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Article

Drought prediction in the Midwestern United States using deep learning

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SUMMARY

Drought is a recurrent and natural phenomenon that has had economic, agricultural, and social effects on the Midwestern United States (U.S.). While many drought prediction models exist, none are specifically designed to forecast drought occurrences in the Midwestern U.S. Therefore, an opportunity exists to develop a drought prediction model that would be more accurate for the Midwest. In this study, we used deep learning models to train a drought prediction model for the Midwest. After comparing the Conv1D and LSTM models, we chose the Conv1D architecture to develop a drought forecasting model trained on 23 years of weekly data from the U.S. Drought Monitor. The hypothesis is based on the significant role of existing drought and precipitation status in influencing drought conditions and the importance of selecting an appropriate look-back period (temporal window) for accurate forecasting. We hypothesized that optimizing the temporal window of precipitation data input (e.g., using 10 weeks of data) would lead to more accurate drought predictions. Given the time series nature of drought data, the size of the input temporal window plays a crucial role in prediction accuracy. Our model achieved averages of 0.904 for the Pearson correlation coefficient across 12 different Midwestern states, indicating a high level of consistency in the model's accuracy. The study findings suggest that a deep learning model with a properly optimized temporal window provides a viable approach for drought forecasting in the Midwest.

INTRODUCTION

From 1984 to 2024, drought events in the United States (U.S.) resulted in an average annual economic loss of $7.9 billion (1). Droughts affect the economic, agricultural, and social sectors (2). Since 1900, droughts have been responsible for the loss of more than 11 million lives and have affected over 2 billion people worldwide (2). Estimates for total cost of drought-related losses in 2012 reached over $30 billion, with 2012 being the worst drought year since 1988 (3). In the farming sector, the 2012 drought cost the Midwest and Great Plains of the U.S. $14.5 billion USD, which had to be paid by the federal crop insurance program (4). Therefore, effectively predicting droughts also prevents the farming industry from suffering considerable agricultural losses (5). The Midwest in particular has experienced costly droughts, and as one of the largest farming regions in the world, challenges posed by droughts can affect the international economy (6).

According to the U.S. Census Bureau, the Midwest consists of twelve states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin (7). Residents in the Midwest affected by drought are faced with many challenges. In 2023, a drought in Iowa caused the local government to restrict water usage for residents (8). Regarding human health, droughts lead to a wide variety of public health issues, including malnutrition, pneumonia, *E. coli* O157, cholera, and mental health issues such as emotional distress (9). These issues mainly stem from the fact that droughts can cause the water supply to be more concentrated with chemicals and unwanted particles that may have adverse effects on human health (9).

One dataset used for recording drought is U.S. Drought Monitor (USDM) categories. The USDM categories range from D0 to D4, with D0, D1, D2, D3, and D4 being Abnormally Dry, Moderate Drought, Severe Drought, Extreme Drought, and Exceptional Drought, respectively. In this model, we used each category's percentage of area in each state from a scale of 0 to 100 (10).

Traditionally, droughts have been predicted using stochastic and physical models (11). Stochastic models are statistical models that use historical data to predict future occurrences. Although they can be accurate for short-term prediction, stochastic models are unable to account for changes in the landscape and are less viable for long-term predictions (11). On the other hand, physical models excel at simulating geological and hydrological processes, which makes them more accurate because they can account for interactions between ecosystems and human activity (11). However, physical models are complex and more costly to set up (11).

In contrast, methods involving machine learning are more accurate in predicting droughts as compared to traditional methods (11). Artificial intelligence (AI) has shown significant promise in multivariable forecasting, which is crucial for drought prediction since many factors contribute to drought (12). There are a variety of AI models, such as support vector regression (SVR), feedforward neural network (FNN), the one-dimensional convolutional neural network (Conv1D) model and the long short-term memory (LSTM) (2, 12). However, both SVR and FNN are more traditional machine learning models (2, 12). SVR is better suited for data that is not temporally dependent and needs to be trained with smaller intervals. SVR and FNN also are more prone to overfitting and underfitting than other models like LSTM and Conv1D, which have been shown to be more effective (12).

The LSTM structure, a recurrent neural network, has a forget gate that determines what information to keep and

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discard. In machine learning, the recurrent neural network is a computational model that has interconnected node layers, which allows them to model dynamic systems (13). This makes it an especially effective model for forecasting since it removes redundant information (12). The Conv1D model, on the other hand, is effective in capturing spatial patterns in sequential data (14). Depending on the dataset, the combination of intervals (i.e., weeks) and epochs (the number of times a program runs through the entire dataset) vary, so these factors must be calibrated for a given dataset (12).

Optimizing window size is crucial for collecting enough data to prevent overfitting and underfitting. Overfitting is where the model has trained on so much data that it incorporates noise into the predictions instead of the actual trends. Underfitting is where the model doesn't provide very accurate predictions because there isn't enough data to train on (15). The hypothesis is formed from two key observations. One, precipitation plays a major role in affecting drought conditions. Second, accurate forecasting requires determining a suitable temporal window. We hypothesized that optimizing the temporal window of precipitation data input (e.g., using 10 weeks of data) will lead to more accurate drought predictions. The results show that optimizing the temporal window, particularly when using a 10-week interval for this dataset, improves prediction accuracy, supporting our hypothesis. We also measured the performance of both the LSTM and Conv1D deep learning models. By more accurately predicting drought in the Midwest, farmers and policy makers can improve drought resilience.

RESULTS

Since precipitation is one of the most significant indicators of drought, we used a dataset combining weekly drought severity and precipitation in each of the 12 Midwest states from 2000 to 2023 to train the deep learning models to predict drought occurrence and severity (10,16-17).

To determine the best algorithm to use with our selected data, we examined test losses for both the LSTM and Conv1D models. Test loss is a measurement of the difference between the model's predicted value and the actual values. A lower test loss value indicates better predictions, because the prediction values are closer to the actual values (18). We used 5 weeks of D1-D4 drought—increasing drought severity levels—and precipitation data to predict the next week of D1-D4 drought with 10 epochs. The Conv1D model achieved a lower loss than the LSTM model for each state, namely 43.174 versus 52.097, respectively (**Figure 1**). Since the Conv1D model had a lower test loss value, we used this model to test and find the optimal number of weeks of data needed for prediction modeling.

We evaluated the prediction model using 5, 10, 15, and 20 weeks of dataset, obtaining correlation coefficients between the real data and model predictions of 0.760, 0.826, 0.701, and 0.773, respectively (**Figure 2**). These week intervals were chosen to test the performance of the model as the number of weeks increases by equal intervals. The 10-week temporal window yielded the highest correlation coefficient, indicating the most accurate predictions, while the 15-week window produced the weakest correlation. This strong correlation (r = 0.826) for the Conv1D model using a 10-week temporal window suggests a stronger alignment between the predicted and actual values, indicating improved model performance.

Therefore, we used the Conv1D model with 10 weeks of dataset to optimize the number of epochs. The number of epochs tested were 10, 20, 40, and 60 (**Figure 3**). The improvement in prediction stagnates after 40 epochs (**Figure 3D**). Thus, we selected 40 epochs for modeling. We used the optimal modeling parameters (Conv1D model, 10 weeks, 40 epochs) and the datasets for all the other Midwest states to train the model (**Figure 4**).

We then calculated the Pearson correlation coefficient between each state's actual and predicted D1-D4 values to evaluate the performance of the model (Illinois: 0.942, Indiana: 0.913, Iowa: 0.947, Kansas: 0.865, Michigan: 0.928, Minnesota: 0.899, Missouri: 0.938, Nebraska: 0.951, North Dakota: 0.881, Ohio: 0.878, South Dakota: 0.956, Wisconsin: 0.734). All the variables were standardized. A Pearson correlation coefficient value of 0.7 or higher is typically considered a strong correlation, and sufficient for making reliable predictions (19). The Pearson correlation coefficient values of all Midwest states were more than 0.7, with the average Pearson correlation coefficient value at 0.903. The Pearson correlation coefficient values of 11 states were more than 0.86, indicating the high similarity between actual and predicted D1 drought values in all Midwest states.

DISCUSSION

Drought is a recurrent, natural phenomenon significantly impacting the Midwest's socioeconomic well-being (16). Although there are a variety of drought prediction models, none of the models, to our knowledge, focus specifically on predicting drought in the Midwest (11, 16). This study created a deep learning model trained explicitly on Midwest drought and precipitation data. We hypothesized that optimizing the

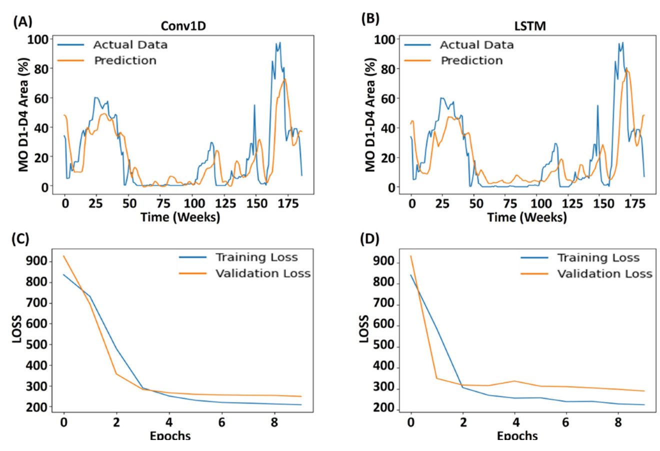

Figure 1: Comparison of actual data with predictions of Conv1D and LSTM models, and their test and validation loss. Missouri drought and precipitation data was used to train the Conv1D and LSTM models. (A) Predicted percentage of Missouri area with D1-D4 drought using the Conv1D model with 5 weeks of USDM statistics and 10 epochs. The actual data and predictions are plotted in blue and orange, respectively. (B) Predicted percentage of Missouri area with D1-D4 drought using the LSTM model with 5 weeks of USDM statistics and 10 epochs. The actual data and predictions are plotted in blue and orange, respectively. (C) The training and validation loss using Conv1D modeling, plotted in blue and orange, respectively. The loss value was 43.174. (D) The training and validation loss using LSTM modeling, plotted in blue and orange, respectively. The loss value was 52.097.

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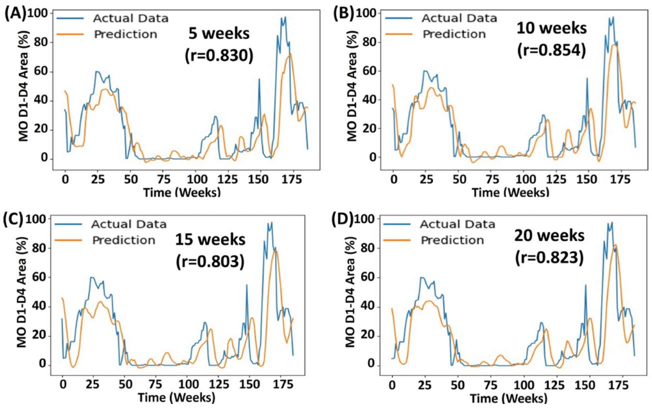

Figure 2: Effect of the size of temporal window of the training dataset on Conv1D prediction results. Five, ten, fifteen, and twenty weeks of training datasets were used to train a Conv1D model with correlation coefficients of r=0.830, r=0.854, r=0.803, and r=0.823, respectively. The actual data and predictions are plotted in blue and orange, respectively. (A) Predicted and actual percentage of Missouri land area with D1-D4 drought using the Conv1D model with 5 weeks of USDM statistics. (B) Predicted and actual percentage of Missouri area with D1-D4 drought using the Conv1D model with 10 weeks of USDM statistics. (C) Predicted and actual percentage of Missouri area with D1-D4 drought using the Conv1D model with 15 weeks of USDM statistics. (D) Predicted and actual percentage of Missouri area with D1-D4 drought using the Conv1D model with 20 weeks of USDM statistics.

temporal window of precipitation data input would lead to more accurate drought predictions. We assessed the model's performance as the duration of the time window increases by increments of 5 weeks and found that our results support our hypothesis. While optimizing the model, the correlation coefficient for 10 weeks achieved the highest correlation coefficient—averaging 0.904 across the 12 states—and outperformed the 5-, 15-, and 20-week time models. This indicates that the model's accuracy is dependent on selecting the optimal temporal window for input data.

Eleven states exhibited correlation coefficients greater than 0.86, further highlighting the reliability of the model's predictions. This also indicated a high level of consistency in the model's accuracy across the entire region (19, 20).

This model could help several aspects of drought management. First, drought forecasting can help form water management strategies, which can mitigate the impacts of drought on the water supply in many areas across the Midwest (23). For example, predicting droughts earlier can help farmers reduce crop losses (23). Farmers can plan out planting schedules, harvest drought-tolerant crops, and adopt new irrigation practices. In addition, the federal government's crop insurance, Federal Crop Insurance Corporation, can utilize predictions from this model to gauge insurance coverage and financial assistance for farmers affected by droughts. Finally, policymakers can use drought forecasting to predict the severity of droughts, which shapes the policies for drought preparation and relief measures (23). Doing so may entice policymakers to invest more in response efforts, which could enhance drought resilience overall for all residents in the Midwest.

This drought prediction model faces several limitations. Firstly, USDM statistics currently are only available weekly, limiting the model from capturing shorter-term trends. Secondly, only the USDM statistics and precipitation were used as input variables. Other variables such as temperature, soil moisture, and groundwater are also known to impact drought probability, but were not used in our drought prediction model (16, 21). Thirdly, a conventional LSTM model was compared to the Conv1D model instead of a deep LSTM. A deep LSTM model with additional layers might improve the prediction (22). Future studies should test varying temporal windows for different geographic areas to ensure the performance of the model.

In future studies, the current drought prediction model could incorporate more relevant datasets such as Drought Severity and Coverage Index (DSCI), temperature, moisture, etc. to improve the accuracy of drought prediction. Another possible future study is creating a hybrid deep learning model combining the Conv1D and LSTM structures. While LSTM is proficient in capturing temporal dependencies, Conv1D is better at extracting spatial features from sequential data (24). With the added parameters from both LSTM and Conv1D layers, the hybrid models could fit more closely to the training data and provide more accurate drought prediction.

In conclusion, a deep learning model based on Conv1D structure developed in this study was trained on 23 years of weekly drought and precipitation data from 2000 to 2023. Optimizing the size of the temporal window in the training dataset for the deep learning model resulted in a greater accuracy of drought predictions. The results demonstrated a strong correlation between the predicted and actual drought conditions. This specific drought forecasting model (Conv1D model, 10 weeks, 40 epochs) has the potential to be used by organizations in the Midwest to help with water management, mitigating crop loss, and developing policies for drought resilience and adaptation. Given the increasing frequency and severity of droughts in the region, an accurate and timely

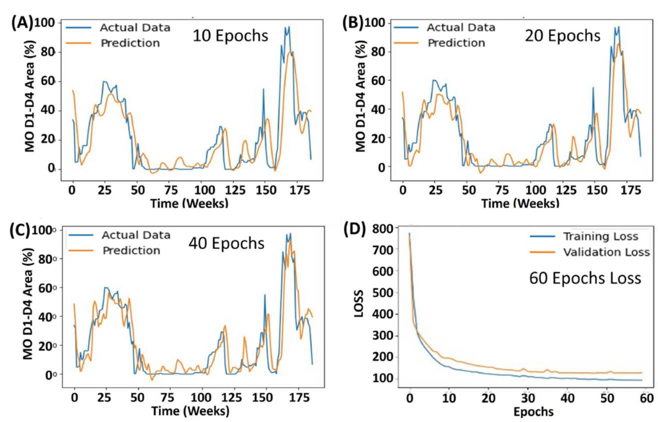

Figure 3: Effect of different epochs on Conv1D model prediction results. Training data was run through a Conv1D model with a 10-week data window for the indicated epochs. The training and validation loss are plotted in blue and orange, respectively. (A) Predicted percentage of Missouri area with D1-D4 drought using the Conv1D model with 10 weeks of USDM statistics and 10 epochs. (B) Predicted percentage of Missouri area with D1-D4 drought using the Conv1D model with 10 weeks of USDM statistics and 20 epochs. (C) Predicted percentage of Missouri area with D1-D4 drought using the Conv1D model with 10 weeks of USDM statistics and 40 epochs. (D) The training and validation loss using Conv1D modeling with 60 epochs. Loss for both training and validation plateaus after 40 epochs.

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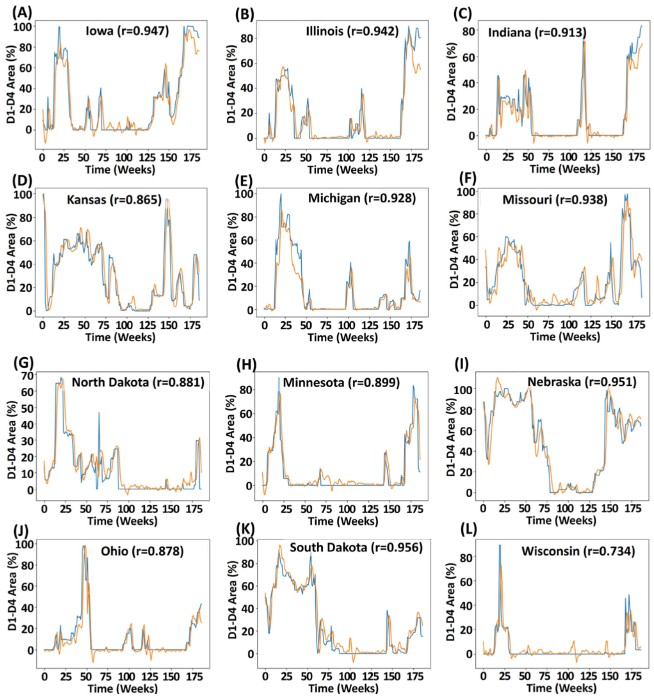

Figure 4: Comparison of actual and predicted drought levels across 12 Midwest states using the Conv1D model. The observed and predicted drought conditions in 12 Midwest states using a Conv1D model trained with 10 weeks of USDM data and 40 epochs. The x-axis represents weekly time intervals, and the y-axis shows the percentage of each state's area under D1-D4 drought level conditions. Actual drought data is plotted in blue, with model predictions in orange. Data is shown for 12 states, namely Iowa (A), Illinois (B), Indiana (C), Kansas (D), Michigan (E), Missouri (F), North Dakota (G), Minnesota (H), Nebraska (I), Ohio (J), South Dakota (K), and Wisconsin (L).

forecasting tool like this model is essential for proactive decision-making, helping stakeholders minimize economic and environmental impacts.

MATERIALS AND METHODS

Data preparation

We collected D1-D4 percent area data from the cumulative USDM statistics, where D1 through D4 represent increasing levels of drought severity. In addition to this drought data, we compiled precipitation data for each state from the National Centers for Environmental Information, as precipitation is a crucial indicator of drought (21). Since the precipitation data is collected daily, we averaged the total precipitation over seven days to align with the weekly USDM statistics. Both datasets cover the period from 2000 to 2023. To prepare the data for modeling, we used cumulative USDM statistics. This approach helped to capture the evolving nature of drought conditions over time, providing a more comprehensive basis for predictive modeling (10). The shape of the training data set was a 3-dimensional array: the first dimension was the weekly time series, which indexed the current week, the second dimension included six variables (D0, D1, D2, D3, D4, and precipitation), and the third dimension consisted of the past weeks' data, which provided previous context for the temporal dependencies (**Table 1, Figure 5**). Each weekly time series data set contained historical data that included these six variables, which the model used to forecast the severity of D1-D4 level drought for the next week.

Training model

The code for the setup and training of the deep learning models can be found at this Github link: https://github.com/rt1009/JEI__Code.git

We used the dataset from the 10-week dataset to build a data frame for the algorithm and split the dataset into training and test sets by using the function "train_test_split()". For the training, 85% of the data was used, and 15% was used for testing. We evaluated two algorithms for drought prediction in the Midwest: Long Short-Term Memory (LSTM) and One-Dimensional Convolutional Neural Network (Conv1D).

Each model incorporated environmental variables, including precipitation and historical drought indices to improve prediction accuracy. Conv1D was more efficient, so we proceeded with further optimization of this model. We further optimized Conv1D by tuning parameters, such as input week range (5, 10, 15, and 20 weeks) from the years 2000-2023 and epochs (10, 20, 40, and 60 epochs).

To address spatial variation, we also built separate Conv1D models for each Midwest state. The same dataset was used but segregated by state.

Validation

Finally, we assessed the model's accuracy using test data and evaluated the prediction value against the actual data. This was done by calculating the correlation coefficient between the prediction and actual drought level. The type of correlation coefficient used in this study was Pearson's product-moment correlation coefficient, used to determine

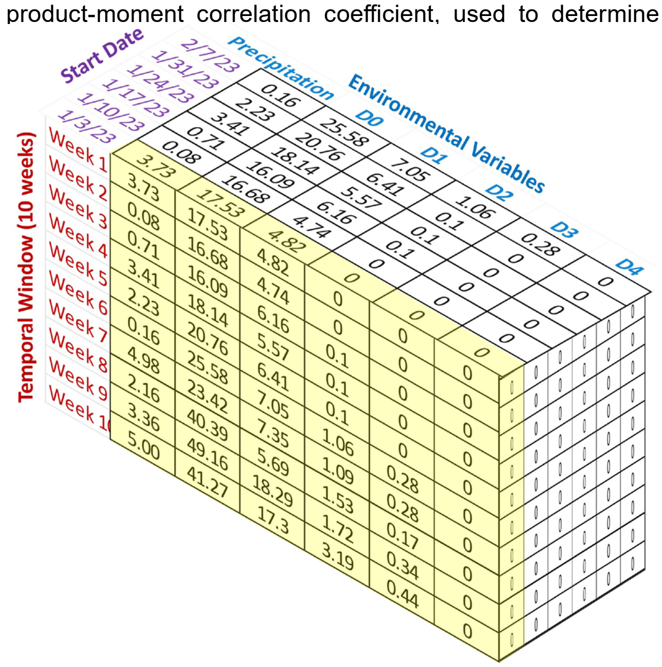

Figure 5: 3D visualization of 10-week datasets as model inputs. The three-dimensional structure shows how multiple 10-week datasets were compiled as inputs for models. The start date indicates the beginning of each weekly observation window. The temporal window (10 Weeks) represents the sequential weeks of historical data used as model input. The environmental variables include precipitation and drought levels D0-D4. The highlighted portion corresponds to one 10-week dataset.

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Week	Start	End	Precipitation	D0	D1	D2	D3	D4
Week 1	1/3/2023	1/9/2023	3.73	17.53	4.82	0	0	0
Week 2	1/10/2023	1/16/2023	0.08	16.68	4.74	0	0	0
Week 3	1/17/2023	1/23/2023	0.71	16.09	6.16	0.1	0	0
Week 4	1/24/2023	1/30/2023	3.41	18.14	5.57	0.1	0	0
Week 5	1/31/2023	2/6/2023	2.23	20.76	6.41	0.1	0	0
Week 6	2/7/2023	2/13/2023	0.16	25.58	7.05	1.06	0.28	0
Week 7	2/14/2023	2/20/2023	4.98	23.42	7.35	1.09	0.28	0
Week 8	2/21/2023	2/27/2023	2.16	40.39	5.69	1.53	0.17	0
Week 9	2/28/2023	3/6/2023	3.36	49.16	18.29	1.72	0.34	0
Week 10	3/7/2023	3/13/2023	5.00	41.27	17.3	3.19	0.44	0

Table 1: Example of 10-week data sets from 1/3/2023 in Missouri. Weekly drought and precipitation data, represented as one-dimensional entries across 10 consecutive weeks, forming a two-dimensional dataset. D0 through D4 indicate drought levels.

the linear relationship between two continuous variables (19). Pearson's product-moment correlation was used because the predicted and actual values are continuous variables. The Pearson correlation coefficient was calculated in Microsoft Excel worksheet.

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