Enhancing Water Stress Classification using Drift-Aware Dynamic Neural Networks

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Problem and Motivation

- Water stress or drought poses a substantial worldwide risk to crop production in tension between rising population and climate change.
- It is crucial to identify crops under drought stress and optimize agronomic inputs to mitigate physiological damage and minimize crop yield losses.

Objective

- To frame the water stress identification problem as a time-sensitive model that actively addresses the phenomenon of concept drift and can be trained end-to-end.
- To address the challenge of predicting the condition of unseen crops facing water scarcity by developing methods for generalizing across domains under temporal variations.

Dataset & Data Preprocessing

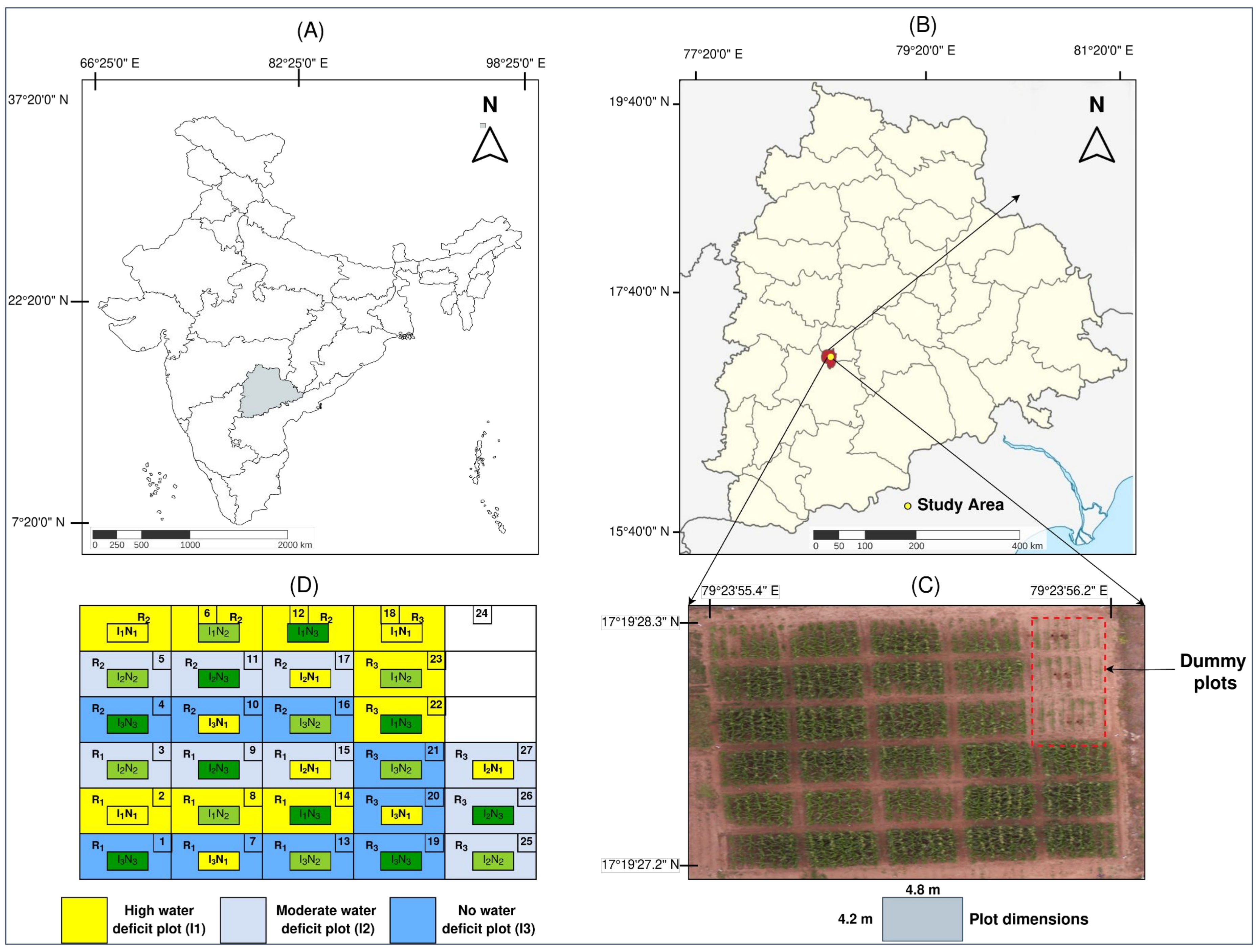

Fig. (A) Indian map. **(B)** Location of experiment field in Telangana map. **(C)** Top view of the field captured by the UAV with dummy plots highlighted. **(D)** Field layout of treatments where I_1, I_2, I_3 represent high, moderate and no water deficit plots respectively.

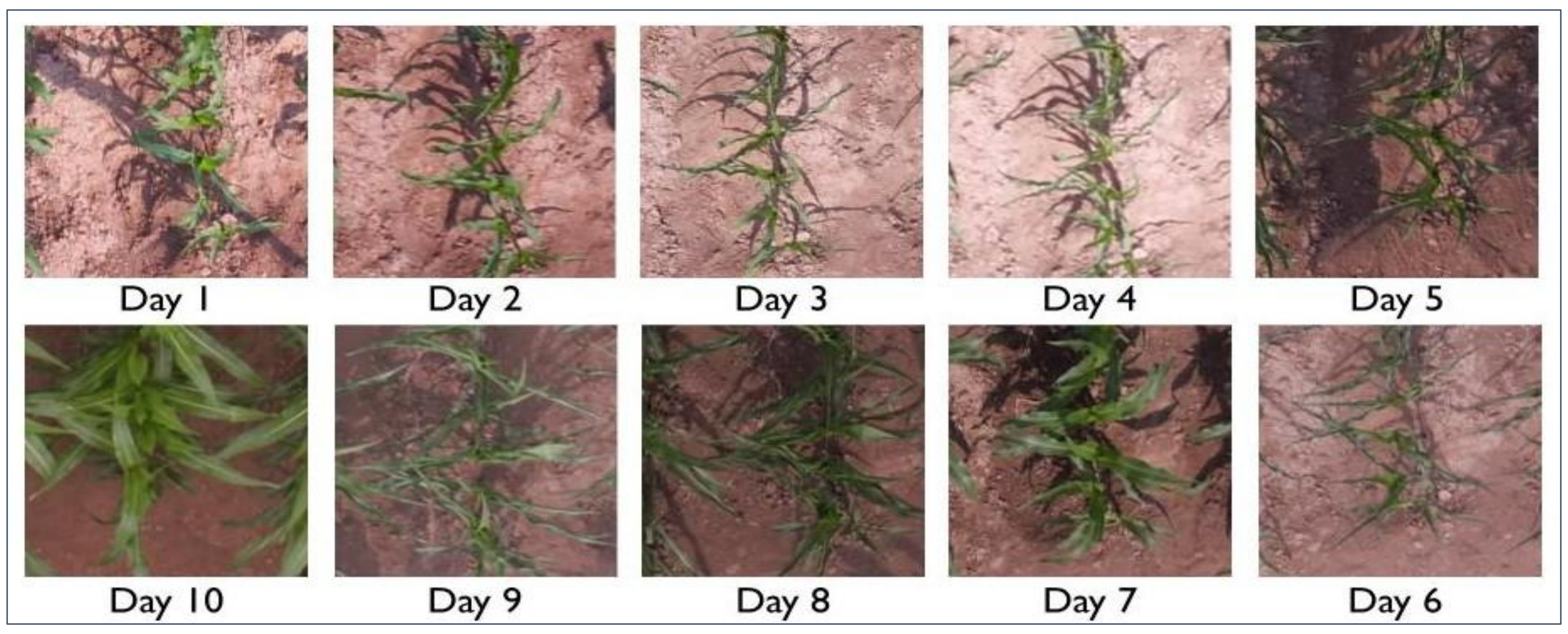

Fig. Samples of maize crop of I1N2 category between vegetative and start of reproductive phase.

- The experimental investigation took place in Hyderabad (Telangana, India) from October to February during Rabi season of 2018-19.
- $D_s = (x^{(s)}_i, y^{(s)}_i)$ are provided to us during training. These domains are sampled from distributions on T arbitrary time points, $t_1 \leq t_2 \leq \ldots \leq t_T$, for each of the (T=9) observed source domains, where $x^{(s)}_i$, $y^{(s)}_i$ and N_s denote the input feature, label, & sample size at timestamp t_s. Changing distribution of input features from Day-1 to Day-10 attributed to temporal drift in data distribution.

Methodology

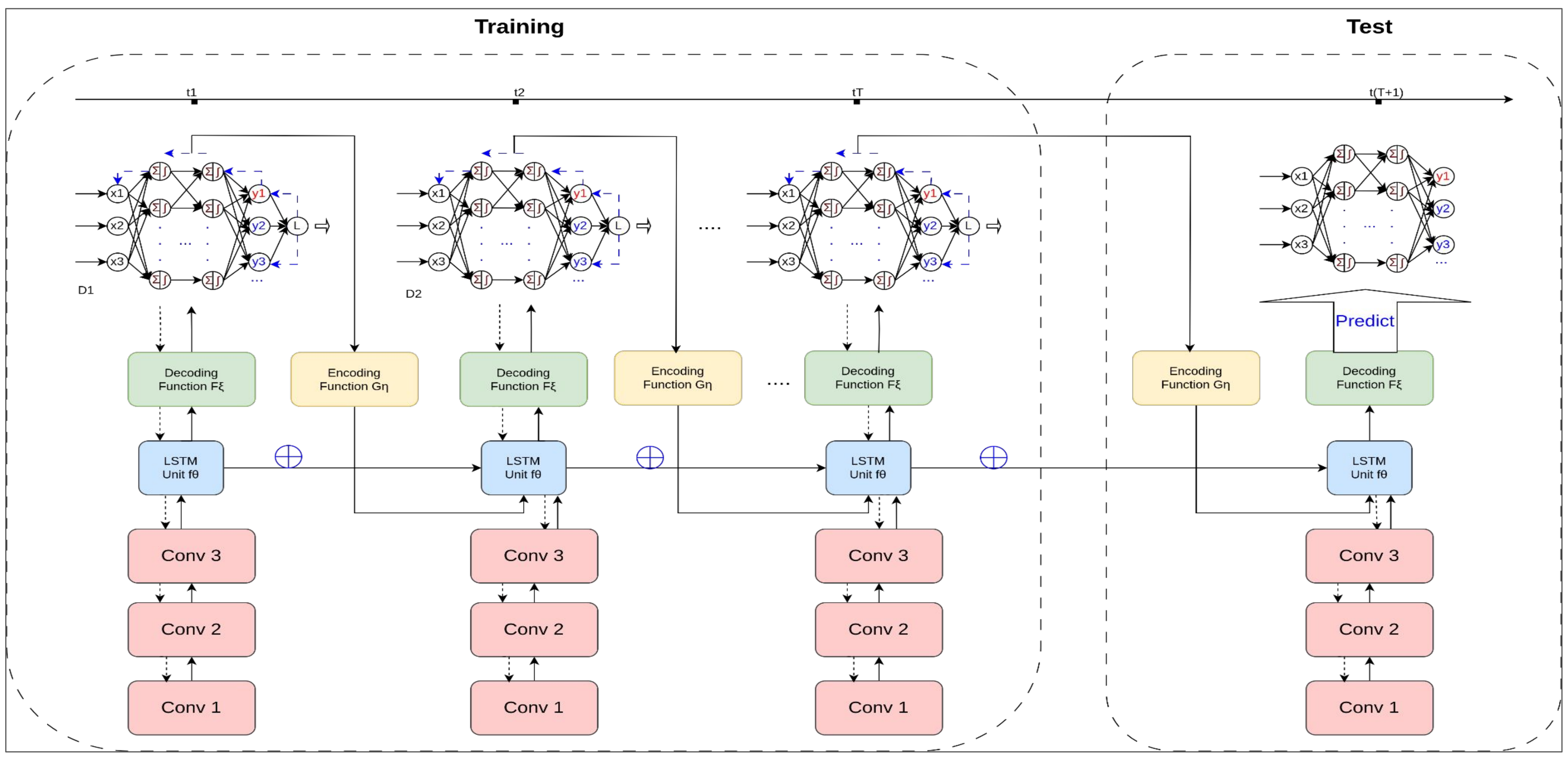

Fig. Overview of proposed method

$$\Pr(\omega_{T+1} \mid \mathcal{D}_{1:T}) = \int_{\Omega} \underbrace{\Pr(\omega_{T+1} \mid \omega_{1:T}, \mathcal{D}_{1:T})}_{\text{inference}} \cdot \underbrace{\Pr(\omega_{1:T} \mid \mathcal{D}_{1:T})}_{\text{training}} \, d\omega_{1:T},$$

$$\Pr(\omega_{1:T} \mid \mathcal{D}_{1:T}) = \prod_{s=1}^{T} \Pr(\omega_s \mid \omega_{1:s-1}, \mathcal{D}_{1:T})$$
$$= \Pr(\omega_1 \mid \mathcal{D}_1) \cdot \Pr(\omega_2 \mid \omega_1, \mathcal{D}_{1:2}) \cdots \Pr(\omega_T \mid \omega_{1:T-1}, \mathcal{D}_{1:T}).$$

- Utilizing labeled data from distinct source domains, denoted as $D_1, D_2, .., D_T$, we aim to acquire the mapping function $g\omega s : X_s \rightarrow Y_s$ for each domain D_s at timestamp t_s. (Here, ωs signifies the function parameters at timestamp t_s)[1].
- Our goal is to forecast the parameters ωT+1 for the mapping function $g\omega T+1 : X_{T+1} \rightarrow Y_{T+1}$ in an unseen future domain.

[1] G. Bai, C. Ling, and L. Zhao, "Temporal domain generalization with drift-aware dynamic neural networks," arXiv preprint arXiv:2205.10664, 2022.

Results

Approach	Train loss	Test Accuracy	Misclass. error
ResNet-101	0.0052	70%	0.45
ResNet-101+RNN	0.0042	72%	0.33
Proposed Model	**0.0040**	**75%**	**0.25**

- Our work is inspired from [1].
- We adopted two baseline methods where one approach does not consider the concept drift i.e., treating all samples as i.i.d and the second one uses Recurrent Neural Network to process the temporal sequence.

Future work

We intend to create a novel architecture in the future that combines the ideas of diffusion based autoencoder models to address the drift in a time fashioned manner.

Acknowledgements

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