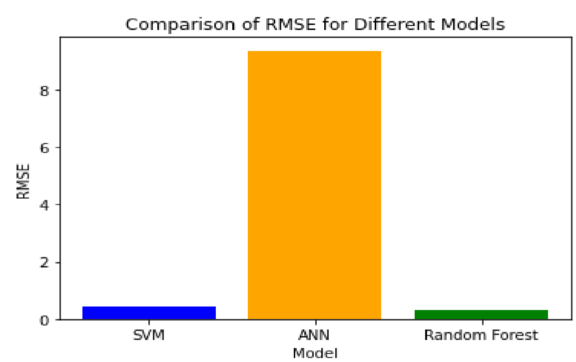

Figure 8. Region 5 RMSE computations. The RF had the lowest value of 0.3251

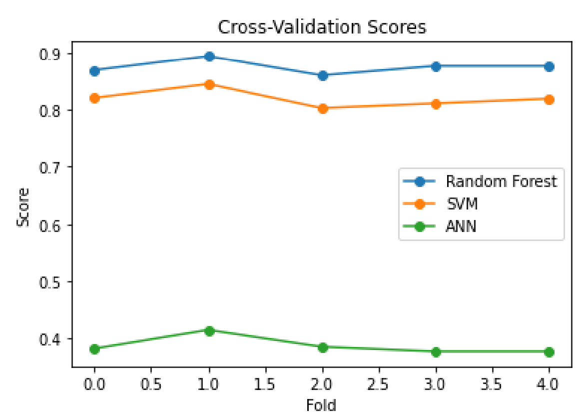

Figure 9. Region 3 Cross-validation scores. The RF had the highest values across all folds.

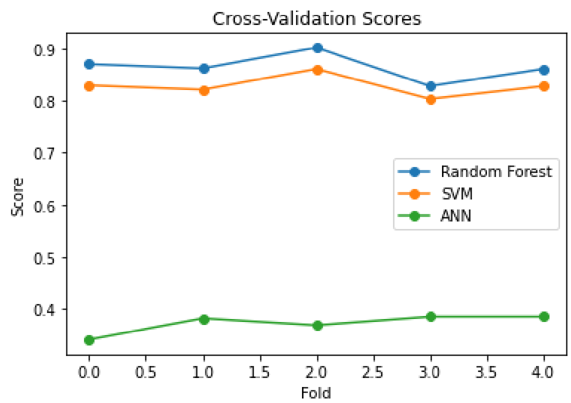

Figure 10. Region 4 Cross-validation scores. The RF had the highest values across all folds

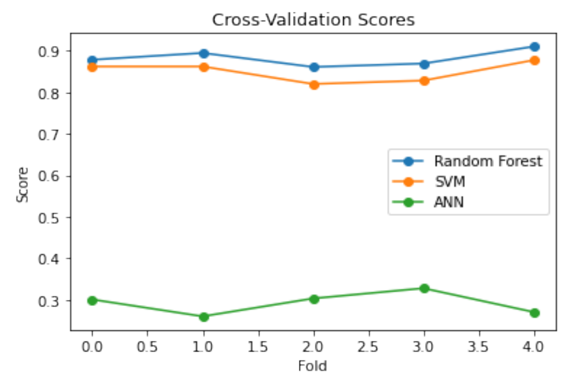

Figure 11. Region 5 Cross-validation scores. The RF had the highest values across all fold.

4.3 Proposed Improvements

The study proposes that drought prediction using modern AI techniques ought to be localised and projected on various lead times to enhance accuracy. It is also critical to assess the performance of several models concurrently to establish the one best suited for the cause. Parametric insurers may also leverage artificial intelligence and optimise pricing by tailoring the SPI classification values to match their preferred thresholds.

5. Conclusion

Aimed at applying machine learning techniques in drought forecasting for parametric insurance, the study concluded that ML models, especially the RF, are efficient in forecasting drought and are effective in managing basis risk in parametric insurance. The optimal lead-time may not be consistent with the traditional seasons anticipated in the region, an expected disruption due to climate change. Therefore, it is prudent to forecast drought conditions at lower lead times like 1 month due to the erratic rainfall patterns being experienced generally. This is in line with Felsche and Ludwig (2021)'s findings on the importance of seasonality. With substantial variabilities in the drought experiences of different regions, wetter regions are more susceptible to drought than drier regions, necessitating region-specific pricing of products and region inclusivity as a risk-pooling tool. Mokhtar et al. (2021) shared similar sentiments, highlighting that AI models' performance would improve when applied using a localized approach. The study's results may also be used to establish region-specific underwriting by manipulating SPI value thresholds and designing localized products.

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