TweeetDrought: A Deep-Learning Drought Impacts Recognizer based on Twitter Data

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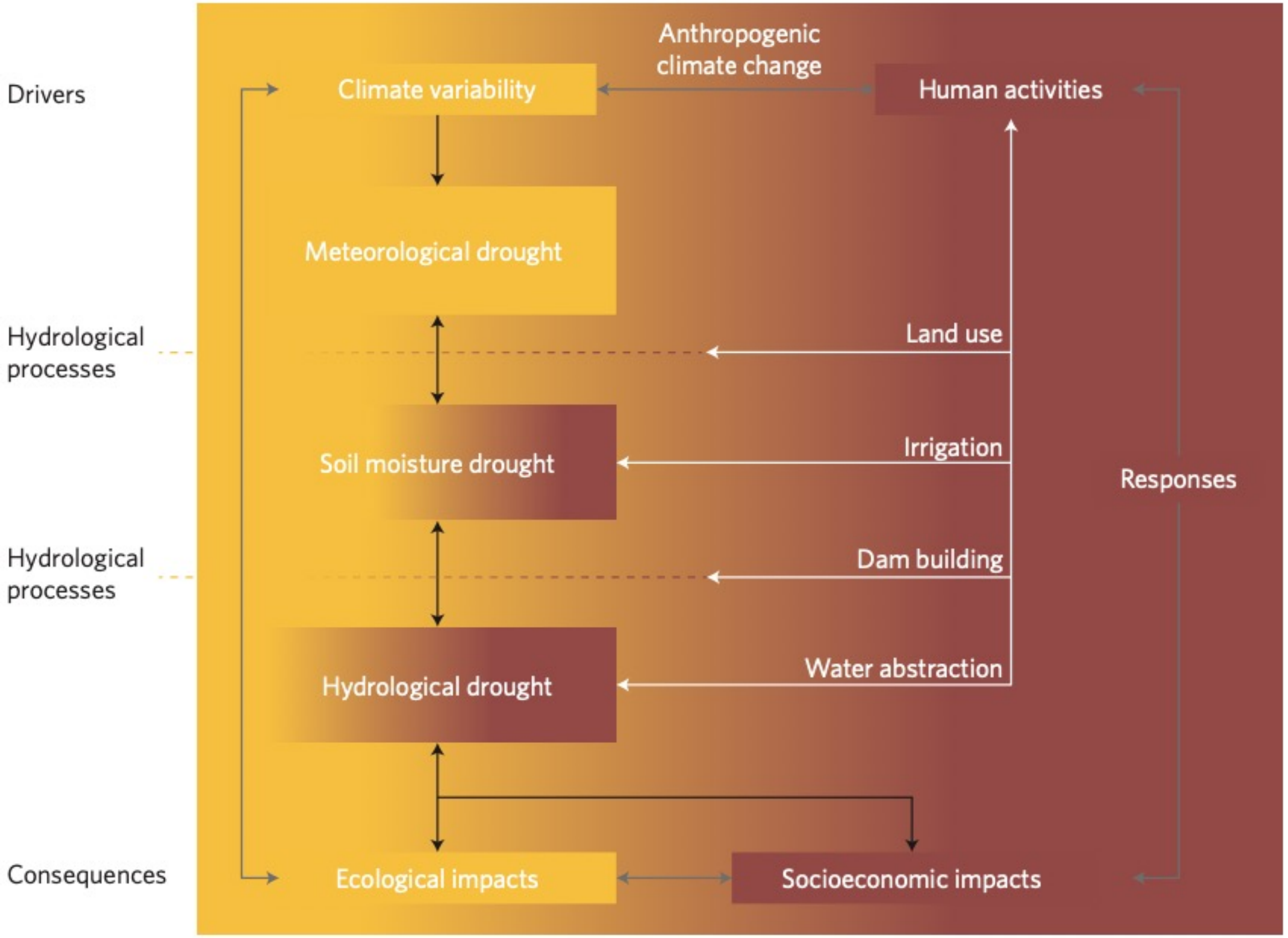
Motivation



(Van Loon et al., 2016)

Drought monitoring/forecasting ->
Hydro-meteorological variables, climate indices ...

Drought impacts ->
Vegetation Indices, crop yields, LULC changes ...

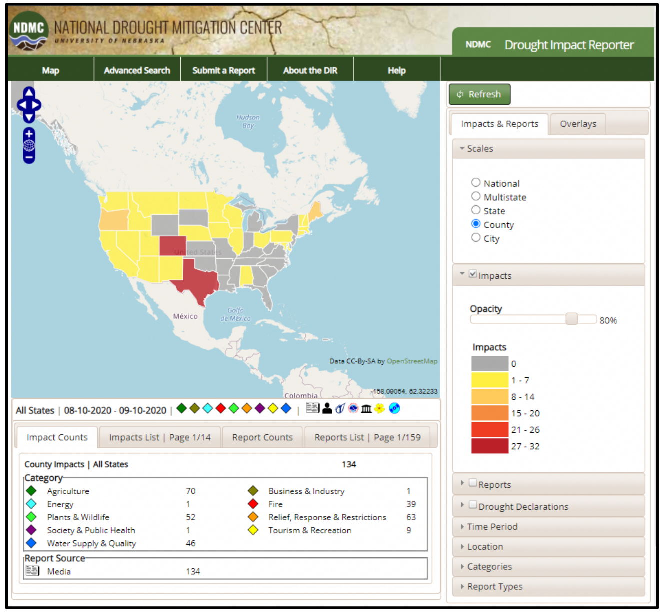
How to identify the comprehensive impacts on the human dimension?

Can we recognize drought impacts utilizing social media, for example, Twitter?

Data & Method

Training data set

Drought Impact Reporter (DIR)



- **9** categories of drought impacts
- **14178** records (multi-labeled)
- The average text length: **~ 10 words**
- **2011 – 2020**

Apply the fine-tuned BERT model to tweets

The fine-tuned BERT model:

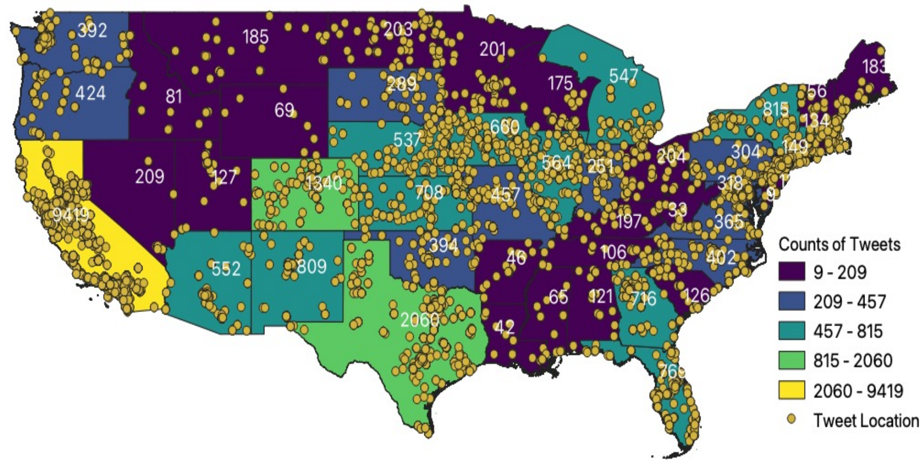
BERT base model (uncased):
12-layer, 768-hidden, 12-heads, 110M parameters

&

Classifier:
dense layer (ReLu, 50-hidden), output layer (Sigmoid, 7 units)

Testing data set

Drought-related Twitter data



- **26654** records
- The average text length : **~ 15 words**
- January 9, **2017** – October 8, **2020**
- #drought, #drought<u>21</u> (2-digit year), #drought<u>ca</u> (state abbreviation)

Results | Summary of the fine-tuned BERT’s performance on the DIR test data set

After being fine-tuned, the BERT-based model had a promising overall performance on the DIR test data set.

Category of Drought Impacts	Recall	Precision	F1
Overall (micro/macro)	0.86/0.82	0.95/0.95	0.90/0.87
Agriculture	0.93	0.98	0.96
Economy	0.72	0.95	0.85
Fire	0.88	0.97	0.92
Plants & Wildlife	0.78	0.88	0.83
Relief, Response & Restrictions	0.92	0.93	0.93
Society & Public Health	0.56	0.98	0.72
Water Supply & Quality	0.87	0.92	0.89

High

Medium

Low

Results | Transfer learning on tweets

Summary of the fine-tuned BERT's performance on **keyword-labeled** tweets in **CA**.

Category of Drought Impacts	Recall	Precision	F1
Overall (micro/macro)	0.72/0.67	0.52/0.58	0.60/0.58
Agriculture	0.54	0.78	0.63
Economy	0.42	0.44	0.43
Fire	0.81	0.95	0.87
Plants & Wildlife	0.65	0.67	0.66
Relief, Response & Restrictions	0.81	0.52	0.63
Society & Public Health	0.58	0.09	0.15
Water Supply & Quality	0.92	0.59	0.72

High

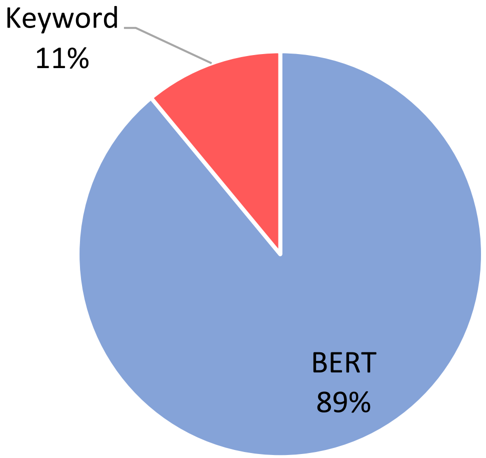
Medium

Low

Results | Spot-check validation

Agriculture

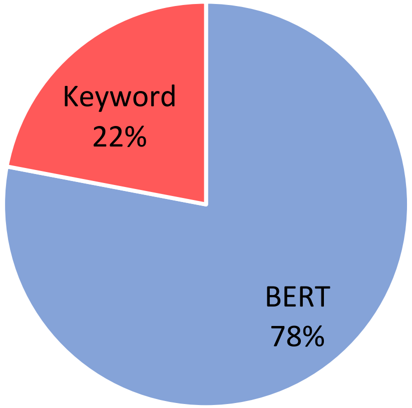
Which method's predicted labels were more rational ?



36/39 tweets with the **FP** labels were related to **soil moisture and food**.
53/61 tweets with the **FN** labels were grouped as the impacts on **plants & wildlife** by BERT (*parks, lawn, trees*…).

Society & Public Health

Which method's predicted labels were more rational?



20/64 tweets with the **FP** labels reflected **personal feelings** about drought: *worried, frustrated, hopeful...*
50/64 tweets with the **FP** labels were also labeled as **water supply & quality**.
22/45 tweets with the **FN** labels were grouped as the impacts on **agriculture** by BERT (*food, crops*…).

Conclusions & Future Work

- The BERT-based model with fine-tuned hyperparameters had a promising performance on the DIR data (**overall macro-F1: 0.87**).
- With the transfer learning to tweets, the fine-tuned BERT model had a satisfying performance. Although the overall macro-F1 on the keyword-labeled data was 0.58, **the spot-check validation indicated that the BERT model predicted more rational labels than the keyword-based method**.
- Drought impacts on **society & public health** are the most **challenging** category to be identified.
- Compared to keyword-based recognitions, **the BERT had a better generalization capability and sensitivity to drought impacts and could distinguish between rural and urban areas.**
- We recommend developing more studies to analyze and interpret the BERT predictions of drought impacts:
  - **Investigate spatial patterns of various drought impacts.**
  - **Differentiate tweets with actual impact information from demonstrations of drought awareness.**

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Thank you!