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Article

Creating a drought prediction model using convolutional neural networks

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SUMMARY

Droughts kill over 45,000 people yearly worldwide, with climate change likely to worsen these effects. Despite this, researchers have struggled to develop a method that accurately predicts the location of droughts. One of the most recent and accurate drought prediction models is DroughtCast. DroughtCast utilizes a neural network along with precipitation, temperature, and other weather data to predict the United States Drought Monitor (USDM) index of a given week; however, this model does not consider the contextual aspect of weather forecasting. Predicting weather exclusively using data from a single location will never be as successful as predicting the weather using data from that point in addition to its surroundings. As a result, we created a novel Convolutional Neural Network (CNN) based upon the U-Net architecture to predict future USDM indices by using the current USDM index, historical USDM indices, and a 10-year (2010–2019) dataset containing weather data such as precipitation and Snow Water Equivalent that was obtained from DAYMET, a NASA database for weather across all North America. While the data utilized in our model is similar to DroughtCast's data, the model architectures are different. We hypothesized that this new architecture would improve the accuracy of our prediction. In comparison to DroughtCast, the mean-squared-error of the CNN Model dropped by 85%, 98%, and 97% for prediction times of 1 week, 6 weeks, and 12 weeks respectively, meaning that a vastly more accurate prediction.

INTRODUCTION

Droughts are one of the many natural disasters of the world. The effects of droughts may not be immediately apparent, but their longevity makes them quite potent. Droughts kill over 45,000 people yearly and affect the livelihoods of 55 million others worldwide, with climate change likely to worsen these effects (1). Most natural disasters have some kind of early detection system. For example, hurricanes have hurricane tracking. Early detection of a natural disaster saves both time and money (2). The longevity of droughts means that detection systems need to provide warning weeks or months in advance for preparation to be useful. Currently, there is no system to accurately predict droughts that far in advance (2). On top of this, the indirect cause of droughts all over the world is global warming and climate change. The increase in global temperatures causes the amount of surface water to be greatly reduced, as water evaporates quite quickly at higher temperatures (3,4). These effects will continue to happen for a very long time and will occur at a quicker rate as the effects of global warming continue. Leading drought prediction models lose their accuracy after 6 weeks, highlighting a need to improve existing systems (5). Improved prediction systems could save millions of lives and dollars in the long run (2).

For the majority of drought prediction systems, droughts are defined as a moment in time when the amount of water entering an ecosystem is less than the amount leaving it, typically resulting in a drastic reduction in the size of natural bodies of water such as lakes and rivers (6). The way in which water enters the ecosystem is a valuable indicator for droughts. For most water systems, a significant portion of the water originates from a snowpack (7). As a result, it seems quite feasible to be able to use the amount of water that has been stored in the ice pack to predict the amount of water that will be in the watershed the following year. The Snow Water Equivalent (SWE) measures the amount of water that has been stored in snow/ice. This value is calculated for all the snow/ice in the world. SWE uses Landsat data to determine the amount of water that would be released if all the snow were to melt (8). However, simply using the amount of water stored in ice to predict the amount of water that will be in the watershed fails to account for the contributions of other types of precipitation. The other part of the watershed comes directly from the sky as precipitation. As a result, any model for predicting droughts should include an input that measures precipitation. As temperature also affects the amount of water in a system, temperature is also a key factor that we considered. There have been models in the past that were used to calculate the amount of runoff from snow that would be produced, most notably the Snowmelt-Runoff Model (SRM) (9). SRM uses 3 primary variables in their model: temperature, precipitation, and snow cover. The SRM demonstrates that SWE is a useful metric, and it has already been implemented in several data science fields (4, 8, 9).

The most recent and accurate method for predicting droughts is DroughtCast. DroughtCast utilizes a neural network to predict the United States Drought Monitor (USDM) drought index and predominantly utilizes temperature and precipitation data. It is able to predict the location and severity of a drought up to 12 weeks in advance, with diminishing accuracy as the prediction length gets longer (i.e., greater than 12 weeks).

For our model, we decided to use the United States Drought Monitor as the source of drought data, which takes into account all three drought types: hydrological, meteorological and agricultural (10). The USDM compiles a variety of data, including soil moisture and hydrological data, that determines water inputs and outputs. After all these

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factors are used to produce a drought state, the results are then cross-referenced with experts in the field to determine the true intensity of a drought. This gives a steady stream of accurate data for every week (4). We chose USDM over other sources of data because USDM is very reliable and accurate, as it is a government run database. On top of this, the format that USDM is in is very user-friendly, and they provide maps that we can compare to.

This project is essentially an image segmentation project. Image segmentation is the process of classifying patterns that are found in a certain image (11). We wanted to use image segmentation to generate a model that is capable of predicting and classifying droughts using prior data from DAYMET and USDM

Image segmentation is typically done using convolutional neural networks (12). In general, a convolutional neural network (CNN) allows the computer to look at an image as a whole, instead of looking at single pixels. CNNs allows it to perform image classification and segmentation. One of the most promising uses of convolutional neural networks for image segmentation is U-Net. U-Net utilizes a multitude CNN layers to make an image prediction. A metric for U-Nets and other convolutional neural networks is intersection over union (IoU). IoU is essentially a metric that is used solely for image classification.

All of the above leads to the goal of the current project: to create a drought prediction model that will be more effective than the prior leading model DroughtCast. First, we hypothesized that if the U-Net architecture is used to create a classification model for predicting United States Drought Monitor classes as opposed to the neural network that is used in DroughtCast, then the U-Net model will have a lower mean squared error. Second, we hypothesized that if a U-Net model is used to create a classification model for predicting United States Drought Monitor Classes, then the prediction of each class will have an IoU value greater than 0.5, indicating a successful prediction. The knowledge IoU provides is important as being able to predict where a drought will occur and how strong it will allow those to prepare for droughts effectively.

RESULTS

The model we created utilized a U-Net architecture to predict future USDM drought indices. The data fed into the novel model were current drought indices, precipitation, temperature, and snowfall. We compared our model to DroughtCast by comparing IoU and MSE. The lead times that were tested with our novel model were 1 week, 6 weeks, 12 weeks, 24 weeks, and 52 weeks. There were 6 different drought classes named No Drought to D4, which were classified by the United States Drought Monitor as ranging from No Drought to Exceptional Drought.

The model had an MSE of under 0.05 for all lead times and IoUs greater than 0.5 for the “No Drought” class. The model tended to converge at 40–60 epochs. An epoch is one iteration of training the model. After 40–60 epochs there were no noticeable changes in the loss function or accuracy. On top of this, as the distance of the prediction increased, the mean IoU of the model decreased from 0.58, for short range models (lead time of 1 to 6 weeks), to 0.25 for long range models (lead time greater than 6 weeks) (Data not Shown).

The IoUs of the model varied greatly depending on the drought prediction class and the length of the prediction. The IoUs of all the drought classes with prediction lengths less than or equal to 6 weeks were above 0.5 (**Figure 1**). There was a very different story for models with prediction lengths greater than 12 weeks. These models have IoUs greater than 0.5 for only the no drought class while the IoUs for the other five classes were greater than 0.5 (**Figure 2**).

The MSE of the models was calculated for all prediction lengths. Every single MSE for the novel model was less than 0.05. We could only compare our model to DroughtCast for the lead times of 1, 6, and 12 weeks, as DroughtCast did not make predictions beyond 12 weeks. The testing MSEs for DroughtCast were all greater than 0.05 for every single lead time (**Figure 3**). The comparison clearly shows a very large gap between the MSE for our model and DroughtCast (**Figure 4**).

DISCUSSION

The IoUs of the model varied by both drought class and prediction time. An IoU that was greater than 0.5 means that the model can predict that class very well (13). The mean IoUs were greater than 0.5 in all drought classes for only the short-range forecasts (up to 6 weeks), indicating that the short-range models could successfully predict every drought class with high accuracy. The long-range forecasts had IoUs that were above 0.5 for “no drought” but below 0.5 for the rest. The “no drought” class is a binary output from the model that tells the user whether or not there is a drought in that location. Since the IoU for the “no drought” class is greater than 0.5, it signifies that the model can accurately predict whether or not there is a drought in a location. The long-range forecasts had IoUs well below 0.5 for the remaining classes. These remaining classes were outputs that determined the intensity of a drought. Since these classes had IoUs less than 0.5, the model cannot accurately predict the intensity of droughts for time periods greater than 6 weeks.

The MSEs of the models increase as the lead time increases. The MSEs of the U-Net model were significantly lower than the MSEs of the DroughtCast model. In the three weeks that could be compared, the novel model outperformed

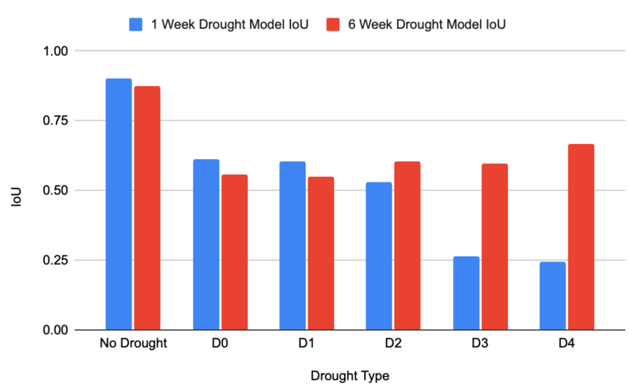

Figure 1. Intersection over union (IoU) values for various lead times of short-range models. This figure displays the Intersection over Union (IoUs) for the various drought short-range model lead times. A short-range model is defined as any model with a lead time of under 6 weeks. The labels on the x-axis specify the drought state; D0 means Drought Level Zero, etc. A model with an IoU value greater than 0.5 is considered successful.

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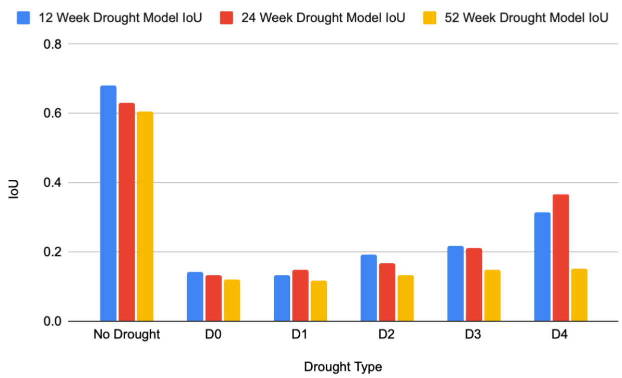

Figure 2. IoUs for various lead times of long-range models. This figure displays the IoUs for the various drought long-range model lead times. A long-range model is defined as any model with a lead time of greater than 6 weeks. The labels on the x-axis specify drought state; D0 means Drought Level Zero, etc.

Name	Description	Temporal Resolution
US Drought Monitor (USDM)	USDM provides categorical drought data for the entire United States. It consists of 6 categories from no drought to exceptional drought	Weekly
DAYMET Snow Water Equivalent	DAYMET provides numerical Snow Water Equivalent Data for all of North America	Daily
DAYMET Precipitation	DAYMET provides numerical precipitation totals for all of North America	Daily
DAYMET Maximum Temperature	DAYMET provides numerical maximum temperature data for all of North America	Daily
DAYMET Minimum Temperature	DAYMET provides numerical minimum temperature data for all of North America	Daily

Table 1. Data Inputs. Description of the data utilized as an input in our drought model.

the DroughtCast model by having an MSE 100 times smaller than DroughtCast. This means that with the novel model people will be more certain about the predictions that were made regarding droughts. As a result, the novel model is a more reliable and accurate way to predict droughts.

A couple of errors could have occurred during the training of the novel model. The split between the train and test sets may not have been perfect. This was as the USDM data was used as both an input and an output. The dual usage of the data could have resulted in the test data getting fitted into the model during training. Another error could have been the fact that the rasterized data and the DAYMET data do not coincide exactly. This was as the spatial resolution of the USDM data and DAYMET data were different. As a result, when they were overlapped, approximations have to be made, potentially causing some error.

The project could have gone much smoother with more processing power. This would allow us to use higher resolution which may have yielded better results. We could also have discounted the no drought category from the accuracy and loss function. These omissions would have prevented the bloated accuracy and shrunken loss numbers (values created by loss function) that were produced. We could also have used worldwide data. The utilization of global data could have prevented the issues that were seen near the edges of the predictions. The locations would be near the coasts of the United States. The issues we saw were that the predictions would not appear for those regions.

The project was a proof of concept that shows that U-Nets can be used for drought prediction models. The model provides a strong machine learning baseline for drought prediction. The usage of machine learning in drought prediction is a developing field. As a result, the model could be used as a potential baseline for future machine learning drought prediction projects. In the short term, the novel model could be retrained for the rest of the world in order to create a global drought forecasting model. Additionally, the principles used in the project could be used to assist in future projects dealing with other weather phenomena, such as flood predictions, wildfire spread models, hurricanes, and any other slow weather events.

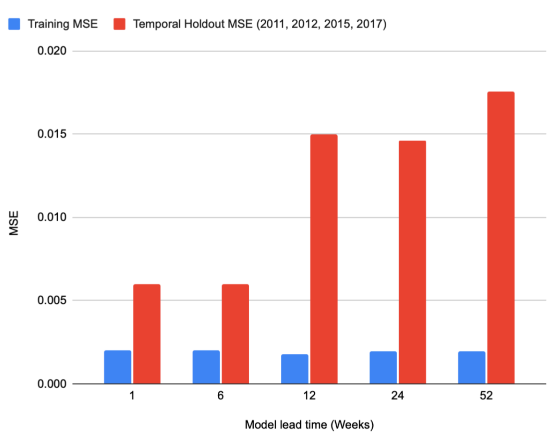

Figure 3. Drought Model Mean Squared Error (MSE). This figure shows the mean squared error (MSE) of our novel model with varying lead times. The Temporal Holdout MSE refers to the testing set, which was not included in the training set.

MATERIALS AND METHODS

Region of Interest

The region of interest for the novel model was the entire Contiguous United States (CONUS) from January 2010 to December 2019. CONUS was selected as the region of interest primarily because data for the CONUS region was found very readily. However, CONUS is also a very valuable region as it spans several climate zones and land types, making it one of the best regions to develop a drought forecasting model (14).

Data Collection

The model utilized both DAYMET and USDM inputs. DAYMET is a NASA database that contains climate data. USDM is a government database that contains drought data. These inputs were images, where each pixel contains additional data such as precipitation and drought state (**Table 1**) (5, 15). The inputs for the models were all current day weather images while the outputs were the desired future drought states. Since the DAYMET and USDM inputs were in different formats and had different resolutions, they needed to be changed as it would allow all data inputs to be of an identical format. To reformat the data, all of the model inputs were projected to the World Geodetic System, and then were cropped to just contain the CONUS region. The data was

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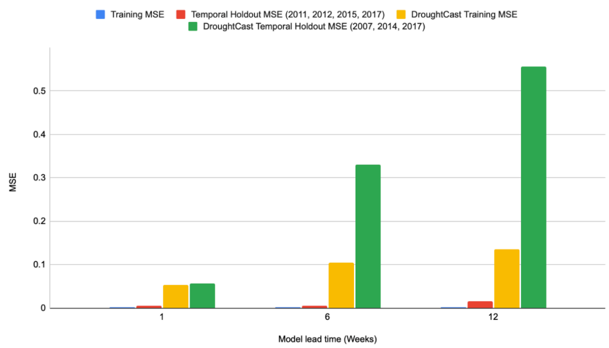

Figure 4. Novel Model Mean Squared Error (MSE) vs. DroughtCast MSE. A comparison between the MSEs of our novel model and DroughtCast. The Temporal Holdout MSE refers to the testing set. It was held out from the training set.

projected to the World Geodetic system in order to allow for a seamless display of the data on maps. The resolution of the CONUS region was then changed to 256 x 256 pixels. Since the USDM data is provided in the vector shapefile format, it was rasterized. Additionally, since the DAYMET data is provided on the Lambert Conformal Conic Projection, it was reprojected to the World Geodetic System. The reprojection was done utilizing the pyproj library (16). After this, the inputs were normalized using batch normalization and split into training and test sets, with 60% of the data in the training set and 40% in the testing set.

Model Construction

The model utilized the U-Net architecture and was programmed in Python 3.0.0. It uses convolutional layers which takes a group of pixels and assigns it one value (17). Python API's Segmentation Models were used to create the vast majority of our model's architecture (18). The Segmentation Models API gives us a U-Net template for us to modify. The first step was to download the base architecture to the local machine. After this, the two parts of the model that were edited were at the input stage and the output stage. Since the images we utilized as inputs have multiple values stored in each pixel, we coded the model to accept multiple values per pixel. The same thing occurred for our outputs. In addition, our model used categorical cross entropy as the loss function to determine how well it was performing and to improve itself.

Measuring Model Effectiveness

There were two metrics that we utilized to measure the effectiveness of our model. The first was mean squared error (MSE). MSE was calculated by squaring the difference between the true value and the predicted value for each data point and taking the average of the squares (19).

The second metric was Intersection over Union (IoU) (13). IoU was calculated by taking the area of the overlap of the true values and the predicted values and dividing it by the area of the sum of the true values and the predicted values minus the overlap (15). The thresholds we used for IoU were greater than 0.5, and the threshold we used for MSE was anything less than the DroughtCast model.

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Appendix

https://github.com/pl256211/researchProject

Code used while constructing the project.