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Flash drought prediction using deep learning

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Abstract

Flash droughts are rapid, short-term drought events that develop within weeks, driven by factors such as low rainfall, high temperatures, and strong winds, which deplete soil moisture and stress vegetation. These events have profound agricultural, economic, and ecological impacts, yet the use of machine learning to predict flash droughts remains underexplored, hindered by challenges like imbalanced datasets and limited data. This study addresses these issues by applying Convolutional neural networks (CNNs) to predict flash droughts in Eastern Australia, a region prone to such events. We identified flash droughts from 2001 to 2022, training the model with data from 2001–2015, validating it on 2016–2017 data, and testing it on 2018–2022 data. The model's performance was evaluated across drought duration, spatial distribution, and seasonal variability. Achieving a balanced accuracy of 80% and an Area under the curve of 93%, the CNN demonstrated strong predictive capability. However, it tended to overestimate the spatial extent of droughts, indicating areas for future improvement. These results highlight the potential of deep learning in flash drought prediction, offering valuable insights for early warning systems and drought management strategies.

1. Introduction

Flash droughts are rapid bursts of extremely dry conditions in a short duration of time, affecting agriculture and natural ecosystems [1]. The concept of flash droughts was given by [2], which observed periods of unusually rapid intensification of drought compared to drought periods which develop slowly and gradually. Flash droughts are driven by a combination of climatic factors, including rainfall deficiency, high temperatures, and strong winds, which accelerate soil moisture depletion and increases stress on vegetation, resulting in substantial agricultural, economic, and ecological impacts.

Researchers have attempted to understand flash drought using sub-surface soil moisture anomalies capturing its onset and evolution [3, 4]. Typically, definitions have some condition that the metric should indicate a state of drought following a period of rapid change, for example, falling to below the 20th percentile after two, four, or eight weeks [2]. For example, Otkin *et al* [5] developed the rapid change index to detect flash droughts using 16 different evapotranspiration stress index (ESI)-based change anomalies concurrently to examine the changes, which can be challenging. Other indicators include Evaporative Demand Drought Index, soil moisture percentiles, combining rainfall, temperature, and soil moisture anomalies, with ESI being most often used. Although these studies have advanced our understanding of flash droughts, it remains a poorly understood ecohydrological problem. Several researchers continue to explore flash droughts using various climatological and/or vegetation indicators [1, 6, 7].

Most flash drought studies have focused on the use of statistical approaches to identify and analyze flash droughts, and the use of machine learning (ML) is very limited [8]. Tyagi *et al* [7] provided a comprehensive review on the use of ML approaches for different aspects of flash drought, including identification and prediction, and the associated challenges. Zhang *et al* [9] studied the relationship between the rate of intensification and nine related climate variables using three different ML models, which were random forests, long-short term memory model and multiple linear regression model. Their study found random forests model to be the best model to identify the relationship between the rate of intensification and flash drought identification which were identified using soil moisture values. Barbosa *et al* [10] used a Convolutional neural network (CNN) model to develop a probabilistic drought detection map across northeastern Brazil for 2012. Speer *et al* [11] used random forest and support vector regression model to examine the relationship between rainfall variability and flash drought occurrences from May to October 2023 in the Upper Hunter region of New South Wales (NSW) to identify the most important climate drivers (attributes) that can be employed as predictors of rapid changes in rainfall associated with the flash drought.

Although these studies have used ML models to examine the relationship between flash drought and associated predictors (variables), none have focused on predicting flash droughts. Predicting flash droughts using any approach (statistical, physical or ML) is challenging, due to two specific problems, (1) lack of a universal definition, including the choice of an index, (2) limited training datasets, given it is an extreme event that is short in duration. This work presents an approach on tackling this challenge by using a deep learning model, CNN to predict a Flash drought index (FDI) developed using ESI [12, 13].

2. Study area and data source

Flash drought occurrences have increased globally over the past two decades [14, 15], and Australia is no exception. In fact, it is one of the hotspots experiencing a rising trend [16]. Given this increase, this study focuses on Eastern Australia, one of the most 'climatically sensitive' regions of the world. Nguyen *et al* [12, 13] extensively studied the 2018 and 2019 flash drought events in Australia. The 2018 flash drought event in the northern part of the Murray Darling basin (MDB) (figure 1) located in Queensland (QLD) was marked by rapid change towards strongly negative ESI with positive rainfall and vapor pressure anomalies. The 2019 flash drought event in Central slopes (covering parts of southern QLD and northern NSW) was found to have occurred from June 2019 to January 2020. Similarly, east coast regions were found to be under flash drought in November and December 2019. This event was linked to large-scale climatic drivers and suggested that the prediction of flash drought would require both local details along with large-scale climatic drivers. However, it is important to understand that this period was the Black Summer Event (largest bushfire in Australia's history) [17] and confirming if flash drought happened during this period is debatable.

In this study, flash drought identification was calculated using the FDI, which is based on anomalies in the ESI. The ESI itself is an anomaly of the ratio of evapotranspiration to Potential evapotranspiration. Using FDI, the percentage of days each pixel experienced flash drought from 2001 to 2022 is presented in figure 1. This metric represents the cumulative days under flash drought conditions, not a continuous count. As shown in figure, eastern NSW, parts of Northern Territory (NT) and south-eastern QLD have suffered the most, with 5%–7% of time under flash drought conditions.

The FDI is predicted using a deep learning model, specifically CNN, to forecast flash drought one day in advance, utilizing a range of climatic variables. The study employs six climatic variables: rainfall, air temperature, runoff, soil moisture, wind speed, and vapor pressure, to predict flash droughts. All datasets used for flash drought prediction and FDI calculation were obtained from AWRA-L v6, provided by the Bureau of Meteorology, Australia. AWRA-L offers daily data at a spatial resolution of 0.05°. AWRA-L uses the daily Australian gridded climate data (AGCD) climate data set that consists of observed air temperature (daily minimum and maximum) and daily rainfall data [12]. Further details about the FDI calculation and the process involved are discussed in the supplementary section. Figure 2 is the flowchart for calculating FDI.

3. Method

3.1. CNN architecture

CNNs provide a natural fit for this task because of their ability to learn hierarchical and spatial features from large-scale climate datasets automatically, without requiring extensive manual feature engineering. While simpler models may offer better interpretability and faster training, they often fall short in capturing the spatial correlations and

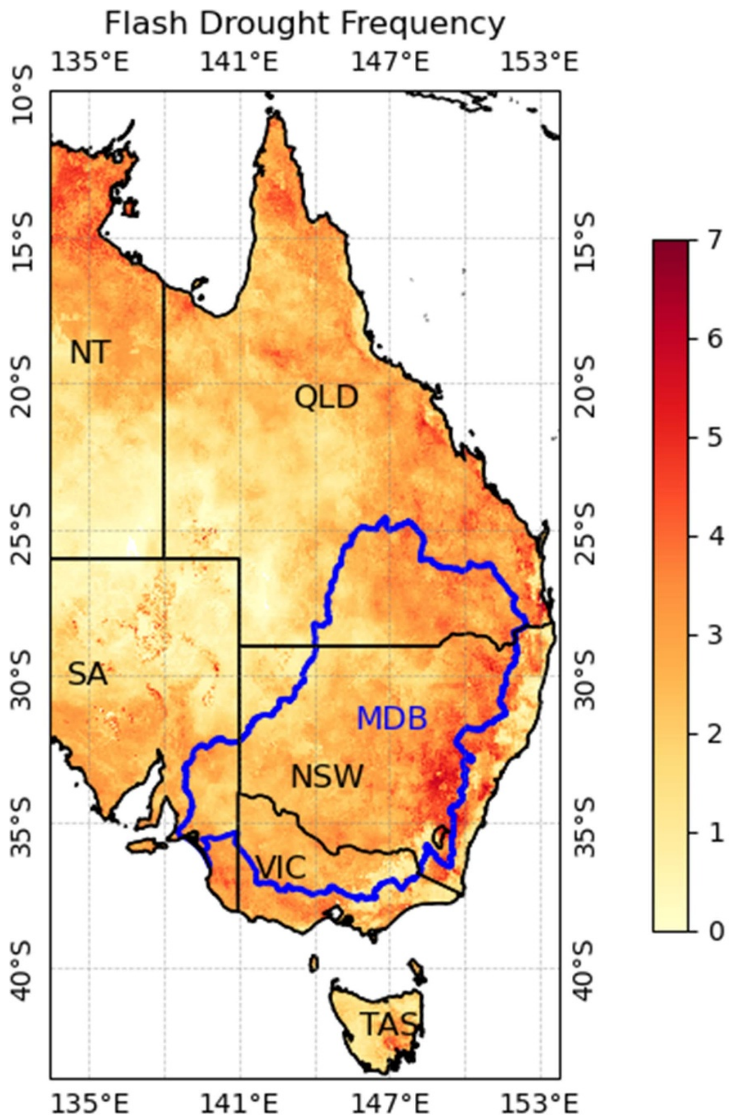

Figure 1. Map of drought frequency (%) in eastern Australia from 2001 to 2022. The states shown are NT—Northern Territory, QLD—Queensland, NSW—New South Wales, TAS—Tasmania, VIC—Victoria and SA—Southern Australia. The blue line shows the boundaries of Murray Darling Basin (MDB).

non-linear interactions that are essential for accurate flash drought prediction. Simpler models, such as logistic regression or support vector machines, are not well-equipped to handle the multidimensional nature of climate data [18]. CNNs, on the other hand, excel in such contexts by exploiting the grid-like structure of data and learning spatial filters through backpropagation [19]. Their hierarchical structure enables CNNs to capture local patterns in the early layers and more abstract, high-level patterns in the deeper layers [20, 21], which are particularly useful for understanding and predicting complex environmental phenomena like flash droughts.

The present model utilizes 84 historical days of input climatic data (rainfall, air temperature, runoff, soil moisture, wind speed and vapor pressure) along with positional and seasonal information to enhance performance. The architecture consists of 7 convolutional layers with a progressively decreasing number of filters (ranging from 512 to 8), each followed by batch normalization and 10% dropout for regularization. ReLU activation functions are applied to intermediate layers, while the final layer employs a Sigmoid activation function for binary classification. The model was trained for 100 epochs, and the best model parameters were selected based on a hold-out validation set. The model with the highest validation F1-score was chosen. This approach serves as a form of regularization to prevent overfitting. The entire training process took approximately 35 h on a single Nvidia V100 GPU. The depth of the network allows the model to capture both fine-grained and high-level spatial dependencies that are critical for flash drought forecasting.

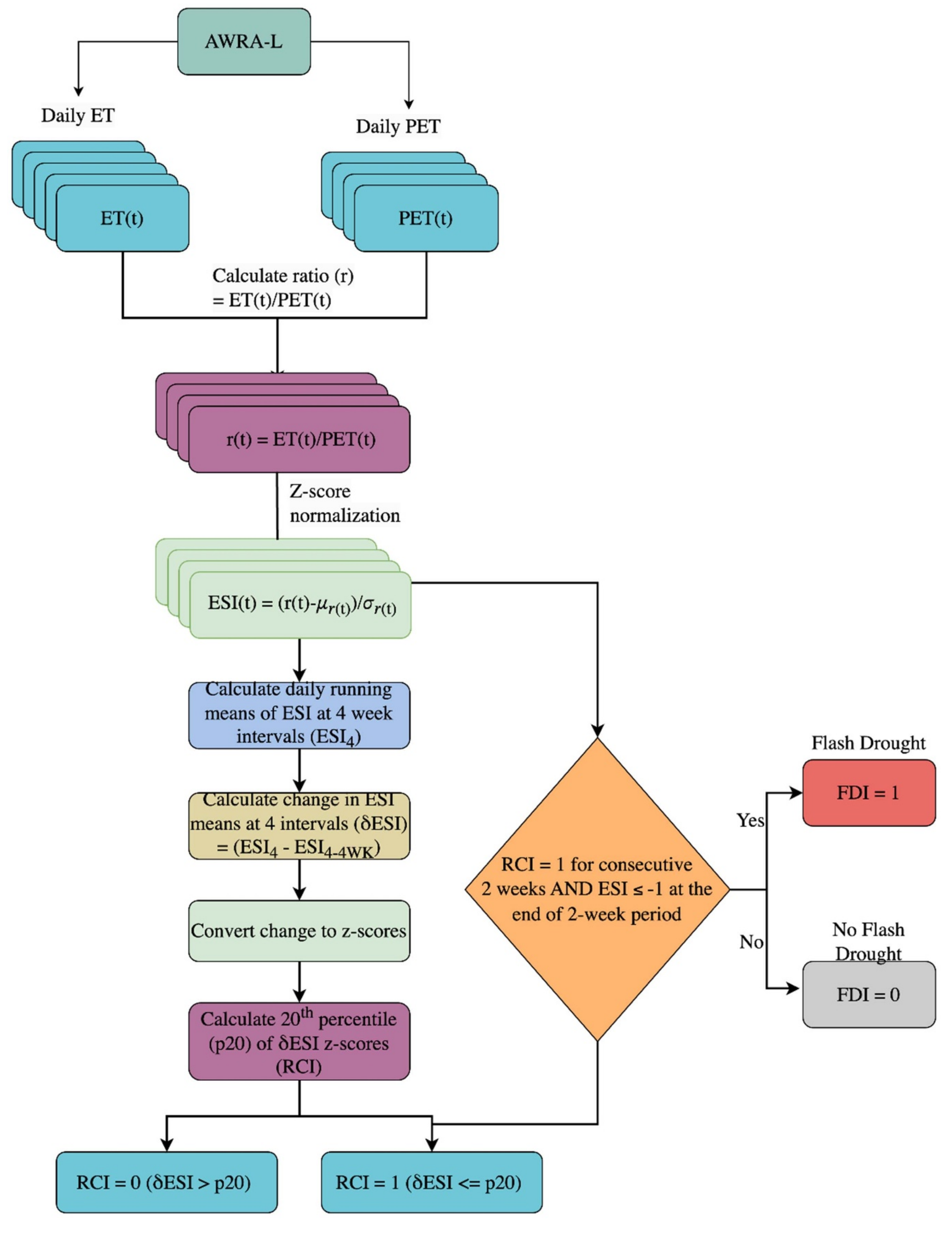

Figure 2. Flowchart to calculate flash drought.

A major challenge in flash drought prediction is the severe class imbalance inherent in the dataset. Flash drought events (positive class) are much rarer than non-drought events (negative class), which can lead to biased models that predict only the majority class (non-drought). To effectively handle this imbalance, we employed a weighted binary cross-entropy loss function, where greater weight is assigned to the minority class (flash drought events). This approach ensures that the model does not become biased toward predicting non-drought events and learns to detect the rarer, yet critical, flash droughts. The mathematical equation of the loss function is:

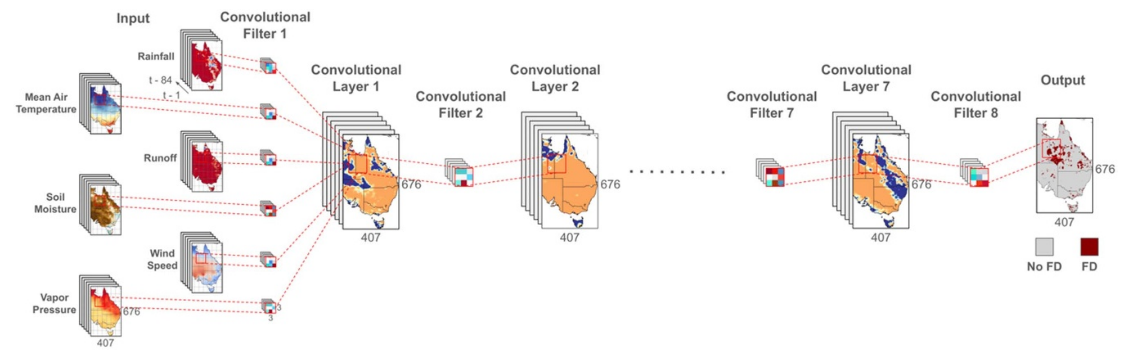

Figure 3. Architecture of the CNN model used.

$$\text{Weighted BCE Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left[w \cdot y_i \cdot \log\left(\widehat{y_i}\right) + (1-w) \,.\, (1-y_i) \,.\log\left(1-\widehat{y_i}\right)\right] \quad (1)$$

- $\widehat{y_i}$ —Predicted probability for the positive class for the ith sample. $\widehat{y_i} \in [0,\ 1]$
- y_i —Ground truth label $y_i \in \{0,\ 1\}$
- w —Weight assigned to the positive class $w \in [0,\ 1]$
- N —Total number of samples

Overall, the CNN architecture, combined with the use of a weighted loss function, allows the model to effectively address both the complex spatial dependencies of flash drought events and the severe data imbalance. This approach provides a robust and scalable framework for flash drought prediction, offering significant advantages over simpler models that lack the capacity to handle the intricacies of climate data and the challenges posed by class imbalance. CNN's ability to learn spatial features and focus on rare, high-impact events makes it a powerful tool in advancing our understanding and forecasting of flash droughts. More details about the convolutional process and architecture (figure 3) have been added in the supplementary section.

4. Results

The entire dataset (2001–2022) was divided into three parts. Firstly, we trained the CNN model with flash drought data from 2001–2015. The validation set of January 2016 to December 2017 was used to pick the best model among all the epochs, and the rest of the data was used for testing. The quantitative evaluations of the model during these periods are presented in table 1. The definitions of the statistical metrics, and in-depth analysis of the quantitative metrics is presented in the supplementary information.

To gain a deeper understanding of the model's outcomes, we conducted comparisons between two different scenarios. First, we examined the spatial differences between the observed and predicted flash drought regions on the day with the highest number of observed flash drought pixels during the testing period. Second, we analyzed these differences on the day when the number of predicted flash drought pixels was at its peak. Figure 4 shows the differences between observed and predicted flash drought pixels which occurred on 26 January 2018. On this day, 27.9% of observed pixels showed flash drought with the majority of them occurring in the state of QLD. The predicted map follows the same pattern as observed, yet it seems to predict more pixels (7.1%) compared to observed. The difference between the predicted and observed flash drought pixels, shows that the predicted map predicts more pixels around the regions of observed flash drought leading to some false positives. However, for a regional monitoring system false positives around the buffer area may not be a bad proposition. The blue regions in the difference map highlight areas where the model failed to predict flash droughts that were observed, indicating false negatives. This suggests the model may not be fully capturing the conditions or triggers that led to these observed events. Such gaps could arise from limitations in the training data, missing or underweighted environmental variables, or biases in the model's sensitivity to localized climatic patterns.

During the testing period, the summer months of 2018 had the most number of flash drought pixels. Figure 5 shows the number of days pixels experienced flash drought conditions during the summer period of 2018 (December 2018—January 2019). The color bar represents the duration of flash drought during this time frame. The observed map shows that the flash drought event was largely concentrated in southern QLD, NT with sporadic events in NSW and Tasmania. The model outputs were able to capture the location and duration of these events, and the predicted map shows a longer duration in almost all of the flash drought regions.

Table 1. Statistical metrics of the model during various periods.

Time period	Recall	Precision	F1-score	Balanced accuracy	ROC-AUC
Training	79.93	33.28	47	88.28	97.65
validation	63.63	29.18	40.01	80.26	95.67
Testing	64.85	29.24	40.31	80.12	93.84

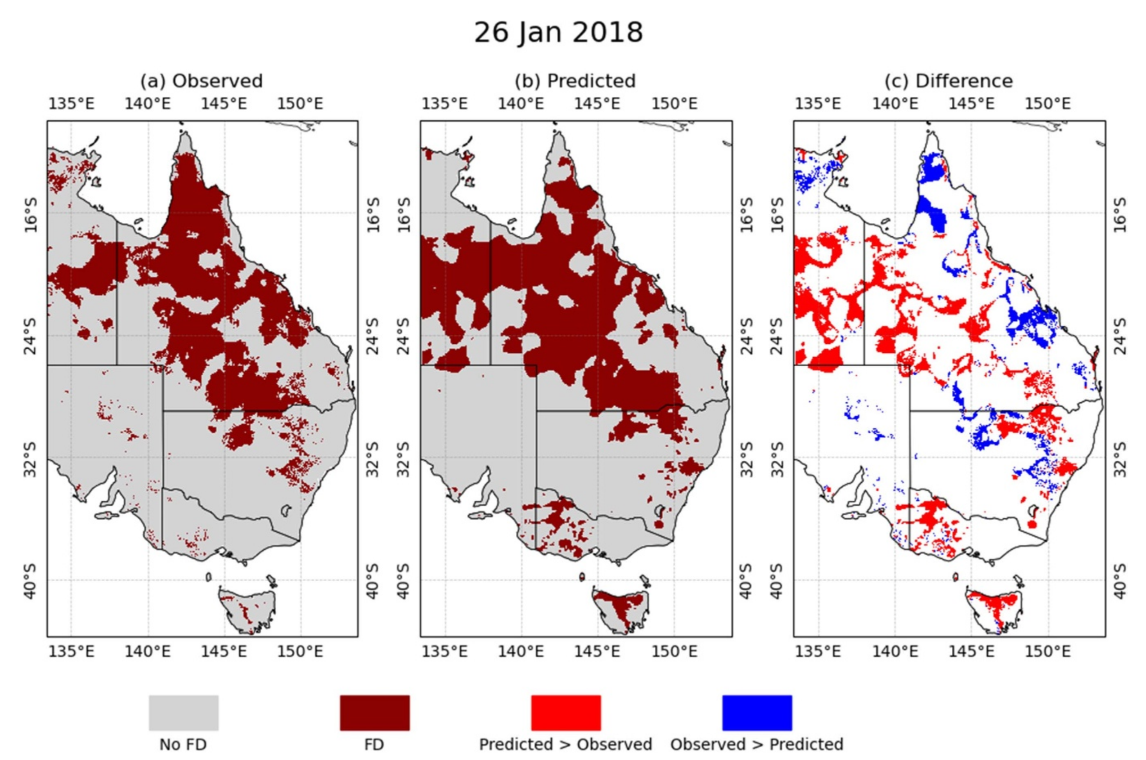

Figure 4. Comparison of predicted and observed flash drought pixels on the day which had the most number of flash drought (observed) during the testing period.

5. Variations in summer season

To examine the differences in observed and predicted flash drought pixels, the 2018–19 Australian summers (December—January—February) were divided into periods of 15 d (figure 6(a)). This comparative visualization helps in understanding both the spatial and temporal patterns of flash droughts as well as the effectiveness of the prediction model across different regions and time periods. The observed flash drought pixels do not show a progression of such events, rather it occurs in some regions, ends quickly and then reemerges again. For example, the first half of December shows that flash drought began in some parts of south-west Victoria, which ends for one month and then reemerges in February.

Initially, from 1 December to 15 December, drought events were relatively sparse, primarily concentrated in southern QLD and northern NSW. As the season moves into late December (16–30 December), the observed data indicate a moderate expansion of drought regions, especially in QLD and parts of NT. By January, the observed flash drought areas expand significantly. The most affected regions include QLD, NT, South Australia and Tasmania. In the final phase of the summer season, from late January to February, observed flash droughts remain prominent but begin to show some variability in spatial distribution. The drought conditions persist in central and southeastern Australia, with slightly reduced severity compared to the peak in January. Notably, the coastal areas seem to experience more localized and patchy droughts during this time, indicating the influence of short-term weather patterns that provide intermittent relief from prolonged dryness.

The observed flash droughts show a gradual intensification, with notable peaks around the early January to early February period. This trend indicates that flash droughts were more severe and widespread during the summer peak, which aligns with the Tinderbox drought period, which was one of the worst drought periods in the country [22]. This period was the driest 3 year period since 1911 and can be visualized from the rainfall and mean temperature anomalies (figure 6(b)). The rainfall and mean temperature anomalies are standardized anomalies using the AGCD data [23] from 2001–2022, and each subplot is the mean of these values during the specified

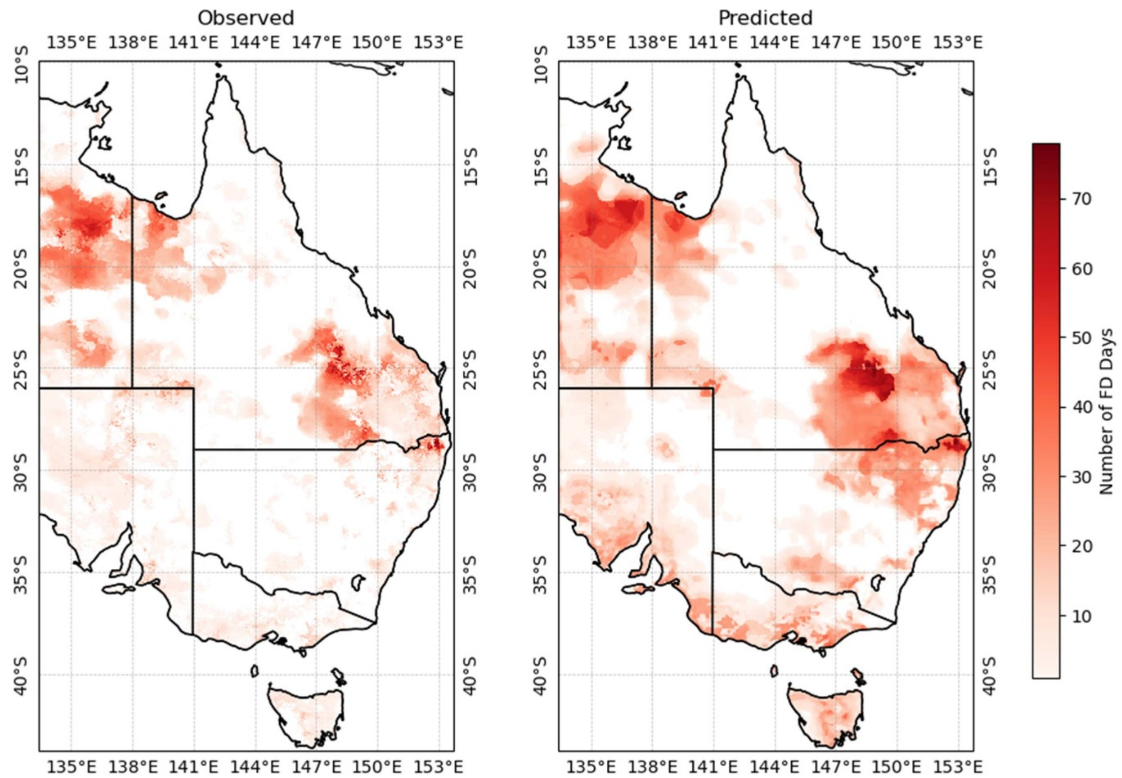

Figure 5. Comparison of observed and predicted flash drought pixels number of days which pixels were under the flash drought during summer of 2018 (December 2018—February 2019).

period. The temperature anomalies were negative in late December in coastal QLD and till end February there is a sharp decrease towards negative anomalies in the majority of QLD and Southern Australia.

Spatially, the predicted and observed flash drought patterns share some similarities but also exhibit some differences. In general, the CNN model shows a reasonable level of accuracy in predicting the occurrence and timing of flash droughts. The predicted flash drought seems to over-predict the extent of flash droughts, as visible from 30 Jan—13 February 2019. During this period, large regions of Victoria and Southern Australia were predicted to be under flash drought, whereas the observed flash drought was limited to coastal regions of Victoria and Southern Australia. Similar observation can be made for the 2021–22 summer season, as shown in the supplementary information.

6. Variations in winter season

Like the above discussion on summer season, analysis was conducted for winter season (June- July—August) of 2018 (figures 7(a) and (b)). The observed maps clearly show that flash drought began in QLD which progressed to NSW by the end of winter 2018.

During the early part of winter, from 1 June to 15 July, the observed flash drought data indicates relatively isolated and scattered drought conditions, primarily in QLD and Northern NSW. These drought events appear as small patches, suggesting that the occurrence of flash droughts in this region during early winter is sporadic and does not progress over a large area. In the later stages of winter, from the end of July through August, there is a significant change in the observed flash drought patterns. During this period, the drought regions expand notably in NSW and extend towards some parts of Victoria and NSW. The extent of flash droughts in these areas suggests an increase in flash drought area as winter approaches its end. The most prominent drought activity is observed in the period from 15 August to 29 August, where large parts of NSW are severely affected. Similar observation can be made for the 2022 winter season, as shown in the supplementary information. This widespread drought pattern indicates that as winter transitions into the pre-spring period, the soil moisture deficit becomes more pronounced, affecting a larger area. This is consistent with the mean temperature anomalies which were negative during the second half of August 2018. Similarly, rainfall anomalies were slightly negative throughout this period.

7. Discussions

This work is focused on how to develop a data-driven model to predict an event which is short in duration and does not have enough samples. This does not endorse the use of ESI as the most appropriate index for flash drought identification [24]. The focus of the

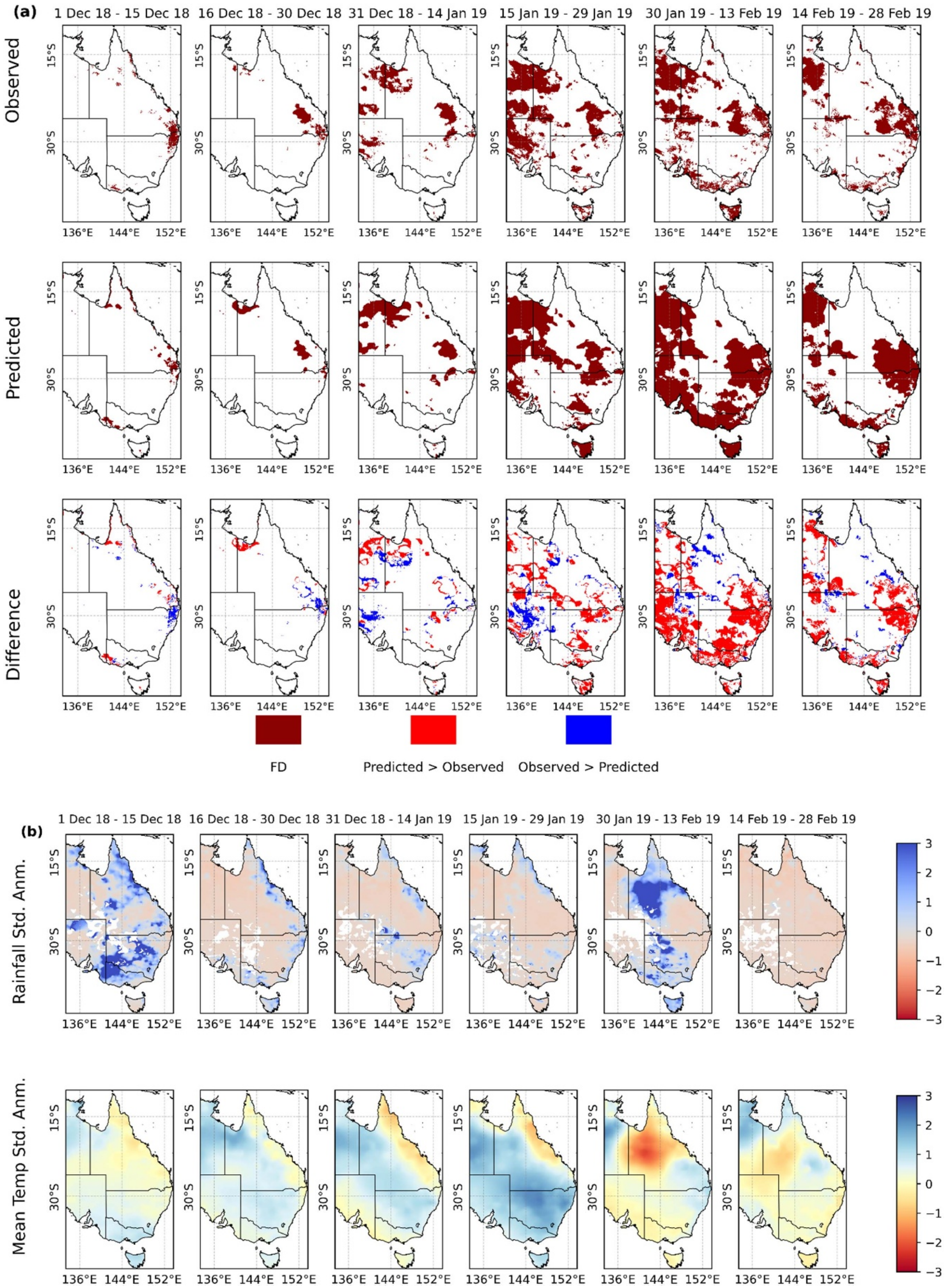

Figure 6. (a) Comparison of observed, predicted and the difference in flash drought periods across the 2018–19 summer season divided across 15 d. (b) Rainfall and mean temperature standardized anomalies across the 2018–19 summer season divided across 15 d. Daily standardized anomalies were computed by excluding the target year to calculate the mean and standard deviation and then standardized as (value—mean)/standard deviation.

work is to study whether a flash drought index be predicted using only climatic variables given the number of imbalanced training datasets. The predicted index is a binary number of either flash drought occurring or not occurring and does not reflect the intensity of the flash drought.

For this, a CNN architecture with a focus on a different loss function was used. The study focused on understanding whether the model can correctly predict a flash drought pixel and how well can it predict the duration of a flash drought event. In terms of correctly predicting a flash drought pixel, the results

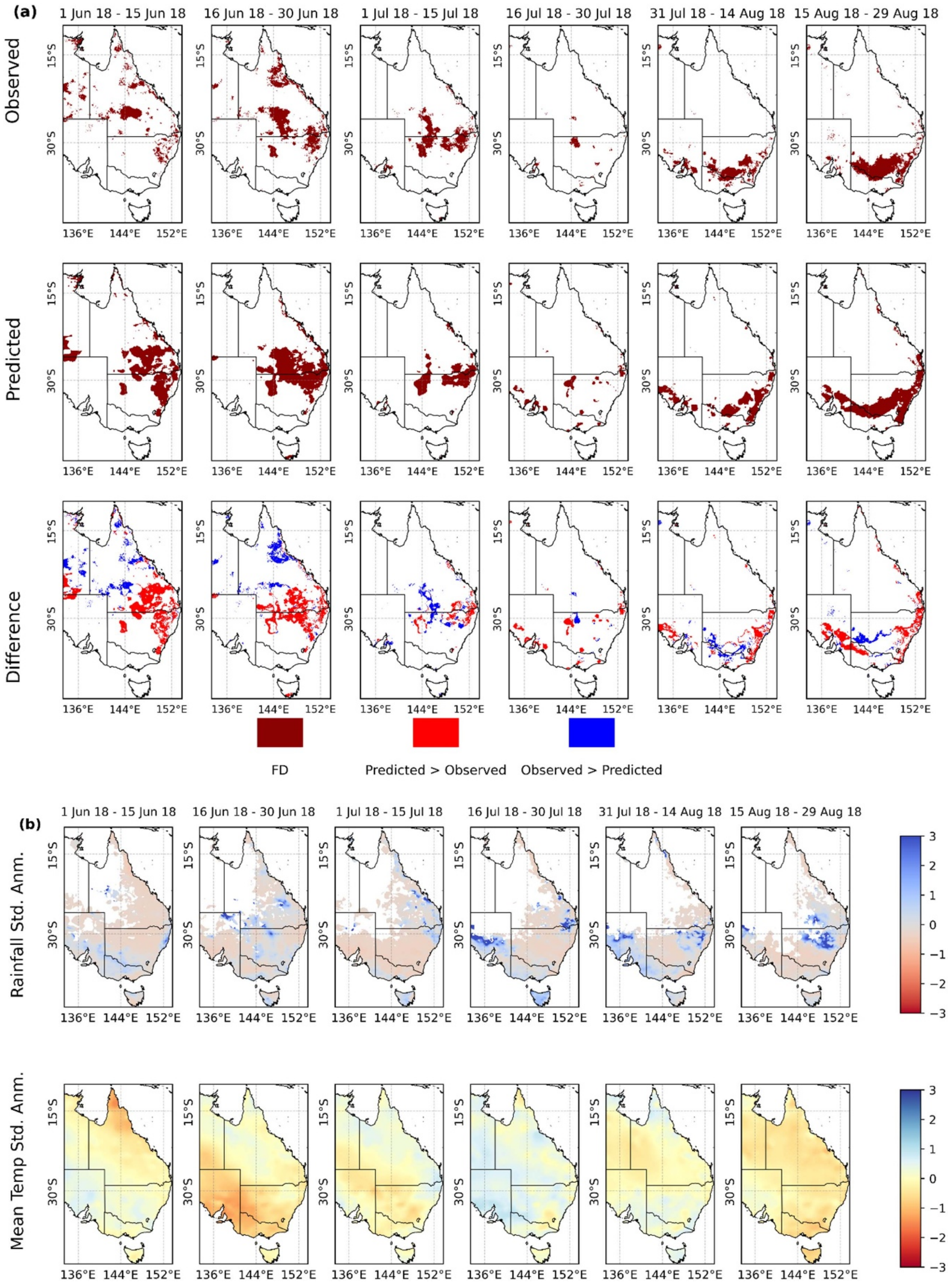

Figure 7. (a) Comparison of observed, predicted and the difference in flash drought periods across the 2018 winter season divided across 15 d. (b) Rainfall and mean temperature standardized anomalies across the 2018–19 winter season divided across 15 d. Daily standardized anomalies were computed by excluding the target year to calculate the mean and standard deviation and then standardized as (value—mean)/standard deviation.

suggest that the model was able to correctly identify 94% of the flash drought pixels. To further analyze the capability of the model, a comprehensive analysis between predicted and observed flash drought pixels were conducted across two seasons (summer and winter) for 2018. Given that the testing period extended from January 2018 to December 2022, and that 2019/20 was marked by extreme bushfires, 2018 was the only period without significant external factors influencing the results. Any occurrences of flash drought following the fire period need to be examined in conjunction with the burned area and fire dynamics.

Research on the use of ML models to examine flash droughts has primarily focused on identifying their onset, termination and forecasting flash drought-based indices. The present work is unique in that it predicts whether a given pixel will experience a flash drought based on climatic factors. Previous examples of ML applications in this domain include the studies conducted by Xu *et al* [25] which used a light gradient boosting machine model to predict global root-zone soil moisture (RZSM) for flash drought detection, using meteorological forecasts from the ECMWF sub-seasonal to seasonal model. The model combines static features (e.g. land cover, vegetation type, soil type) and dynamic features (e.g. temperature, dewpoint, wind, precipitation, radiation) to predict RZSM over 1–14 d time scales. The results show that the ML model can correctly predict 33% of flash drought onsets and 24% of terminations at a 7 day lead time, outperforming the state-of-the-art dynamic model, which predicts only 19% and 11%, respectively.

Lorenz *et al* [26] applied a Gradient boosting machine model to forecast soil moisture and ESI. The model utilized predictors such as soil moisture variables at different depths, precipitation, and dewpoint depression. This study improved upon earlier linear regression approaches by increasing the sample size through the inclusion of surrounding grid points, which enhanced model robustness. Notable improvements were observed in regions with high soil moisture autocorrelation, such as the Midwest and Southeast United States, where the ML model reduced prediction errors and increased forecasting skill. However, predictions for ESI showed limited improvements compared to soil moisture, likely due to the complex interactions between vegetation and atmospheric conditions, as well as the challenges posed by limited data availability. This is the first study of its kind aimed at predicting the flash drought index based on historical flash drought events and climatic factors, with a particular focus on addressing imbalanced datasets. Xu *et al* [25] correctly predicted 84% of flash drought onsets, but their method determines the onset based on a range of days rather than a specific day. In contrast, our approach identifies the onset on a specific day. Hence, for comparison purposes, we considered only those flash drought events with a minimum duration of 14 d and defined the flash drought onset range as 2 weeks ($\pm$7 d). Under these conditions, our model correctly predicted 85.28% of flash drought onsets, slightly outperforming the findings of Xu *et al* [25].

8. Conclusions

Flash droughts represent a complex and rapidly developing type of extreme dry event that has posed significant challenges for researchers in terms of definition, analysis, and prediction. The sudden onset and intense nature of flash droughts, coupled with their relatively short duration, set them apart from traditional droughts, making it difficult to capture their characteristics using conventional drought indices. One of the key challenges in studying flash droughts is the inherent scarcity of such events in historical datasets, which leads to a significant imbalance in data when compared to non-drought conditions. This imbalance complicates the development of predictive models, as standard ML approaches often struggle to identify patterns in underrepresented classes.

To address these issues, our study implemented a deep learning approach using CNN with a particular emphasis on handling the imbalanced nature of flash drought datasets. While CNNs are traditionally well-suited for identifying spatial patterns, they are not inherently designed to capture temporal changes. However, in this model, the input data has been structured in a way that allows the CNN to effectively recognize temporal patterns. The comparison between observed and predicted flash drought events was thoroughly analyzed across both summer and winter seasons, focusing on the duration and spatial distribution of flash droughts. The model demonstrated a robust performance, achieving an accuracy of 80% in accurately predicting flash drought pixels. The outcomes of this study underscore the potential of CNNs as a powerful tool in advancing our knowledge of flash drought patterns and improving our ability to forecast these sudden and extreme events. Continued research in this area, focusing on enhancing model precision and integrating observational data and large-scale climatic indicators, will be crucial for developing robust predictive models capable of supporting effective drought preparedness and response strategies.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

All the datasets are provided by the Bureau of Meteorology and are publicly accessible. The code for the CNN model can be found here: https://github.com/pratikej/flash_drought_ml.

Author contributions

Conceptualization—A.D., B.P., and A.H; Methodology—P.J.E., N.C., and A.D.; Software—P.J.E., N.C.; Validation—B.P., N.C.; Formal analysis—A.D., N.C.; Investigation—A.D., P.J.E.; Resources—A.D., J.P.E.; Data curation—A.D.; Writing—original draft preparation, A.D.; Writing—review and editing—J.P.E., B.P., and A.H.; Visualization—A.D.; J.P.E.

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