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Tracking Drought Impacts from Texts: Towards AI-Assisted Drought Impact Detection

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ABSTRACT: Drought is recognized for its extensive and varied impacts. Based on the drought-related textual datasets from the National Drought Mitigation Center, our research applies advanced artificial intelligence techniques, including deep learning and natural language processing, to enhance the monitoring of multifaceted drought impacts in the United States. This study also delves into predicting drought-related impact labels from informal social media texts through transfer learning from the textual databases. Our findings reveal that deep learning models based on Transformers significantly outperform the baseline model based on the word frequency in labeling various drought impacts from media-sourced data and a collected tweet dataset spanning 2020 to 2022. Comparative analyses of predicted labels of drought-related tweets underscore the added value of social media data, which offers distinct insights into drought impacts beyond what is captured in news media or citizen science contributions. Case studies in California and Nebraska illustrate dynamic characteristics of drought impacts from the predicted labels of the tweet dataset at spatial and temporal scales. The analyses indicate that the monthly quantity of drought-related information in California is linked to drought severity, urban areas, and water supply and quality. In contrast, it is associated with the growing season, irrigated cropland, and agriculture in Nebraska. Consequently, this study suggests applying social media as a valuable supplementary data source, boosted by cutting-edge deep learning models, for monitoring drought impacts with the potential for quantitatively defining socioeconomic droughts from societal and public perspectives.

1. Introduction

Drought is recognized as a natural disaster with extensive impacts and substantial economic costs. In the United States, drought events with damages exceeding one billion dollars have become increasingly frequent, occurring in 19 of the 23 years from 2000 to 2023, with an average cost of these events estimated at $10.27 billion (NOAA NCEI 2023). Recent studies suggest that droughts are likely to intensify in frequency and rapid onset as a result of climate change (Zhao and Dai 2022; Rodell and Li 2023; Yuan et al. 2023). Thus, monitoring and predicting multi-dimensional drought impacts have become more crucial and indispensable to provide information for decision-makers and stakeholders to provoke proactive actions and planning on mitigating the costs and damages caused by drought events (Hayes et al. 2012; Cravens et al. 2021). However, the inherent complexity of drought, characterized by the absence of universal definitions and the delayed manifestation of its direct and indirect effects, complicates the quantification and identification of its impacts across various sectors, leading to a scarcity of high-quality drought impact data (UNDRR 2021). For example, Stephan et al. (2023) highlights that quantitative drought impact data is most readily available for agriculture, so agriculture has been the focus of impact-based prediction for drought. The other drought impacts across multiple dimensions beyond agriculture are relatively unexplored. In response, recent research has started to employ text-based datasets as valuable sources for capturing more effects of drought across multiple dimensions. The textual datasets are usually collected from volunteer-based observations and news reports, documented with contexts of various affected aspects ranging from vegetation health to socioeconomic conditions (Smith et al. 2021).

In the United States, the concept of better identifying and assessing drought impacts compelled the National Drought Mitigation Center (NDMC) to launch an online archive named the Drought Impact Reporter (DIR) in 2005. The drought impacts are defined as a loss or change at a specific place and time because of drought (Svoboda et al. 2016). The DIR underwent considerable updates in 2008 and 2011, developing into an integrated database of user- and media-reported cross-sector drought impacts (Smith et al. 2014). In 2018, the NDMC replaced DIR user reports with Condition Monitoring Observer Reports (CMOR), which are collected in a separate database and displayed on different maps (Smith et al. 2021). An upgraded online platform, Drought Impacts Toolkit (DIT), was then developed to integrate drought impact monitoring products, including the DIR and other datasets, available for the public (NDMC 2024). Now, DIT datasets contain over a hundred thousand text descriptions of drought impacts, each manually tagged with nine distinct impact types and accompanied by time and location. Despite their potential as a rich data source, textual drought impact datasets remain underutilized in research in the United States, with only a limited number of studies employing them for analysis. Noel et al. (2020) used the DIR to link drought severity and various impacts qualitatively. Sutanto et al. (2019) and Zhang et al. (2023) applied machine learning (ML) to predict drought impacts and assess their relationships with drought indicators. Stahl et al. (2012) established a similar database - the European Drought Impact Inventory (EDII), to collect reports on drought impacts in the pan-European area. Relatively more studies were conducted based on the EDII compared to the DIT products, with two primary focuses: investigating the relationships between drought indices and various impacts (Blauhut et al. 2015; Bachmair et al. 2015; Stagge et al. 2015) and developing models to predict and forecast drought impacts on multiple sectors (Bachmair et al. 2016a, 2017; Stephan et al. 2023).

The effective use of text-based datasets, as seen with the DIT and the EDII, demonstrates their potential as robust sources for assessing multi-sectoral drought impacts. However, while such datasets have typically been processed into frequencies or occurrences of impacts based on labels and then used with drought indices to create descriptive or predictive models, the wealth of information contained within the text itself has not been fully harnessed. Recent studies have shown the potential of rule-based models to analyze and evaluate drought impacts from news articles (de Brito et al. 2020). Furthermore, Sodoge et al. (2023) applied traditional natural language processing (NLP) methods, including bag-of-words (BoW) and term frequency–inverse document frequency (TF-IDF), in conjunction with logistic regression with lasso regularization, to classify various drought impacts. Comprehensive studies focused on natural disasters have explored applying state-of-the-art models that combine NLP with deep learning (DL), such as the Bidirectional Encoder Representations from Transformers (BERT), Generative Pre-training Transformer (GPT), and their variations, on text data from social media and have shown better results compared to ML models (Powers et al. 2023; Goecks and Waytowich 2023). However, there is seldom attention paid to employing cutting-edge NLP and DL methods to identify various drought impacts based on robust and reliable textual data.

Expanding upon our preliminary work (Zhang et al. 2021), this study demonstrates the practical application of advanced DL models for identifying multi-dimensional drought impacts based on textual data in the United States. This predictive task is naturally a multi-label question because a drought event could often affect more than one sector. We utilized the fine-tuned BERT-like models based on DIT datasets and the latest GPT model configured with handcrafted interpretable prompts. These models were also benchmarked against the traditional TF-IDF model. The test task involved identifying the categories of drought impacts from the news media data. Subsequently, we deployed these NLP models on tweets to identify drought-related information, following the suggestions by Smith et al. (2020) that social media can be used to monitor drought impacts. Beyond the model evaluation metrics for multi-label classification, we also calculated the correlation between the counts of predicted labels for each drought impact type and the Drought Severity and Coverage Index (DSCI) to indicate comprehensive relationships between drought and its impacts (Akyuz 2017). The temporal and spatial characteristics of the predicted labels from the tweets were analyzed in the selected states. Our study significantly streamlines the maintenance of textual drought impact datasets and enhances the integration of new data sources into drought impact monitoring frameworks. The study also illuminates the intricate and evolving characteristics of drought impacts, substantiating the feasibility of utilizing social media data to identify socioeconomic drought and assess multi-dimensional impacts and awareness of drought.

2. Data Description, Processing, and Exploration

The labeled text-based DIT datasets from 2010 to 2022 at the state and county levels were acquired in this study. The utilized datasets comprise five subsets from three sources: news media, user submissions, and observations by the Community Collaborative Rain, Hail, and Snow Network (CoCoRaHS) volunteers. Media reports on drought events were systematically gathered using the CustomScoop, a news media monitoring service. These reports were subsequently reviewed and labeled by NDMC experts into ten categories, including the general awareness of drought and nine types of drought impacts on multiple dimensions. Meanwhile, the moderators wrote descriptions of drought impact based on media reports. By definition, “general awareness” is a non-impact category, so none of the moderated drought impact descriptions are tagged with general awareness. A separate dataset of media impacts was created in this step. CoCoRaHS, a nonprofit and community-based organization of volunteer citizen scientists, contributes precipitation observations and allows volunteers to append optional drought descriptions and labels to their reports for the dry conditions (Reges et al. 2016). The labels used in the CoCoRaHS reports are consistent with those used for media reports and impacts. Before 2018, there was a feature to submit drought reports with corresponding labels collected as the user report dataset. After, it was supplanted by the CMOR on the DIT platform, a more sophisticated system for collecting drought-related data, which included a 7-point scale and photo upload capability, though it omitted labels for general awareness and drought impacts related to relief, response, and restrictions (Smith et al. 2021).

All five DIT subsets underwent standardized processing to prepare them for DL applications. To maximize the textual information for the BERT-like and GPT-like models, all website URLs were replaced with a generic token. Commonly used symbols with specific meanings, such as percentage signs and units of measurement like Fahrenheit and inches, were translated into text. Other non-alphanumeric characters were removed. For the word-frequency-based model as the baseline benchmark, numbers and stopwords were also excluded from the input text. The entries with duplicate descriptions in the datasets were dropped after the cleaning process. Because of input length restrictions for the BERT-like models, the texts exceeding 512 tokens were truncated using a head-tail approach, which balances preserving meaning with processing efficiency (Sun et al. 2019; Fiok et al. 2021). Entries with fewer than five tokens were discarded on the empirical basis of potential information insufficiency. Table 1 shows the descriptive statistics of the processed DIT subsets. Media reports are written in a longer format with a median of 399 words. Media impact summaries are notably more concise. User reports are longer than CoCoRaHS and CMOR entries, with CMOR reports being the most succinct due to their survey-based nature. CoCoRaHS is the primary data source, constituting over 75% of the employed DIT subsets.

The ten binary classes, including general awareness and nine sector-based types of drought impacts, were used to construct consistent datasets. Each text entry can have more than one assigned category. Figure 1 shows the class distribution across DIT subsets, highlighting the imbalance and variability in drought information descriptions among different sources. The figure also reflects the unique focus of each subset: media content often addresses relief, response, and water quality; CoCoRaHS reports concentrate on general awareness and environmental impacts; user and CMOR submissions frequently discuss agricultural effects, with user reports heavily

TABLE 1. Descriptive statistics of the five DIT subsets.

	Sample Count	Word Count in a Sample		
		Minimum	Median	Maximum
Media Impacts	11,878	16	69	462
Media Reports	5,684	22	399	478
CoCoRaHS Reports	76,428	5	36	488
User Reports	1,596	9	82	475
CMOR Reports	4,735	5	37	203
Total	100,321	5	44	488

focusing on agriculture, and CMOR reports adding societal and health perspectives. Less attention is given to impacts on business, industry, energy, and tourism. Figure 2 presents the twenty most frequently used words across the DIT subsets. Media impacts frequently mention Texas and California, indicating these large and populous states with robust media coverage prominently affected by drought, with mentions peaking between May and August. Although media reports are also at a general scale, the time or place words are diluted in the longer text. CoCoRaHS, user, and CMOR reports target local and community-level impacts. CoCoRaHS observations often include weekly reports on soil, grass, and trees. User reports detail agricultural impacts, highlighting terms like hay, grass, cattle, pasture, livestock, crop, and producer. CMOR reports similarly reflect livestock and crop-production interests. The word frequency analysis, aligning with the class distribution, shows each subset's distinct focus on drought information, influenced by the source characteristics.

The other primary dataset in this study is the social media textual data from Twitter (now X) collected through Sprinklr, a media-monitoring platform originally developed for marketing, which is also useful to researchers. We applied queries to download drought-related tweets and to initially clean tweets by filtering out off-topic tweets based on classification filters provided by Sprinklr and our developed dictionary of keywords. Further processing followed the steps in Nguyen et al. (2020). Additionally, stop words in tweets were removed to reduce the redundancy in the informal and irregular texts. Details of the acquisition and process for the social media data are illustrated in Appendix A of the supplementary file. In total, 78,690 tweets with geospatial coordinates and time tags from April 2020 to December 2022 were employed in this study. The minimum, median, and maximum word count for tweets are 1, 19, and 85, which reflects tweets are generally shorter

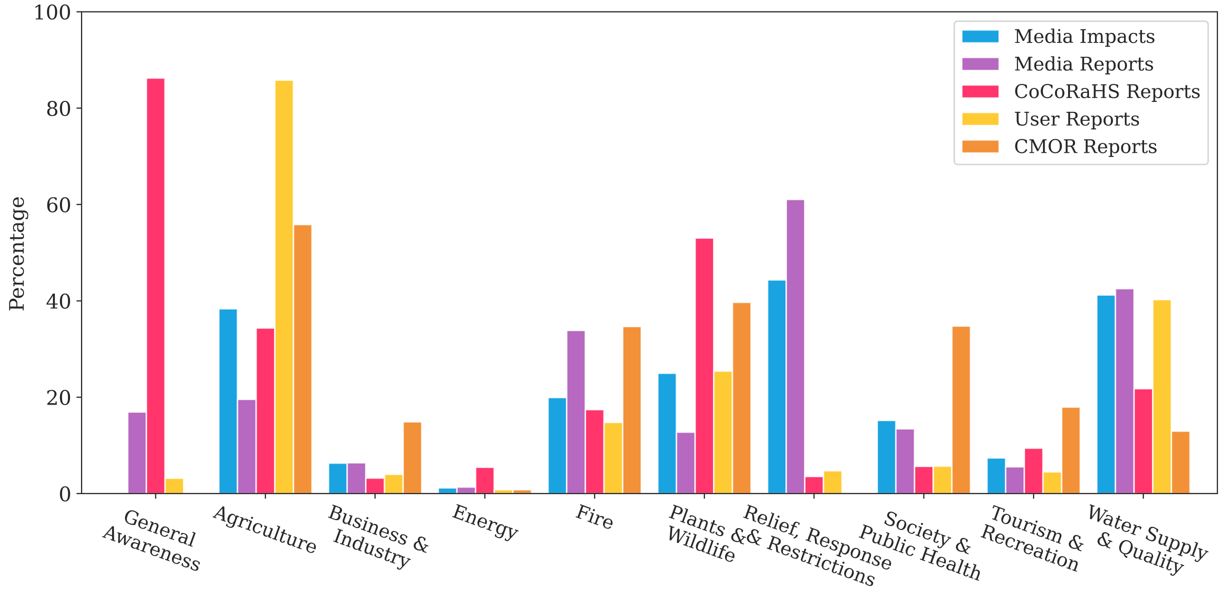

Fig. 1. The class distribution of each DIT subset. Media impacts and CMOR reports do not have records labeled as general awareness, and CMOR reports also do not include entries labeled as relief, response, and restrictions.

than the DIT datasets. The DL-based NLP models were applied to these tweets through transfer learning. Further analysis of the predictions enhanced our understanding of AI-assisted drought impact monitoring.

3. Methodology

a. NLP Models

In this research, the TF-IDF model combined with logistic regression serves as the baseline model. TF-IDF is a basic yet fundamental NLP method that transforms words into their frequency in the document by balancing the number of occurrences in the word corpus, helping to differentiate their meaning. Previous studies have utilized this method to develop a drought impact classification framework to detect drought impacts from newspaper articles in German (Sarkar 2019; Sodoge et al. 2023). In our case, TF-IDF generates word vectors representing the relative importance in the DIT datasets. The word vectors are then inputted into an LR model with L1 regularization for drought label classification. Although TF-IDF is easily and widely used to benchmark other

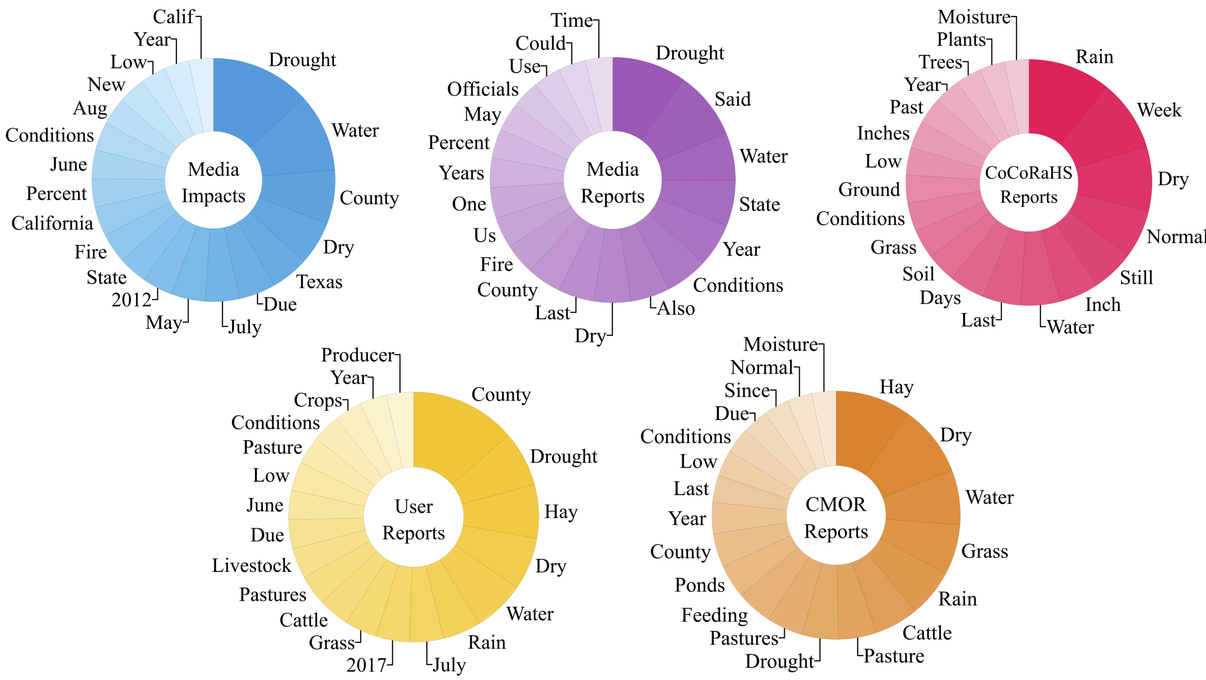

FIG. 2. Word frequency of the twenty most commonly used words for the five DIT datasets.

NLP models, it lacks the ability to grasp the contextual nuances of words or adjust across varying datasets, which is crucial for accurately classifying complex drought impact (González-Carvajal and Garrido-Merchán 2020).

The development of BERT and GPT models offers a remarkable leap in the performance of the NLP tasks. Both BERT and GPT models are built based on the transformer architecture, a type of autoencoder model in deep learning, and utilize self-attention mechanisms to process text data without the need for recurrence or convolution (Vaswani et al. 2017). BERT and its upgraded models are primarily based on the "encoder" part of the transformer and are designed to capture the contextual meaning of a word from both directions in a sentence (Devlin et al. 2018). We employed three BERT-like models in this study: RoBERTa, DistilRoBERTa, and ClimateBERT. RoBERTa is an optimized BERT model with more robust training strategies and larger pre-training datasets, achieving superior results across various NLP applications (Liu et al. 2019). DistilRoBERTa, a lightweight version of RoBERTa, maintains high performance while reducing model size through knowledge distillation (Sanh et al. 2019; Hugging Face 2023). ClimateBERT, based on DistilRoBERTa, is particularly pre-trained on climate-related texts, incorporating specialized climate-related texts and tokens in the pre-training (Webersinke et al. 2021). These models were fine-tuned on the DIT datasets to adapt their broad linguistic comprehension to the specialized task of classifying drought impacts.

GPT-4, the latest model in the GPT series, concentrates on the “decoder” segment of transformer architecture, trained across an extensive and varied internet text corpus (Radford et al. 2018). As one of the most sophisticated NLP models, GPT-4 is also one of the best models for predicting the next word in sentences and generating texts for academic applications (Ouyang et al. 2022; Achiam et al. 2023). Diverse prompting techniques, such as zero-shot and Chain-of-Thought, have been developed to guide the model in efficiently generating robust outputs Amatriain (2024). With the input of pre-designed instructions in natural language and the definitions of the nine types of drought impacts and general awareness, GPT-4 categorized drought-related textual data entries through text generation. The prediction was made based on contextualizing and understanding the definition and the description of drought impacts. The prompt, which used the zero-shot prompting technique, did not include examples of categorizations with results, as descriptions of some drought impacts could be vague and indirect.

b. Experimental Setup

The fine-tuning phase for the BERT-like models is particularly useful for improving the performance of a domain-specific applications (Gillioz et al. 2020). In this study, because of the diversity among the DIT datasets, exploring different dataset selections and compositions can help maximize the model performance in the fine-tuning process and improve the utilization of DIT datasets in NLP tasks. Therefore, we built up three fine-tuning datasets from the DIT subsets, and each of them was applied to fine-tune the BERT-like models. The media-sourced dataset, which includes media reports and impacts from 2011 to 2021, formed the basis for fine-tuning, while the rest of the media-sourced data from January 2022 to June 2023 served as the test dataset. The first fine-tuning dataset solely employed the 2011-2021 media-sourced dataset according to our primary goal of directly categorizing the news media texts. The balanced fine-tuning dataset incorporated other DIT subsets throughout the study period, focusing on expanding the textual data to cover rarer drought impacts and reduce the effects of imbalanced class distribution. The complete dataset included all DIT datasets to take advantage of the labeled textual datasets for predicting drought impacts. Figure 3 shows the class distribution of the three composite datasets used in the

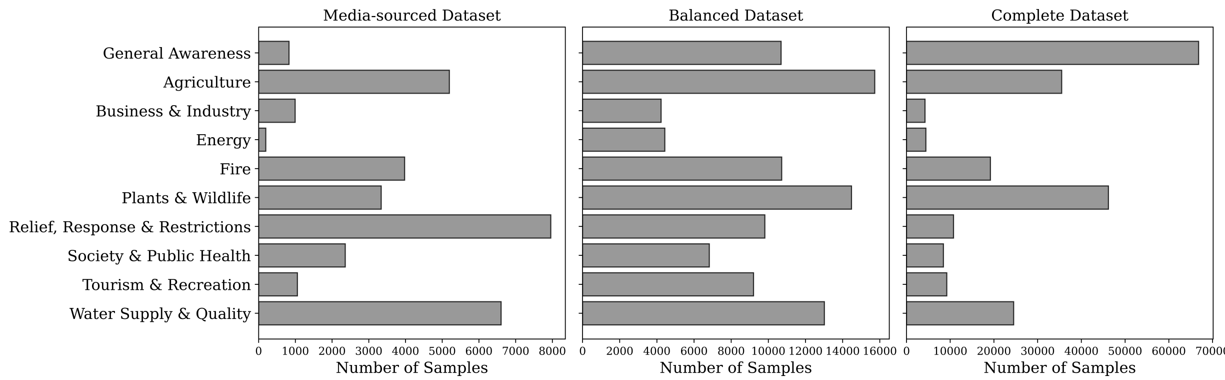

Fig. 3. The class distribution of each fine-tuning dataset. The media-sourced dataset includes the media reports and impacts from 2011 to 2021. The balanced dataset adds the samples labeled with infrequent drought impacts from the other DIT subsets from 2011 to 2022 to the media-sourced dataset. The complete dataset employs all selected DIT datasets.

fine-tuning phase. The balanced dataset has more samples of drought impacts related to business and industry, energy, society and public health, and tourism and recreation. The distribution of the complete dataset is similar to the distribution of the CoCoRaHS dataset because CoCoRaHS was the largest data subset that we used. In the fine-tuning process, each dataset was randomly split into the training and test datasets by 80% and 20% using the iterative stratification for the multi-labeled data (Sechidis et al. 2011). For GPT-4, zero-shot prompt engineering guided the model in outputting a dictionary of drought-related labels based on the context of the inputting text. The keys of the dictionary are drought general awareness and nine types of drought impacts, and values indicate the presence (1) or absence (0) of related information in the text. Comprehensive details on fine-tuning BERT-like models and GPT-4 prompt engineering are provided in Appendix B of the supplementary file.

Model performance was evaluated and compared using metrics suitable for multi-labeled classification, including the Exact Match Ratio, Hamming loss, and Weighted F1 score. The Exact Match Ratio measures the percentage of samples for which the set of predicted labels exactly matches the set of true labels. The Hamming loss is the fraction of the incorrectly predicted labels over the total number of labels. The Weighted F1 score is calculated from the individual F1 score for each label and summed based on a weight depending on the number of true instances for each label to account for the class imbalance. Exploiting BERT-like models' transfer learning capability, we further applied these models to identify drought information in tweets as the downstream task. A sample dataset of a thousand tweets was manually labeled to validate the performance of the NLP models.

4. Results

a. Model Performance on Predicting the Categories of Drought Information from the Media-sourced Data

The first primary goal of this study is to investigate the application of cutting-edge DL and NLP models to predict the categories of drought impacts from the textual data, which could assist the experts and stakeholders in handling big datasets. Therefore, the first result section demonstrates the model performance among the BERT-like models, GPT-4, and the baseline model TF-IDF. The experiments also tested different fine-tuning datasets to examine their effects on the models.

Table 2 indicates that BERT-like models fine-tuned on the media-sourced data achieved the best performance for predicting the categories of drought impacts. The differences between the validation and test datasets were insignificant, indicating no noticeable overfitting issue in the models. While RoBERTa marginally surpassed DistilRoBERTa and ClimateBERT in validation, their test performances were comparable. RoBERTa achieved a higher Weighted F1 score, but DistilRoBERTa and ClimateBERT showed better Exact Match Ratios and lower Hamming losses. The larger model size from RoBERTa or the enriched token dictionary from ClimateBERT did not significantly benefit the model performance. The experiments also demonstrated that increasing the complexity of fine-tuning datasets did not necessarily enhance model performance. As the fine-tuning datasets increased, the RoBERTa models learned better from the more complicated information than the other two BERT-like models. In fact, DistilRoBERTa and ClimateBERT experienced performance drops with the inclusion of more drought descriptions. GPT-4 with the zero-shot prompting performed well, outperforming TF-IDF and even the ClimateBERT model fine-tuned on the complete dataset regarding the Weighted F1 scores. However, the Exact Match Ratio and Hamming loss metrics from GPT-4 were not as good as those of the BERT-like models. The benchmarked TF-IDF models significantly underperformed compared to BERT-like and GPT-4 models. The DL-based NLP models noticeably boosted the performance on predicting drought impacts with an improvement range of 23.1% to 62.2% in the Weighted F1 scores.

TABLE 2. Comparison of model performance on the validation and test datasets to predict the categories of drought information from DIT datasets.

NLP Model	Fine-tuning Data	Validation Dataset			Test Dataset		
		Exact Match Ratio	Hamming Loss	Weighted F1 Score	Exact Match Ratio	Hamming Loss	Weighted F1 Score
RoBERTa	**Media-sourced**	**0.662**	**0.045**	**0.880**	**0.548**	**0.066**	**0.840**
DistilRoBERTa	**Media-sourced**	**0.662**	**0.046**	**0.874**	**0.552**	**0.064**	**0.833**
ClimateBERT	**Media-sourced**	**0.652**	**0.046**	**0.869**	**0.553**	**0.064**	**0.833**
TF-IDF	-	0.465	0.081	0.684	0.372	0.107	0.643
RoBERTa	Balanced	0.483	0.101	0.820	0.549	0.065	0.828
DistilRoBERTa	Balanced	0.471	0.105	0.797	0.506	0.072	0.795
ClimateBERT	Balanced	0.477	0.106	0.801	0.530	0.069	0.817
TF-IDF	-	0.294	0.158	0.620	0.353	0.112	0.646
RoBERTa	Complete	0.458	0.096	0.765	0.522	0.070	0.806
DistilRoBERTa	Complete	0.446	0.099	0.758	0.491	0.076	0.788
ClimateBERT	Complete	0.431	0.101	0.749	0.467	0.081	0.761
TF-IDF	-	0.332	0.129	0.588	0.164	0.158	0.497
GPT-4	-	-	-	-	0.217	0.133	0.778

To further illustrate the model performance in predicting the categories of media-sourced drought impacts, the details of F1 scores for each type of drought impact from the selected models are shown in Figure 4. Given their superior test dataset performance, BERT-like models fine-tuned on media-sourced data were compared alongside GPT-4 and the TF-IDF model. Because the three BERT-like models achieved similar performance, we used RoBERTa as a representative to illustrate the F1 score of each type of drought impact in a spider plot, being analyzed along with the individual F1 scores for GPT-4 and TF-IDF models. Overall, the NLP models performed significantly better in predicting drought impact categories for agriculture, fire, relief, response, restrictions, water supply, and quality, than the others. And the DL-based models improved by 6.26% compared to the benchmark model. However, for predicting other categories, the performance of the TF-IDF model dropped notably. Except for the drought impacts related to plants and wildlife, the other predictions of the benchmark model had zeros in F1 scores due to the imbalanced label distribution and a lack of correct positive label predictions. The DL-based models substantially surpassed the benchmark. However, F1 scores still indicated challenges in labeling general drought awareness and impacts on society and public health and the non-agricultural economy. Within the DL-based

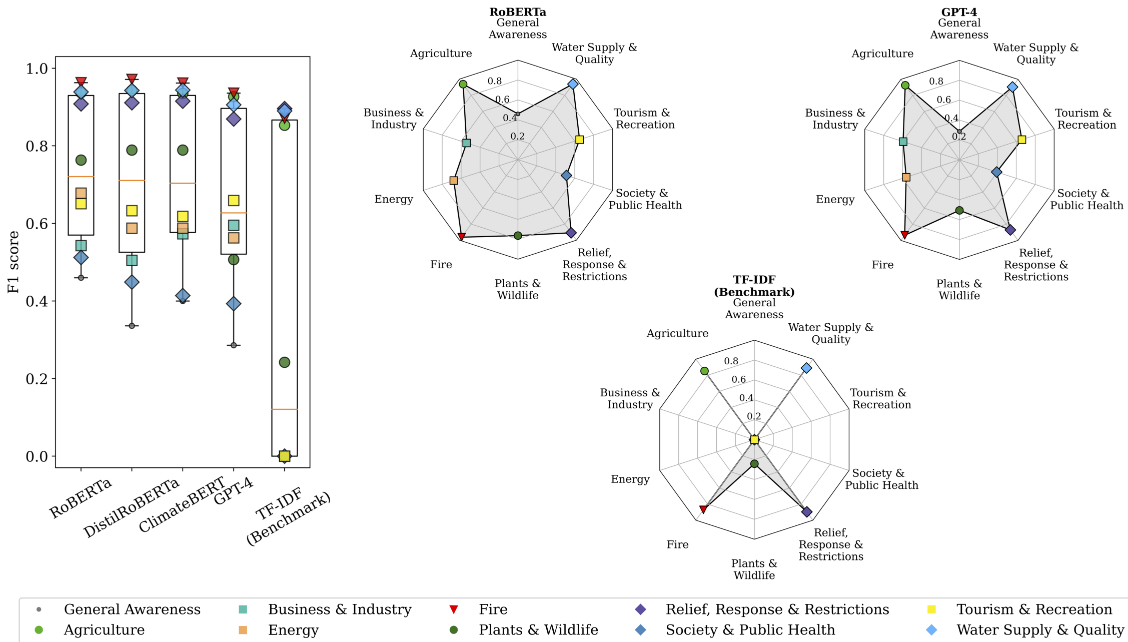

FIG. 4. The F1 scores of the NLP models on the test dataset for the individual category of drought impacts. The BERT-like models fine-tuned on the media-sourced DIT dataset were selected and compared with GPT-4 and TF-IDF.

models, the BERT-like models generally outperformed GPT-4, except for the drought impacts related to business and industry and tourism and recreation that are the two most scarce labels in the media-sourced data. The overall improvement of fine-tuned BERT-like models compared to GPT-4 was 16.6% on identifying drought impact sectors from the media-sourced text descriptions from 2022 to 2023.

b. Transfer Learning on the Social Media Dataset to Identify Drought Awareness and Impacts

Our second main objective is to assess the potential of incorporating social media data for AI-enhanced drought impact monitoring. We applied transfer learning to BERT-like models fine-tuned on the DIT datasets, predicting the categories of drought impact and general awareness in the tweet dataset from 2020 to 2022 in the United States. GPT-4 and the benchmark TF-IDF model were also evaluated for comparison. The same prompts but with social media data were input into the GPT-4 model. The model performance evaluation was conducted on the test tweet dataset manually labeled based on the same classes as the DIT datasets. The same evaluation metrics were also applied for the evaluation.

Table 3 underscores the benefits of utilizing comprehensive fine-tuning datasets, extensive model architectures, and domain-specific pre-training. BERT-like models, particularly RoBERTa and ClimateBERT, fine-tuned on the complete dataset, demonstrated superior performance. Specifically, RoBERTa and ClimateBERT achieved the best performance in terms of the Exact Match Ratio. RoBERTa presented a marginally lower Hamming loss than ClimateBERT, while ClimateBERT had a higher Weighted F1 Score than RoBERTa, indicating nuanced differences in their capacity to balance precision and recall across diverse drought impact categories. The performance of BERT-like models was notably influenced by the choice of fine-tuning dataset. In particular, models fine-tuned on the balanced dataset exhibited the lowest Exact Match Ratios and the highest Hamming losses. Although it is expected to observe performance degradation in transfer learning scenarios, this contrast between the model performance on the two applications likely indicates a mismatch between the balanced class distribution within the DIT dataset and the distribution reflected in the tweet dataset. Despite these challenges, all BERT-like models outperformed the TF-IDF models. The two best models, RoBERTa and ClimateBERT, fine-tuned on the complete dataset, achieved increased Weighted F1 scores of 55.9% and 57.3%, respectively. Compared to BERT-like models, GPT-4 demonstrated superior performance in terms of the Weighted F1 Score. However, it exhibited a lower Exact Match Ratio and a higher Hamming Loss. This discrepancy indicates that while GPT-4 was less effective at consistently predicting all labels for drought content within one tweet entry accurately, it was more adept at recognizing specific types of drought impacts and general awareness across the tweet dataset.

The performance of each NLP model in predicting distinct types of drought-related information projected from the tweets is depicted in Figure 5, utilizing F1 scores as the evaluative metric. The figure includes box plots of the BERT-like models fine-tuned on the complete dataset, GPT-4, and TF-IDF, alongside three spider plots to offer further illustrations of their performance, with ClimateBERT serving as the representative for BERT-like models due to its superior Weighted F1 score. The fluctuations of the F1 scores for the predicted labels in the tweet dataset are more pronounced in the BERT-like models during transfer learning, with a notable decline in correctly predicting drought impacts related to the non-agricultural economic sectors, including

Table 3. Performance comparison of the NLP models on the downstream task to predict the category of drought information from tweets.

NLP Model	Fine-tuning Dataset	Prediction of Tweets		
		Exact Match Ratio	Hamming Loss	Weighted F1 Score
RoBERTa	Media-sourced	0.307	0.103	0.423
DistilRoBERTa	Media-sourced	0.251	0.120	0.359
ClimateBERT	Media-sourced	0.277	0.111	0.380
TF-IDF	-	0.341	0.088	0.236
RoBERTa	Balanced	0.191	0.197	0.407
DistilRoBERTa	Balanced	0.198	0.166	0.419
ClimateBERT	Balanced	0.156	0.207	0.443
TF-IDF	-	0.312	0.104	0.256
RoBERTa	**Complete**	**0.390**	**0.090**	**0.574**
DistilRoBERTa	Complete	0.335	0.102	0.557
ClimateBERT	**Complete**	**0.390**	**0.093**	**0.579**
TF-IDF	-	0.343	0.098	0.368
GPT-4	-	**0.300**	**0.105**	**0.608**

energy, business and industry, and tourism and recreation. Despite the expected decrease of model performance for drought impacts related to agriculture, fire, and water supply and quality, these remain the most accurately identified labels within tweets. Conversely, the F1 scores of the predictions of general awareness from the BERT-like models appear to improve on the tweet dataset. GPT-4 exhibits a relatively well-rounded performance predicting various types of drought content on tweets. It not only provides better predictions on those categories where the BERT-like models perform well but also shows enhanced F1 scores on the non-agriculture economic impacts, especially concerning energy and tourism and recreation. The benchmark model based on TF-IDF was significantly behind the DL-based NLP models across all categories of drought information. Its ability to discern various drought-related content from tweets is markedly limited, save for the general awareness of drought and agricultural impacts. This stark disparity underscores the advanced capability of the BERT-like and GPT-4 models in enhancing the application of text-based social media data for monitoring drought impacts.

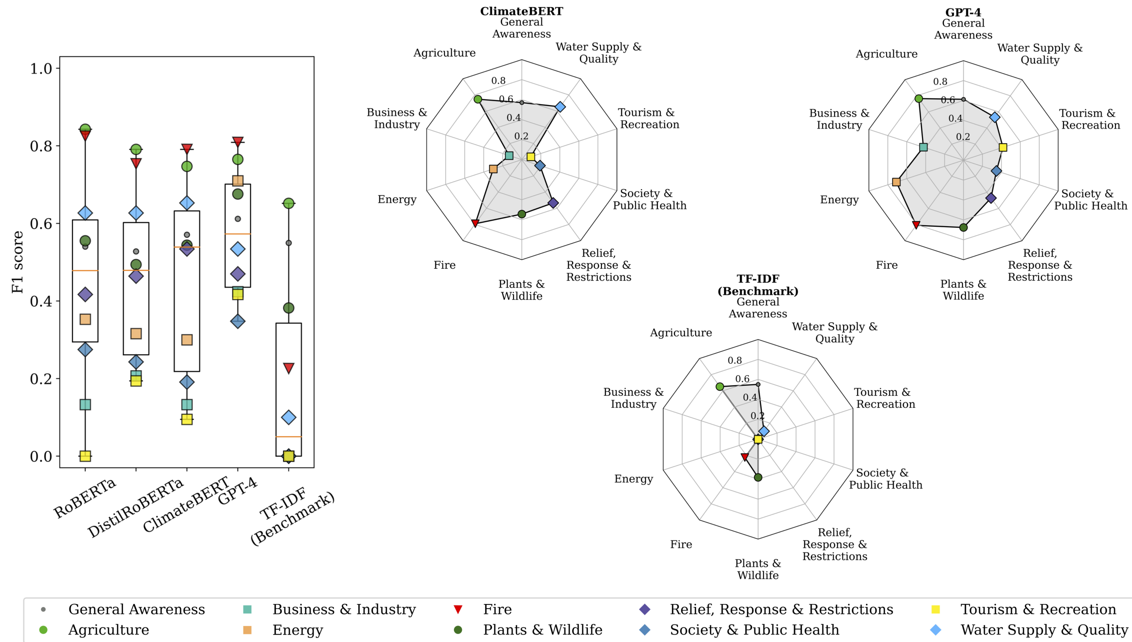

FIG. 5. The individual F1 scores of the model performance on the downstream task to predict the drought impacts and awareness on the tweet dataset. The BERT-like models fine-tuned on the complete dataset were selected and compared with GPT-4 and TF-IDF.

c. Considerations in Applying Social Media for Drought Impact Monitoring

Beyond demonstrating the superiority of the DL-based NLP models for boosting drought impact monitoring from news and social media, the other sub-objective of the second main goal is to investigate if tweets can bring additional information on multi-dimensional drought impacts compared to the current sources employed in the DIT subsets. In this section, we analyzed the temporal and spatial patterns of drought general awareness and impacts reflected in the tweet dataset using the predicted labels from the advanced NLP models. Based on the models' performance on the labeled validation dataset, the BERT-like models fine-tuned on the complete dataset and the GPT model were employed. The benchmark model was dropped in this section because of its poor predictions on the tweets. The analysis and discussion are at the state and county levels. Considering the various spatial distributions of the tweets, climate conditions, and the occurrence of drought events, we selected seven states that had more than a thousand tweets and multiple drought events during 2020 to 2022. California has the highest number of tweets (19,818), more than two-fold that of the state of Texas, which has the second-largest number of tweets (7,087). The other selected states are Massachusetts, Arizona, Nebraska, Iowa, and Washington, in descending order of the number of tweets from 2,130 to 1,257. The selected states have different climates, agriculture, and socioeconomic structures, providing a more thorough case study to showcase the value of applying social media for drought impact monitoring.

The monthly accumulated counts of all predicted drought-related labels at the state level were used to proxy the intensity of drought impacts. We calculated the Spearman correlation between the monthly counts of the predicted labels from different DL-based NLP models and the DSCI to analyze contemporaneous relationships between the drought severity and the intensity of drought impacts reflected by textual data. The correlation between the DSCI and the monthly counts from the media impacts and reports and CoCoRaHS reports was also calculated for comparison. All Spearman correlation coefficients are shown in Table 4. The CMOR reports were dropped because their scarcity introduced more biases than beneficial information, with fewer than five monthly reports in a state. Overall, the DSCI is better correlated with the counts of the DL-predicted drought-related labels from the tweets than the counts of the labels from the media-sourced or CoCoRaHS datasets. Notably in California and Massachusetts, the correlations between the DSCI and the counts of the predicted labels from the tweets by GPT-4 are 0.902 and 0.896, respectively. In Arizona, Texas, Iowa, and Washington, the correlations between the DSCI and the counts of the predicted labels are also significantly higher than the recorded drought-related labels from DIT datasets. Only in Nebraska, the intensity of drought impacts indicated by media-sourced impacts and reports is better correlated with the DSCI than by the tweets. Among the employed NLP models, the counts of predicted labels by GPT-4 had the leading correlation coefficient in three states, and the BERT-like models were slightly better in the other states. However, the differences among the models were marginal.

1) Temporal Patterns of Drought Impacts and Awareness in California and Nebraska

To further illustrate and compare how the predicted labels from the tweet dataset reveal additional characteristics of drought general awareness and impacts, Figure 6 showcases the monthly time-series plots of the counts of the predicted labels from the tweets and the observations from the two DIT sources in California and Nebraska from April 2020 to December 2022. The plots for the other five states are included in Appendix C of the supplementary file.

TABLE 4. Spearman correlation between the monthly counts of predicted labels from the tweets by the employed DL-based NLP models and the DSCI in selected states to indicate the relationship between the intensity of drought impacts and drought severity. This table also shows the correlation between the monthly counts of drought-related labels from the media-sourced and CoCoRaHS textual datasets and the DSCI for comparison.

State	Tweets				Media-sourced	CoCoRaHS
	RoBERTa	DistilRoBERTa	ClimateBERT	GPT-4		
Arizona	0.540	0.545	0.544	**0.551**	0.104	0.348
California	0.899	0.897	0.899	**0.902**	0.648	0.465
Texas	0.627	0.650	**0.656**	0.653	0.302	0.225
Iowa	0.597	**0.611**	0.601	0.587	0.120	0.534
Massachusetts	0.878	0.892	0.881	**0.896**	0.331	0.209
Nebraska	0.404	0.365	0.371	0.356	**0.615**	0.568
Washington	**0.572**	0.540	0.533	0.527	0.284	0.249

In California, the stronger correlation between the counts of the predicted labels from the tweets and the DSCI is demonstrated in the time-series plots. The trend of the counts of the predicted labels, particularly the counts of the labels of drought general awareness, from January to March 2021, goes through a valley, fitting well with the detailed variations based on the DSCI. However, the media-sourced drought reports and impacts barely show this trend because the label counts are close to zero. For the CoCoRaHS reports, the trend is opposite to the DSCI, with the label counts of general awareness, plants and wildlife, and water supply and quality increasing while the drought severity is decreasing. Another conflicting trend observed from the CoCoRaHS reports is in the spring of 2021, when the drought event becomes more severe, but the counts of drought-related reports are decreasing. The counts of the predicted labels from the tweets also reflect the variations in the DSCI from January to March 2022, while the two derived datasets from the DIT are less efficient. However, two drops of the counts of the predicted labels from the tweets in the summer and fall of 2021 are not well explained when the drought severity peaked in California. Step decreases in the same period can also be observed in the media-sourced and CoCoRaHS datasets, but the monthly fluctuations are not synchronous in the three plots. The counts of predicted labels from the tweets are also better correlated with the DSCI in 2022. In addition to the good alignment with the drought severity, the counts of the predicted labels from the tweets reveal different and beneficial patterns of general awareness and drought impacts. The media-sourced observations are more focused on drought impacts related to water supply and quality, and relief, response, and restrictions, reflecting government management in California. The CoCoRaHS citizen scientists pay more attention to plants and wildlife, wildfire, general awareness, and water supply quality. The tweet dataset's size is significantly larger than the other two data sources. The predicted labels from tweets associated with general awareness, water supply and quality account for the majority of the monthly counts. The predicted labels for drought impacts related to non-agricultural economic sectors are the fewest. The shaded area of each predicted label in California indicates the variations of predictions from the NLP models change by time and the types of drought information. The predictions of the most frequent categories, such as water supply and quality, are associated with higher variations in the counts but still with identical trend lines. Overall, as a proxy of the intensity of drought impacts, the counts of the predicted drought-related labels from the tweet dataset in California are better correlated with drought severity than the DIT datasets and reflect more explainable and nuanced details of various types of drought impacts and general awareness.

In Nebraska, tweets still provide the highest amount of drought information among the drought-related textual data sources. For the media-sourced impacts and reports, in 2020 and 2021, the counts of individual types of drought information are sparse, consistently below 3. The slightly increasing observations in the fall of 2020 and winter of 2021 fit well with the trend of drought severity. The number of media-sourced records increases as the drought becomes more severe in 2022, peaking in May 2022. Drought impacts related to agriculture, wildfire, and relief, response, and restrictions have relatively higher numbers of observations. Similar observations and inferences can be found in the CoCoRaHS reports. For the counts of the predicted labels from the tweets in Nebraska, although they are not as well correlated with the drought severity as the other two datasets, interesting and unique patterns are reflected in the time-series plot. Drought impacts related to agriculture and general drought awareness account for most predicted labels and follow a similar trend over time. Instead of correlating with the drought severity, the peaks of the counts of the predicted labels are associated with the seasons. The count of the predicted labels of agricultural impacts reaches the highest point in the summer: July 2020, August 2021, and August 2022. A peak in the spring is also observed in March 2021 and April 2022, respectively. After the summer, even when the drought severity rises or remains the same from September to December in 2020, 2021, and 2022, the count of the predicted labels of agricultural impacts decreases. The same patterns are also observed for the count of the predicted labels of drought general awareness. A potential explanation for these repeatable patterns is that tweets identified with drought information are highly associated with agricultural activities and farmers' concerns in Nebraska. For example, the increasing drought severity in the winter of 2020 is not well associated with the rise of predicted labels from the tweets. However, accumulated perturbation caused by the drought event might contribute to the spike of the predicted labels in agriculture and general awareness in the pre-growing season in 2021. The effect of these accumulated concerns on the counts of predicted labels could be also found in 2022, presenting as the two peaks. Because of these noticeable associations, if the labels of general awareness and agriculture are excluded, the Spearman correlation between the counts of the predicted drought-related labels from tweets and the DSCI increases to 0.470 in Nebraska. Additionally, the counts of the predicted labels of agricultural impacts by different DL-based NLP models are more consistent because these models are highly accurate. The trends of the counts of the other predicted labels are identical among the four models, further ensuring the robustness of the predictions and reflected patterns. Moreover, similar temporal patterns, where agricultural drought impacts are better associated with seasonality than drought severity, are also found in Iowa uniquely from the tweets and are more noticeable than in Nebraska.

2) Spatial Patterns of Drought Impacts and Awareness in California and Nebraska

We further investigated the spatial patterns of the tweets with predicted labels in the two selected drought events in California and Nebraska. The predictions from GPT-4 were employed because of its balanced performance on the tweet dataset. Monthly USDM maps and the geospatial coordinates of the predicted labels from the tweets were plotted for the 2021 drought event in California, which is one of the billion-dollar weather and climate disasters in the United States, and the 2022 drought event in Nebraska. We also produced the maps for the selected drought events in the other five states included in Appendix C of the supplementary file. A tweet can indicate different labels of drought impacts, resulting in overlapped labels at the same location. The maps are only used to qualitatively display and interpret the spatial distribution of the predicted labels from the drought-related tweets.

Figure 7 provides the maps for the California drought event. This drought event started in 2020 but progressed in 2021 to extreme and exceptional drought conditions in more than 80% of the area

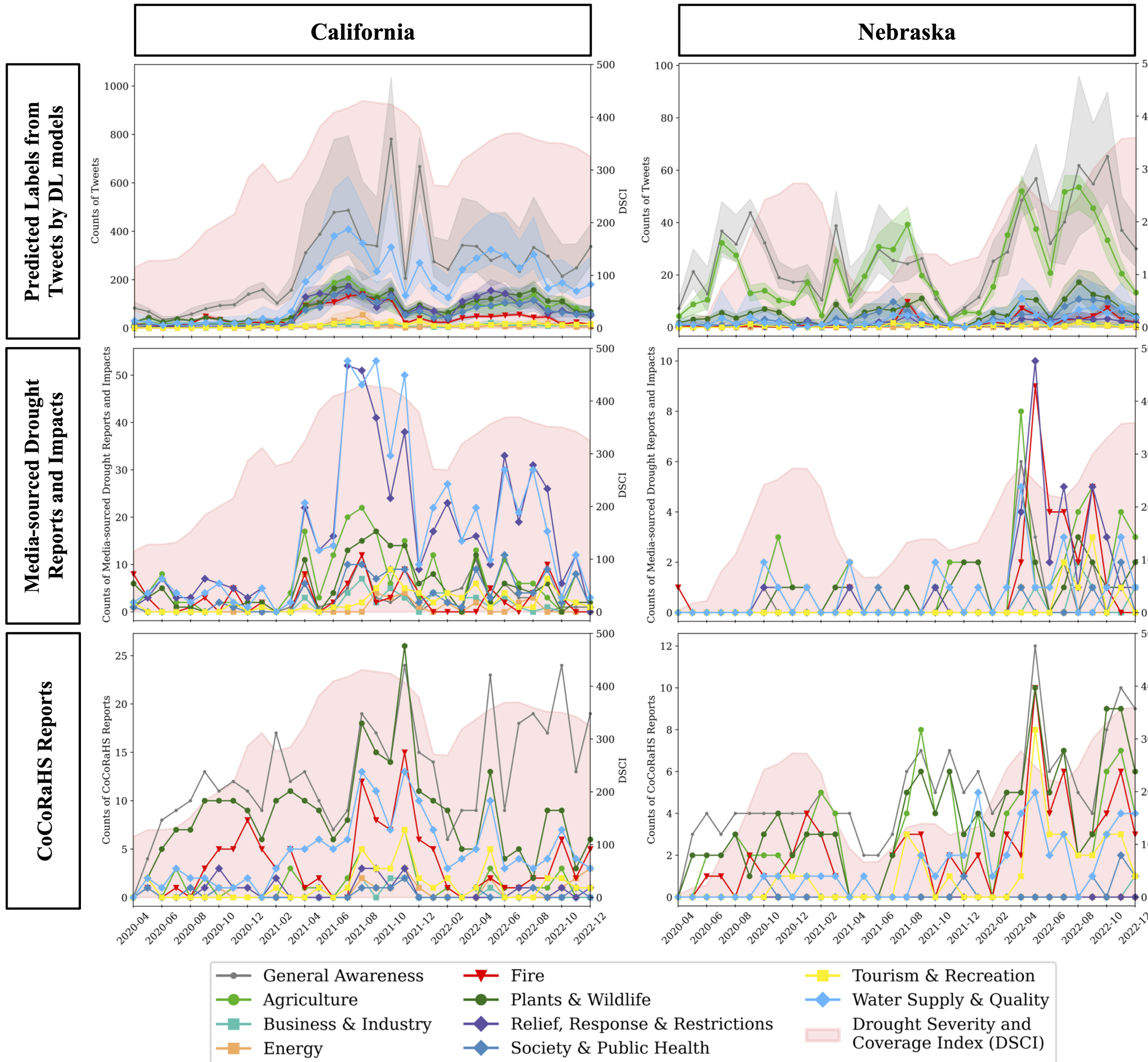

FIG. 6. Time-series plots for the counts of predicted drought general awareness and impacts from the tweets based on the DL-based NLP models, media-sourced reports and impacts, and CoCoRaHS reports. The major y-axis shows the monthly counts of tweets or DIT observations with predicted or observed labels for drought general awareness or various impacts, and the minor y-axis shows the DSCI ranging from 0 to 500, representing from no drought to exceptional drought conditions in the corresponding state. The DSCI is presented in the red-shaded area. The counts of different drought-related labels predicted from the tweets are shown in colored lines that are the mean of predictions from the four applied DL-based NLP models, and the shaded area in the corresponding color that indicates the range of predictions.

in California from June to November. Based on the density of the points of the labels predicted from the tweets, there is a significant increasing trend in drought impacts and general awareness when the drought worsens. The most noticeable spatial pattern observed among the time-series maps is that the distribution of drought impacts is associated with urban areas and population. The top three counties with the most predicted labels are Los Angeles County, San Francisco County, and Sacramento County. The number of predicted labels from the tweets in the Central Valley area, California's most productive agricultural region, has an increasing trend in the summer and early fall of 2021. The Tulare Basin in the southern Central Valley experienced exceptional drought from July to November. However, the increasing number of predicted labels in the Tulare Basin is not as significant as in the Los Angeles metropolitan region because the latter area is more populous and potentially has a higher total number of tweets. The pie charts show the categories of the predicted drought-related labels in the top three counties, providing more details in the metropolitan area. The temporal variation is not significant among various categories. The general awareness of drought and impacts related to water supply and quality are always the two most significant labels, which are reflected in more than 50% of the predicted labels. They are followed by the other drought impacts related to agriculture, wildfire, and relief, response, and restrictions.

The spatial characteristics of the 2022 Nebraska drought event, shown in Figure 8, reveal different and unique patterns compared to California. This prolonged drought started in 2020 and significantly deteriorated from August to December 2022. The maps also shows the count of the predicted drought-related labels from tweets increases with the coming growing season. In April 2022, the predicted labels are primarily located in eastern Nebraska and indicate drought impacts on agriculture and water supply and quality. During the growing season, the predicted drought-related labels from tweets are concentrated along the Platte River, particularly in South-Central Nebraska, which has the highest density of irrigation wells. Correspondingly, agriculture is the most common category of drought impacts from July to September in Nebraska. Beginning in October 2022, although the drought severity increases, the number of predicted labels from the tweets decreases. In northeastern Nebraska, where this drought event is most severe, the predicted labels from tweets are sparsely distributed, focusing on general awareness and societal impacts. Overall, in Nebraska, being different from California, the predicted labels from the tweets did not originate within major cities but from agricultural regions relying on the irrigation system. But,

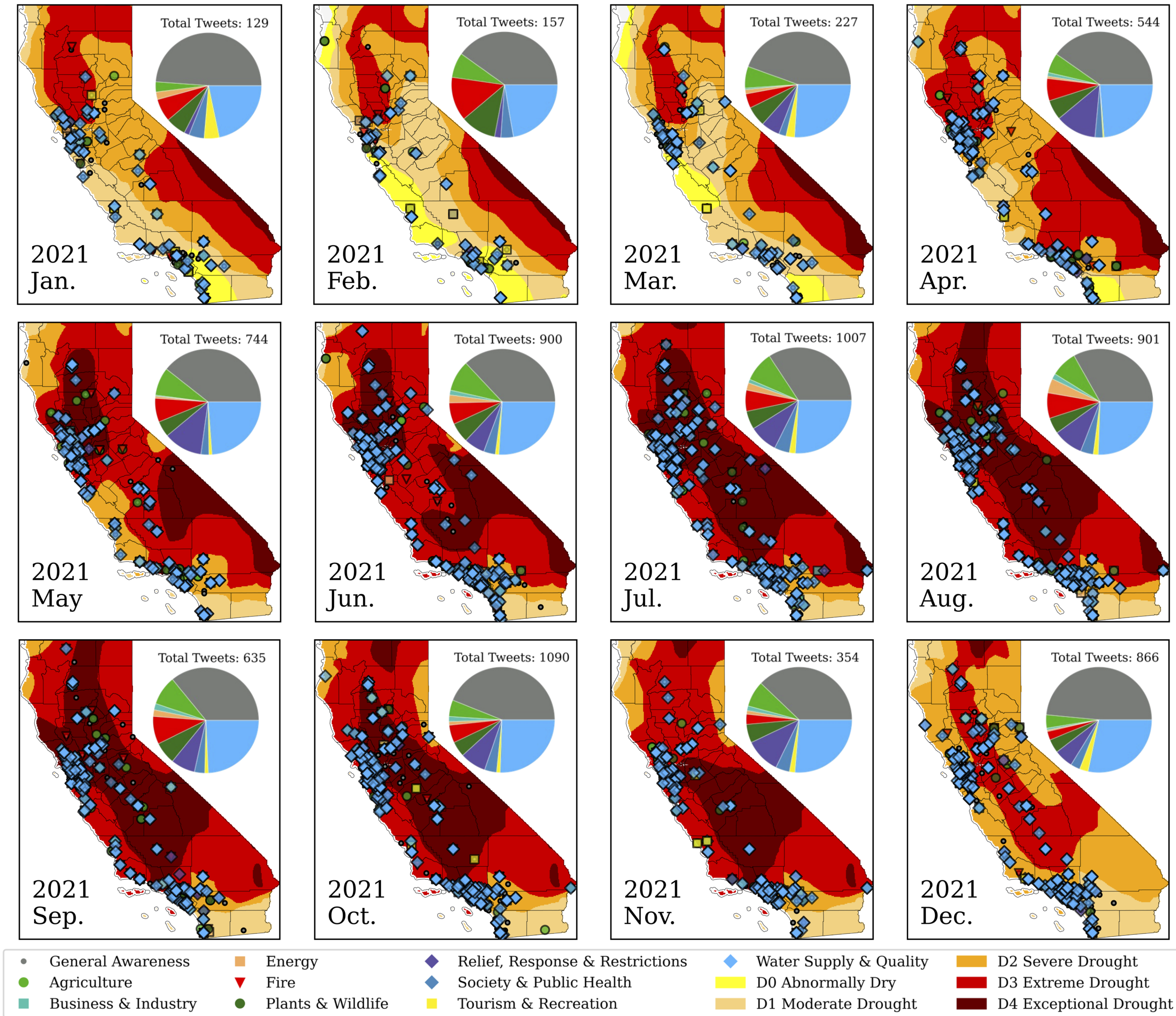

FIG. 7. The locations of tweets with the predicted labels of each type of drought impact and general awareness in California and a background of the monthly USDM map showing the drought severity in 2021. Because the symbols of different labels cover each other, the pie chart for the top three counties with the most drought-related tweets predicted from GPT-4 is included on the top right corner for each map to demonstrate the distribution of drought impacts and general awareness.

similar to California, the locations of the predicted drought-related labels from the tweets are also off from the areas in extreme or exceptional drought conditions.

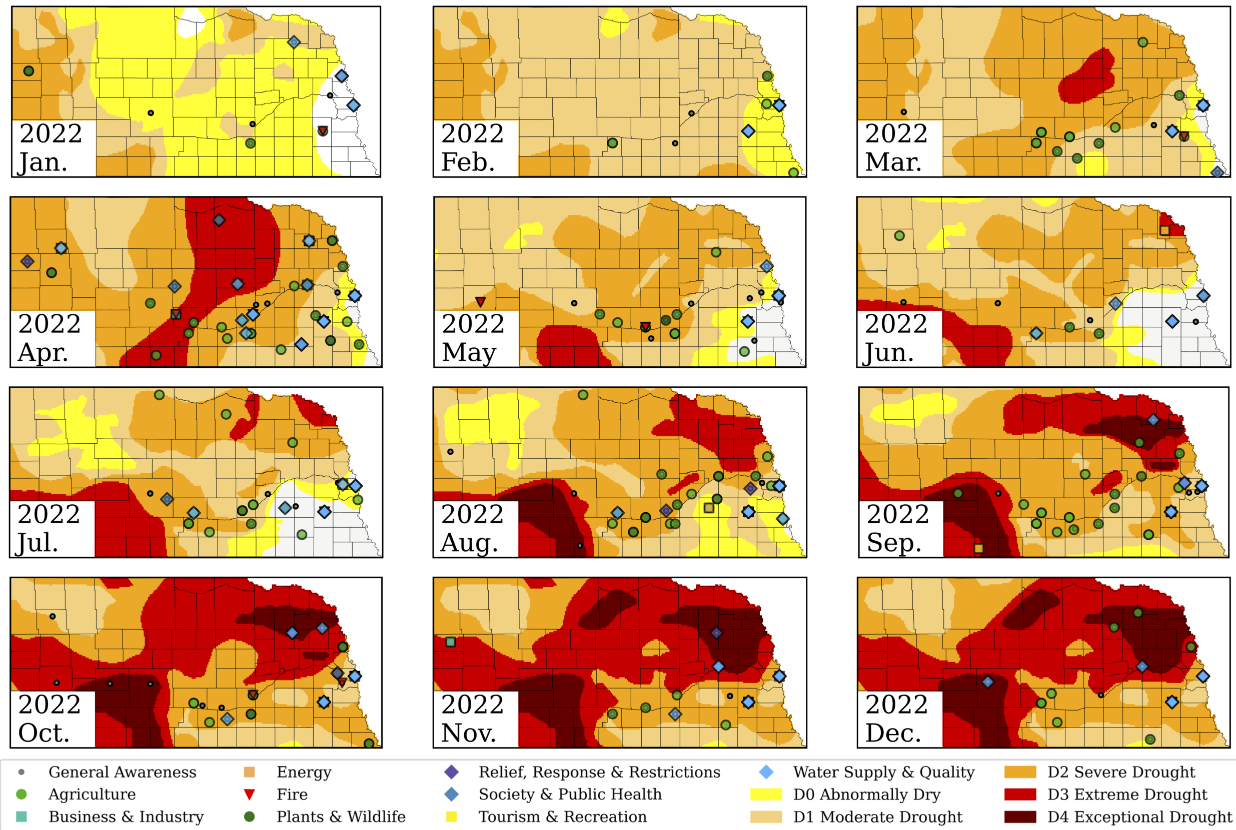

FIG. 8. The locations of tweets with the predicted labels of each type of drought impact and general awareness in Nebraska and a background of the monthly USDM map showing the drought severity in 2022.

5. Discussion

a. Performance Analysis and Selection of NLP Models

Our study applied DL-based NLP models on the DIT datasets and tweets to predict the categories of drought-related impacts and general awareness from textual data across the United States. DL-based NLP models surpassed the baseline TF-IDF model in all of the experiments. The outcomes of the experiments also revealed the capabilities of DL-based models in accurately identifying thematic labels for various drought impacts and general awareness, some of which are only vaguely described in the context of the given texts. Although it has been expected that the climate-specific BERT-like model would achieve higher performance in the relevant tasks (Webersinke et al. 2021), the difference between ClimateBERT and DistilRoBERTa is not significant on the media-sourced test dataset. This finding aligns with similar observations in domain-specific NLP applications, such as in the medical field, where generalized pre-training might match or exceed domain-specific pre-training models (Turchin et al. 2023). Additionally, the more balanced or larger fine-tuning datasets failed to improve the performance of the BERT-like models on the media-sourced test dataset. A potential explanation for these characteristics is that the media-sourced test dataset, mainly collected from the news media, was well unified and cleaned. The reduced data noise and content complexity allow the general pre-trained DL-based NLP models to effectively capture the domain-related information. For the downstream application on the tweet dataset, ClimateBERT, fine-tuned on the complete dataset, exhibited a superior performance. This indicates maintaining the class distribution is crucial to improving the multi-label classifier's performance in the output layer of the DL model. Because the tweet dataset is messier and more informal, the importance of robust pre-training and meticulous fine-tuning is stressed, particularly for transfer learning tasks (Arase and Tsujii 2019). The complexity of text quality and imbalanced class distribution for drought-related information have emphasized the benefit of GPT-4's extensive training. GPT4 can sift through noises and extract relevant drought-related information more effectively than BERT-like models, demonstrating its adeptness at identifying diverse drought-related information from tweets without fine-tuning or showcasing examples.

In this study, BERT-like models and GPT-4 each present unique benefits and challenges. As outlined in Table 5, considerations for deploying DL-based NLP models in drought impact monitoring include development effort, hardware requirements, operational costs, and model scalability. While BERT-like models demand significant resources for fine-tuning and local execution, GPT-4's cloud-based operation via the OpenAI Application Programming Interface (API) offers a more user-friendly alternative. However, the BERT-like models also have strengths in running time, expense, and flexibility after fine-tuning. In contrast, obtaining predictions from GPT-4 is time-consuming and expensive. And there could be operational restrictions, such as input size caps and usage limitations per time period. But GPT-4's flexibility in generating diverse textual analyses, such as sentiment or entity recognition, presents a distinct advantage over the more singularly purposed BERT-like models for multi-label classification. Therefore, also because the BERT-like models and GPT-4 performed better in different tasks, there is no one-size-fits-all solution for the best DL-based model in drought impact monitoring. The selection of the model is determined by task objectives, response time, budget, and available resources.

TABLE 5. Comparison between the BERT-like models and GPT-4 for a practical application based on our experiment of predicting drought-related labels for the tweet dataset. The estimation of the cost for the GPU is based on Google Cloud pricing by hour. The price of cloud service and OpenAI API might vary based on the market.

	BERT-like Models	GPT-4
Development	*Challenging -* Modifying and fine-tuning the pre-trained BERT-like models.	*Easy -* Prompt engineering through the API for GPT-4 from OpenAI.
Running Time	*Short -* Up to 49 hours for fine-tuning and 0.2 hours for predicting the tweet dataset.	*Long -* No fine-tuning process and 150 hours for predicting the tweet dataset.
Hardware Requirement	*High -* NVIDIA Tesla V100 32GB.	*Low -* No requirement.
Expense	*Low -* Primary cost is on fine-tuning, around $120. Cost of predicting tweets is less than $0.5.	*High -* Cost of the API from OpenAI is by word. It takes $730 for predicting tweets.
Scalability	*Low -* Multi-label classification task in the context of drought impacts.	*High -* Text generation with prompting that can be applied to other drought-related tasks.

b. Insights of Drought Impact Categories Predicted from Tweets

In addition to leveraging AI to assist drought experts in identifying drought impacts on the media-sourced texts, the transfer learning of the DL-based NLP models on the tweet dataset demonstrates the capability of using tweets with predicted drought-related labels for detecting various drought impact categories, confirming and further investigating the suggestion from Smith et al. (2020) that social media can be an informative and meaningful data source. Comparing the DSCI with the monthly counts of drought-related labels from different sources, the case studies showed that the counts of the predicted labels from tweets correlate better with drought severity at the state level than from the media-sourced or the CoCoRaHS datasets. The predicted drought-related labels effectively reflect the dynamic awareness of drought impacts. The media-sourced dataset is constrained by the DIT moderator's capacity, which could be enhanced by integrating the developed DL-based NLP models in the workflow of DIT data collection. Additionally, CoCoRaHS volunteers are encouraged to monitor and report conditions consistently, potentially leading to less temporal variations of label counts. Therefore, it is crucial to recognize that the stronger correlation between the counts of the predicted labels from tweets and drought severity does not necessarily imply that tweets are superior in detecting drought impacts or should replace other sources. Rather, it highlights the distinctive attributes of drought information gleaned from tweets, particularly the temporal patterns.

The time stamps and geospatial coordinates in the tweet dataset, enriched with predicted labels, allow for an in-depth examination of drought vulnerability characteristics and awareness of drought impacts down to the county and sub-county levels. The selected case studies in California and Nebraska showcase two different and distinct patterns of the drought impacts and awareness. At the state level in California, monthly counts of the labeled tweets for individual drought impacts, especially those concerning water supply and quality, closely correlate with the drought severity. However, the spatial distribution of these tweets is more likely to cluster in urban areas rather than regions experiencing the severest drought conditions. In contrast, the counts of predicted labels for drought impacts and awareness at the state level in Nebraska are associated better with the growing season and irrigation practices than the drought severity. The predicted drought-related labels are mainly located on agricultural lands and irrigated regions rather than on urban areas or regions with severe drought.

These findings illustrate the complex and indirect relationships between drought severity and text-based drought impacts and general awareness at sub-state levels, underscoring the intricate and dynamic nature of drought vulnerability across scales. Although research has consistently sought to qualitatively delineate the multifaceted drought impacts on various sectors (Wilhite et al. 2007; Lackstrom et al. 2013; Meadow et al. 2013; Bachmair et al. 2016b; Smith 2019; Sugg et al. 2020), there remains a gap in data-driven analyzing and defining drought impacts through observations. Narrowing this gap, our study reveals the unique advantages of the predicted labels from tweets with DL-based NLP models in demonstrating the patterns that the timing, locations, and types of impacts are all pivotal in understanding the ramifications of drought events. As a complement and enhancement to the text-based drought impact monitoring, our study illustrates the predicted drought-related tweet dataset uncovers another quantitative way to define drought events and their multifaceted impacts from a societal perspective, in addition to traditional hydrometeorological variables and remotely sensed vegetation indices.

c. Limitations and future directions

While applying cutting-edge NLP models to text-based observations has shown considerable promise for enhancing drought impact monitoring, recent changes in Twitter (now X), including user policies and API access, have impacted characteristics and content of this social media platform (Caulfield 2023). While collecting tweets from X, we would also suggest exploring the textual content from other social media platforms to increase data diversity. Additionally, the tweet dataset in this study spans only two and a half years, limited by Sprinklr's service.The temporal and spatial patterns in the case studies need further validation with long-term observations, leading to extra encouragement to apply DL-based NLP models on textual data from various social media platforms to predict labels of drought impacts and general awareness. Despite high overall accuracy, the models' ability to predict drought impact categories in non-agricultural economic sectors and society and public health leaves room for improvement. For example, Exploring data-centric techniques like Retrieval Augmented Generation (RAG) could refine GPT-4's performance and scalability in multi-label classification tasks within the drought domain by incorporating external drought-related facts and data (Lewis et al. 2020; Gupta et al. 2024; Thulke et al. 2024).

Moreover, the definition of drought impacts varies among different groups of stakeholders, which adds complexity to deriving accurate predictions of impacts. In this study, the consistently reliable dataset for drought impacts in the fine-tuning process is the moderated media impacts because the experts reviewed and confirmed the contribution of droughts. The predicted labels of drought impacts and general awareness from the BERT-like models are affected not only by the data sources but also by the class distribution of the fine-tuning dataset. This inherent issue is challenging to address because of the intrinsic characteristics of the data sources and individual interpretations of drought impacts. We suggested further investigating the advanced agentic development of DL-based NLP models to integrate various data sources and provide in-depth name entity and semantic analysis.

6. Conclusion

This study demonstrates the efficacy of DL-based NLP models to predict drought impacts and awareness from textual data, marking a significant advancement in the field. We have established the superior performance of BERT-like models, especially RoBERTa when fine-tuned on the media-sourced datasets, for the multi-label classification of drought impacts from media sources. In transfer learning applications to the tweet dataset, GPT-4 emerged as the leading model, showcasing its robust capability in processing social media data, with ClimateBERT as the standout among BERT-like models. The DL-based NLP models have proven instrumental in providing detailed and accurate predictions of drought impacts, particularly in societal sectors like relief, response, restrictions and water supply and quality, where traditional data sources may fall short. Moreover, the predicted drought-related labels from tweets offer nuanced insights that augment traditional sources. The spatial and temporal analysis of the predicted labels in the selected case studies illustrated the dynamic nature of multifaceted drought impacts, which further endorsed utilizing social media to assess public and societal reactions and define socioeconomic drought. Thus, this study not only advocates for the adoption of AI techniques in enhancing drought impact monitoring but also for the integration and exploration of social media as a complementary data source. By doing so, we can achieve a more comprehensive understanding of drought impacts, benefiting drought experts and the wider community and improving societal responses to droughts during further events.

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Data availability statement. The data incorporated in this study is openly available on Figshare: https://figshare.com/s/9b09700863c3cee0e7f4 (This link will be replaced by a DOI link when the paper is accepted).

APPENDIX A

Tweets Acquisition and Process

We utilized the Sprinklr platform to gather drought-related tweets from X (previously Twitter), establishing a pipeline that incorporates Sprinklr's filtering capabilities and an R script to refine and sanitize the tweet content, minimizing irrelevant data. The filtering process in Sprinklr was comprehensive, covering six dimensions. We specifically targeted tweets mentioning 'drought' while excluding those referencing 'playoff' as a representation of game or sports. The geographic focus was on tweets originating from the United States, specifically from X or Twitter, that contained city information. Additionally, we filtered out retweets and tweets classified by Sprinklr as adult content or those related to topics including, including arts & entertainment, autos & vehicles, beauty & fitness, books & literature, computers & electronics, games, internet & telecommunications, jobs & education, online communications, sensitive subjects, shopping, and sports.

Acknowledging that Sprinklr's categorization methods and tools might evolve, we consolidated the tweet collection in April 2023 to maintain data consistency. For subsequent research, we recommend employing unprocessed tweet data to further explore the capabilities of DL-based NLP models in a more unfiltered data environment.

Post-extraction, the Sprinklr data underwent a rigorous cleaning process using an R script, which eliminated emojis, duplicates, and tweets with international, sexual, or sports-related content, as well as any cliches and spam, based on specific keywords. This R script, along with the keyword dictionary, can be obtained upon request from the authors. Additional verification ensured the geospatial coordinates of tweets corresponded to locations within the United States. Ultimately, the refined tweets, complete with time stamps and geospatial coordinates, were systematically organized for subsequent analysis, similar to the DIT datasets' preparation process.

For the evaluation of the predicted labels for the tweet dataset, we manually labeled a thousand randomly selected tweets. Reading through each tweet, we checked the types of drought impacts and general awareness described or indicated in the text. The table was converted into a binary array as the test data for the transfer-learning application of the DL-based NLP models on the tweet dataset.

APPENDIX B

Fine-tuning process of BERT-like models

We developed and fine-tuned the three BERT-like models using the pre-trained versions available on Hugging Face. The base RoBERTa model ('roberta-base'), the base DistilRoBERTa model ('distilroberta-base'), and the ClimateBERT model pre-trained on a fully-selected corpus ('distilroberta-base-climate-f') were utilized. Adhering to standard practices for domain-specific classification tasks, we added a fully connected layer to the CLS token of each pre-trained model, followed by a classifier layer tailored to the size of the drought impact label set. To mitigate overfitting, we set the dropout rate at 0.1. The models employed the tanh activation function and Binary Cross-Entropy loss with a Sigmoid function for binary classification, with a decision threshold of 0.5 on the Sigmoid function's probability output to categorize each label.

The fine-tuning process included a systematic hyperparameter search to optimize the maximum number of epochs, batch size, and learning rate. The specific combinations explored, alongside other key hyperparameters, are detailed in Table B1. We opted for the default settings of the Adam optimizer, foregoing further adjustments. The hyperparameter tuning results led us to select a learning rate of 1e-4, maximum epochs of 7, and batch size of 32 for all BERT-like models.

TABLE B1. Key differences between RoBERTa and DistilRoBERTa or ClimateBERT from the aspect of model hyperparameters. And the gridded hyperparameter searching in the fine-tuning process.

Key Hyperparameters	$\text{RoBERTa}_{\text{BASE}}$	$\text{DistilRoBERTa}_{\text{BASE}}$ $\text{ClimateBERT}_{\text{FULL-SELECT}}$
Model		
Number of Layers	12	6
Hidden Size	768	768
Attention Heads	12	12
Parameters	125M	82M
Fine-tuning Process		
Max Epochs	[3, 5, 7]	
Batch Size	[16, 32]	
Learning Rate	[1e-5, 5e-5, 1e-4]	
Dropout Rate	0.1	
Weight Decay	0.01	
Warm-up Ratio	0.1	
Learning Rate Decay	Linear	
Validation Rate	0.1	

Prompt engineering for GPT-4

We adhered to the guidelines of *ChatGPT Prompt Engineering for Developers* provided by DeepLearning.AI to craft effective prompt engineering for GPT-4. This approach ensured the generation of robust and reliable multi-label classification outputs from this advanced text generation model. The designed prompt was concise yet comprehensive, enabling the structured output in the directory format, capable of classifying thousands of textual samples consistently without anomalies or outliers. To further ensure a robust and stable result, $temperature$ should be set to 0 and top_p to 1 when sending the request to the GPT4 server.

```
"""
You are an AI assistant focused on climate impacts. A drought event can affect multiple sections.\
The given text includes information of one or multiple impacts information.\
Your task is to label the given text delimited by ``` based on the definitions below.\
Here is the definition of each label following the format Label: Definition.\
Agriculture: Drought effects associated with agriculture, farming, aquaculture, horticulture, forestry, and ranching.\
Business & Industry: Drought effects associated with non−agricultural businesses.\
```

```
Energy: Drought effects associated with power production, electricity rates, energy revenue, and purchase of alternate sources of energy.\
Fire: Drought effects associated with forest, range, and urban fire during drought events.\
Plants & Wildlife: Drought effects associated with wildlife, fisheries, forests, and other fauna.\
Relief, Response & Restrictions: Drought effects associated with disaster declarations, aid programs, requests for disaster declaration or aid, water restrictions, and fire restrictions.\
Society & Public Health: Drought effects associated with changes in public behavior and human health effects.\
Tourism & Recreation: Drought effects associated with recreational activities and tourism.\
Water Supply & Quality: Drought effects associated with surface or subsurface water supplies.\
General Awareness: Non-impact media reports containing condition information, drought monitoring and forecasting, and other general drought information.\

Do the following steps to properly label the given text:\
- Make a dictionary. The keys are the name of each label, following the same order of the labels. The values are all 0.\
- Go through each label. If the given text reflects the information based on the label's definition, change the value of the corresponding key from 0 to 1.\
- Return should only be the dictionary of the labels. No explanations.\

The given text: ```{text}```
"""
```

Each textual sample was input individually. The returned dictionary from the text generation by GPT-4 was then formatted to the table of predicted labels for the ten drought impacts. The corresponding metrics were calculated based on the table.

APPENDIX C

Additional Time-series Plots and Maps for the Selected States

Figure C1 illustrates the temporal correlations between the predicted labels from tweets and the Drought Severity and Coverage Index (DSCI), alongside the media-sourced drought reports and CoCoRaHS reports in five other selected states: Arizona, Iowa, Massachusetts, Texas, and Washington. In Massachusetts and Washington, the correlation between predicted labels and the DSCI is notably stronger than that observed in media-sourced and CoCoRaHS datasets. In Iowa, temporal patterns similar to those emerged in Nebraska, where general awareness and agricultural drought impacts are more closely associated with seasonal changes (growing seasons) than with DSCI-determined drought severity. This observation underscores the diverse and region-specific characteristics of drought impacts, as revealed by textual data, and highlights the influence of local socioeconomic factors on the manifestation and observations of these impacts.

Figures C2 to C6 display the maps of tweets predicted by GPT-4 for the other five selected states, arranged alphabetically. These maps utilize drought events from various years to elucidate the spatial patterns in each state, with accompanying captions offering a summary of these patterns. Overall, the spatial distribution of predicted labels from the tweets reveals that most drought impacts are concentrated in urban areas and regions with high population density, rather than directly correlating with drought severity at the county and sub-county levels. This trend is especially prominent in Arizona, Massachusetts, Texas, and Washington. Conversely, in Iowa, while there is a notable concentration of drought impact tweets around Des Moines, the distribution is more even across the state. There is no clear association between the predicted labels of agricultural drought impacts and irrigated land in Iowa, unlike in Nebraska, potentially because of fewer irrigation practices in Iowa. These observed patterns demonstrate the spatial heterogeneity of drought impacts across different states.

In conclusion, at the sub-state level, the distribution of drought impacts inferred from tweets mainly aligns with population density and urbanization, rather than with drought severity. Nevertheless, the overall density and volume of predicted drought impacts show potential alignment with drought severity as indicated by the DSCI at the state level, highlighting the intricate interplay of drought impacts across temporal and spatial dimensions.

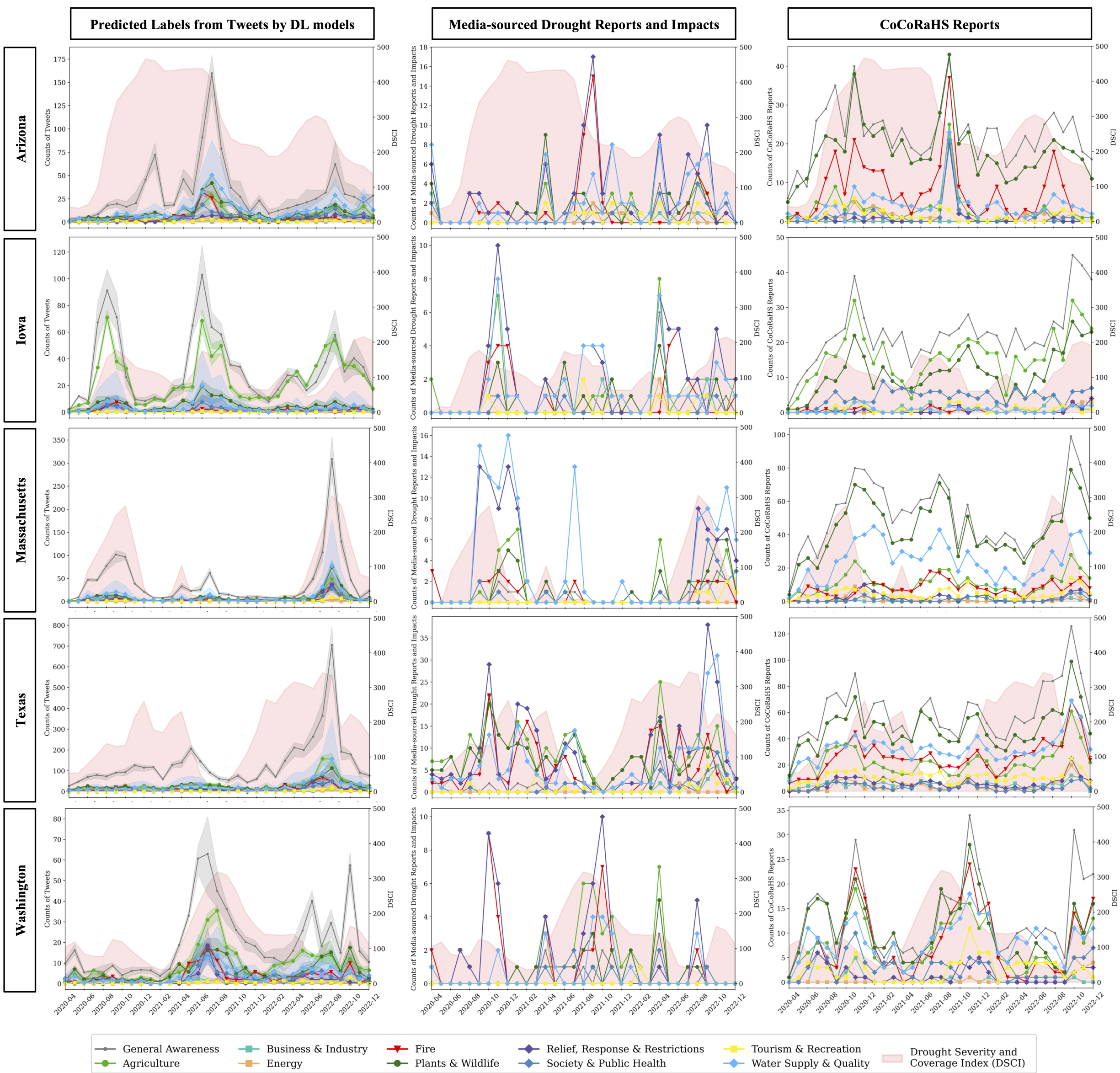

FIG. C1. Time-series plots for the drought impacts and general awareness in the selected states.

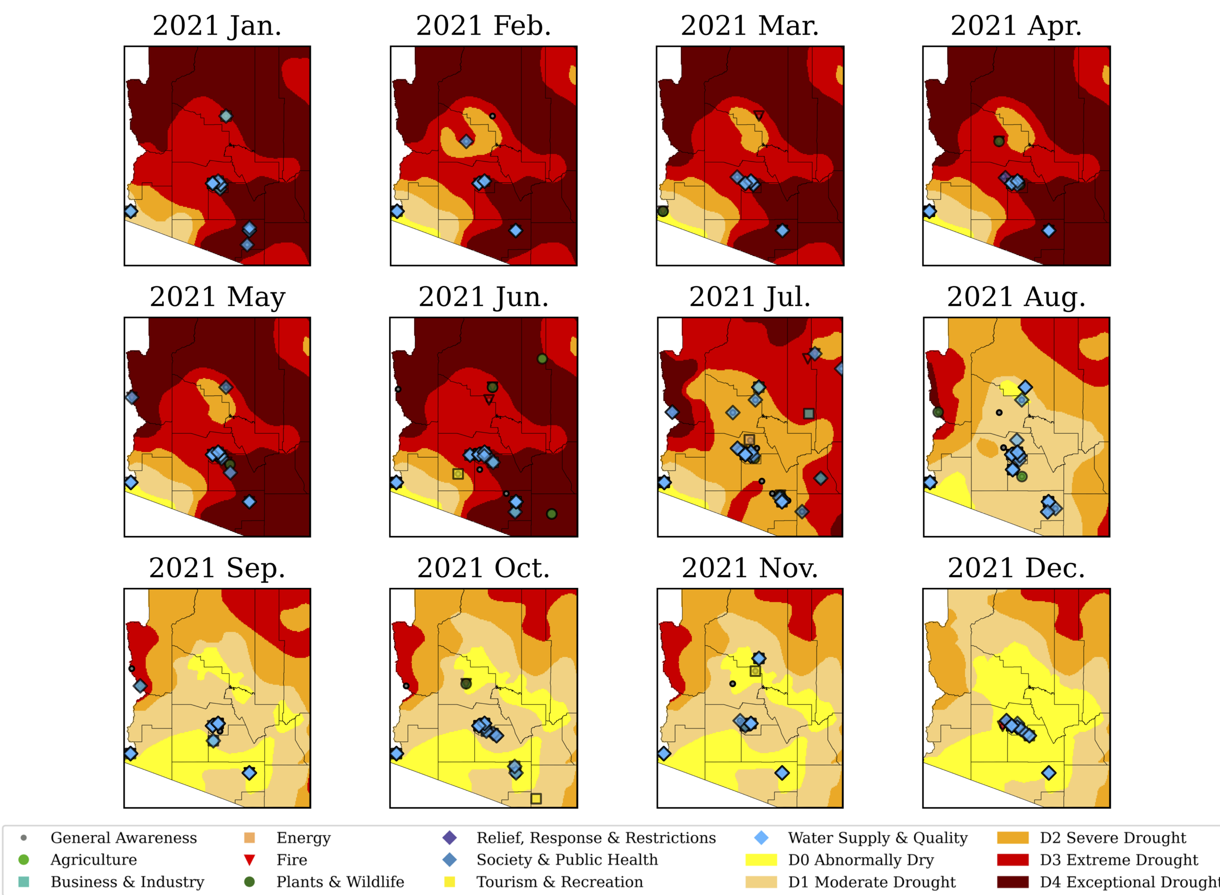

FIG. C2. The locations of tweets with the predicted labels of each type of drought impact and general awareness in Arizona and a background of the monthly USDM map showing the drought severity in 2021. The predicted labels are concentrated around Phoenix with a notable presence around Sedona. This period marked the peak of drought severity in the first half of 2021. Despite this, the distribution of drought impact tweets does not show a clear correlation with the specific timing or locations of heightened drought severity.

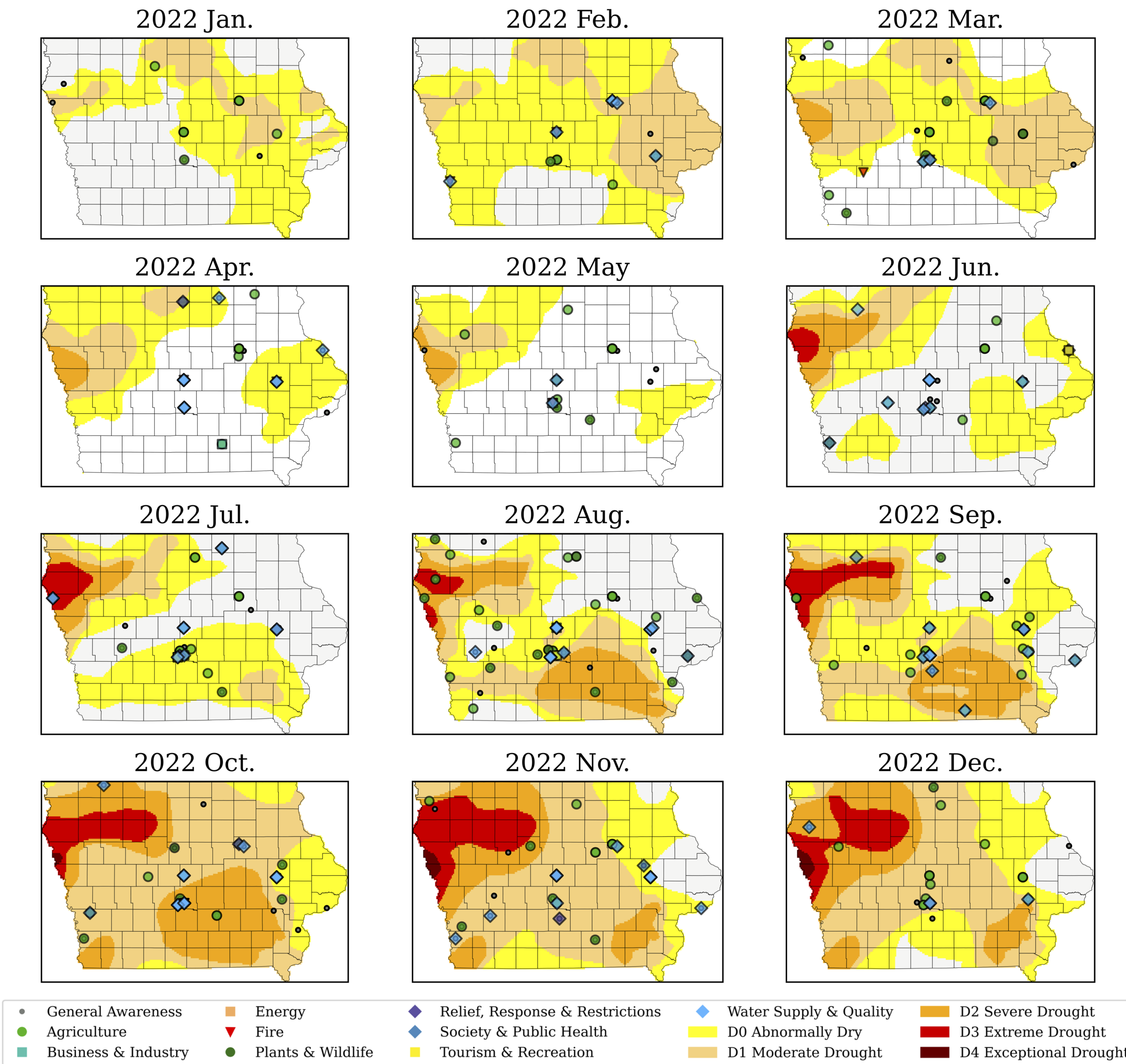

FIG. C3. The locations of tweets with the predicted labels of each type of drought impact and general awareness in Iowa and a background of the monthly USDM map showing the drought severity in 2022. The drought impacts are evenly distributed across the state, with a notable presence around Des Moines. The distribution of drought impacts is not significantly associated with the drought severity.

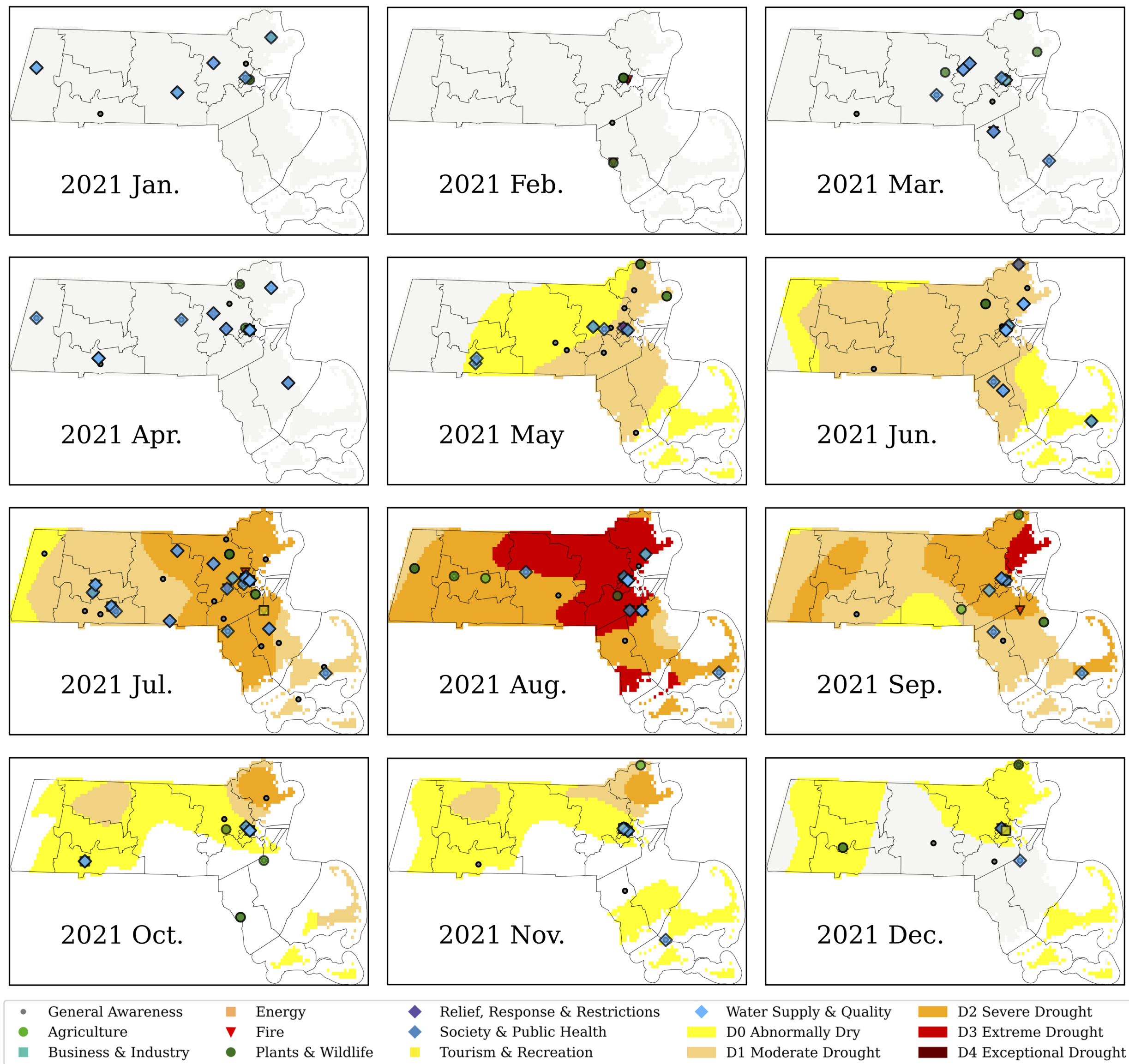

FIG. C4. The locations of tweets with the predicted labels of each type of drought impact and general awareness in Massachusetts and a background of the monthly USDM map showing the drought severity in 2021. The drought impacts predicted from tweets are concentrated around the great Boston area.

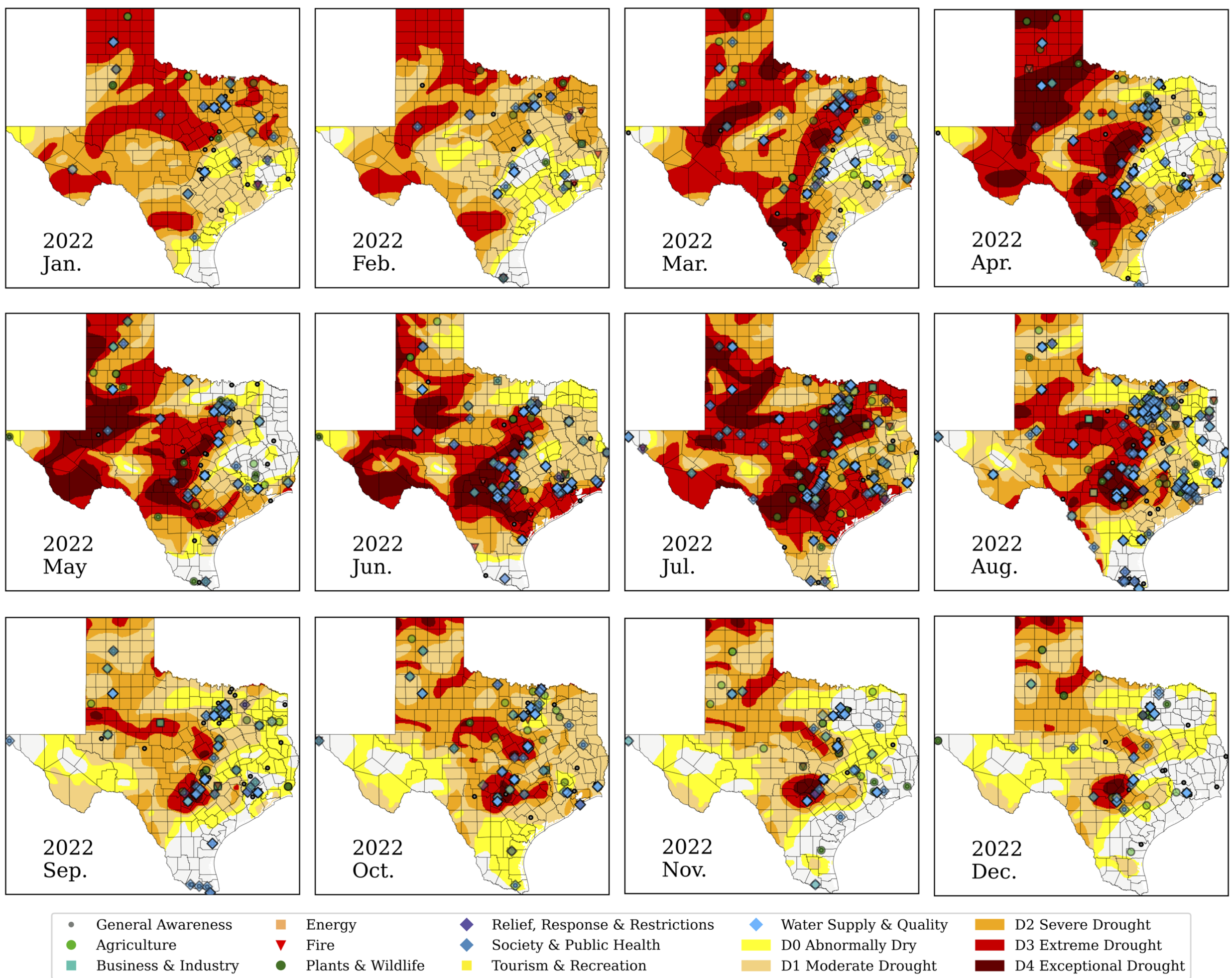

Fig. C5. The locations of tweets with the predicted labels of each type of drought impact and general awareness in Texas and a background of the monthly USDM map showing the drought severity in 2022. As the drought severity increases from April to August, the density of the drought impacts predicted from tweets also increase. However, the predicted labels are predominantly distributed around Dallas, San Antonio, and Huston. Even though an exceptional drought is in northwestern Texas, fewer predicted drought impacts from tweets are located there.

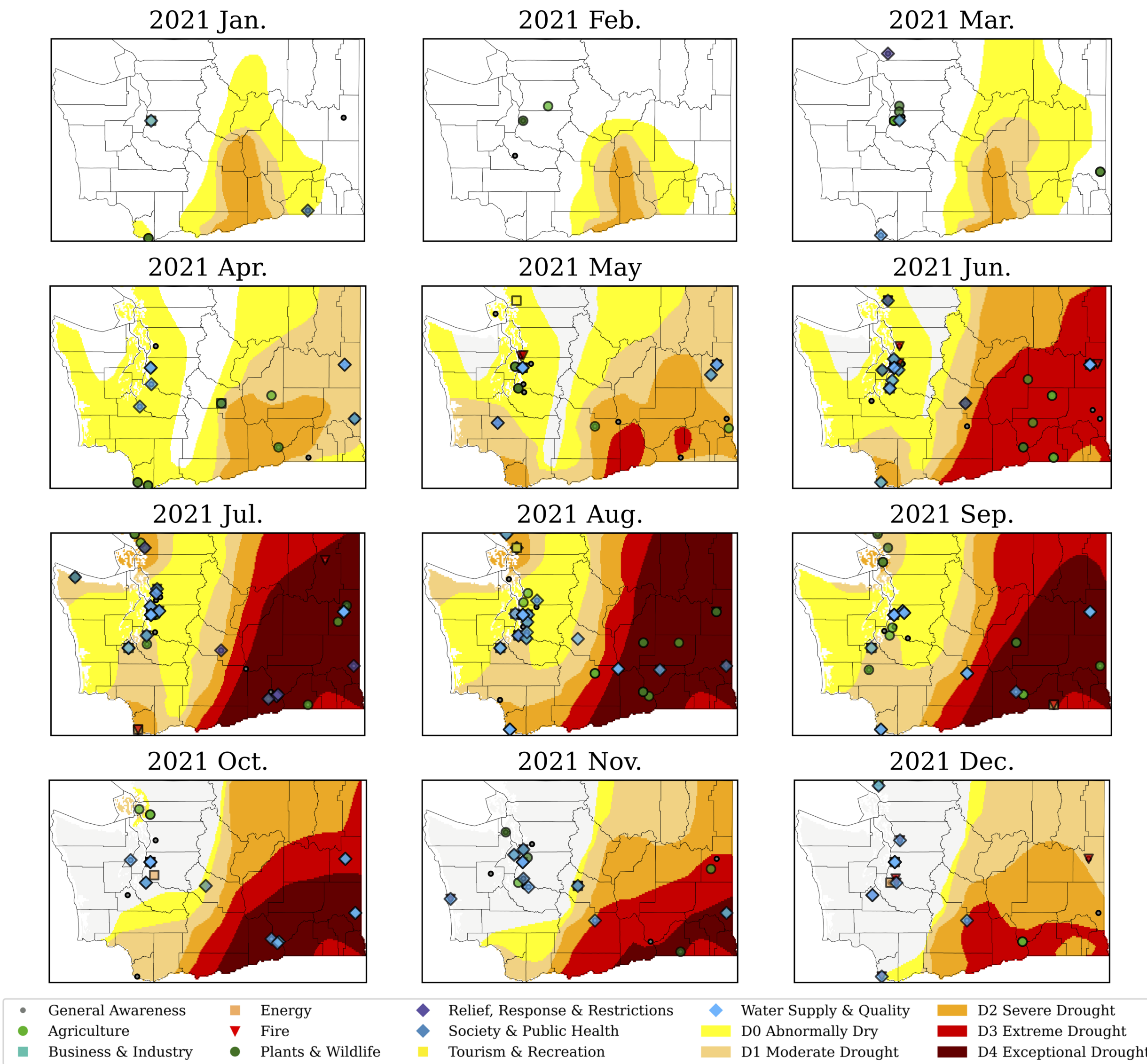

FIG. C6. The locations of tweets with the predicted labels of each type of drought impact and general awareness in Washington and a background of the monthly USDM map showing the drought severity in 2021. The drought impacts predicted from tweets are concentrated around the great Seattle area.

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