Deep Reinforcement Learning for Variability Prediction in Latent Heat Flux from Low-Cost Meteorological Parameters

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Outline

Introduction

- Predicting cropland latent heat flux (LHF) from commonly measured low-cost meteorological parameters (MPs) like net solar radiation, soil & air temperature, vapor pressure deficit, wind speed, and canopy temperature of the crops is essential for modeling crop production and managing water resources economically.
- Within an agricultural ecosystem, various types of energy transport processes exist between the crop surfaces and atmospheric micro-MPs.
- This energy balance enclosure (EBC) is based on the energy conservation principle and equalizes the available energy.
- The above EBC over a cropland monitoring site, situated at the earth's surface, is closely related to the overlying atmospheric boundary layer. Moreover, this EBC and its turbulent exchange are governed by the micro-climate of the plant communities.
- The incoming solar radiation, the latent and sensible heat fluxes are the most vital processes in this land-atmosphere exchanges.

Introduction (contd..)

- The growth, development, and yield of crops are governed by the interactions between the energy and water balance in the crop-fields.
- The net radiation energy is partitioned into latent energy during the day time and is mainly concentrated in the paddy fields.
- The exchange of latent energy in the vegetation-atmosphere interface is the most crucial factor in the crop production system.
- Quantitative understanding and accurate estimation of all the fluxes, including LHF over cropland surfaces, plays a vital role in the development of agricultural production by precise irrigation planning and proper water utilization policy due to the close correlation between the rate of evapotranspiration and the water depletion of the soil.
- Usually, the radiometric surface temperatures of a crop canopy are not unique due to their inherent complicated structure and uneven canopy surface temperature distribution.

Introduction (contd..)

- The ambient air temperature, humidity, and wind profile analysis are essential to evaluate the energy balance components over a crop-field, which requires the establishment of flux towers.
- In developing countries like India, the network of such eddy/flux towers is not feasible due to the enormous deployable cost involved.
- As such, studies envisaging the causal interdependence between the micro-MPs mentioned above, and the LHF is essential for data-driven modeling and LHF prediction.
- Further, LHF trend can indicate the drift in the actual evapotranspiration amount from a crop-field.

Objectives

- The present study aims to determine the LHF fluctuation variability from a set of low-cost micro-meteorological parameters via deep reinforcement learning (deep-RL).
- Our approach is model-free and uses fewer micro-MPs as input and thus minimizes the effect of uncertainties caused by the underlying model and inherent input parameters.
- The proposed scheme is data-driven instead of physics-based or empirical modeling. It holds economical significance as it is a trade-off between the prediction error and reduces the input micro-MPs acquisition cost.
- The deep-RL framework envisages domain-independent modeling for continual adaptation of the profoundly changing non-stationary environments like atmosphere and cropland ecosystem.
- The workflow is illustrated in the next slide.

Pipeline of the proposed framework

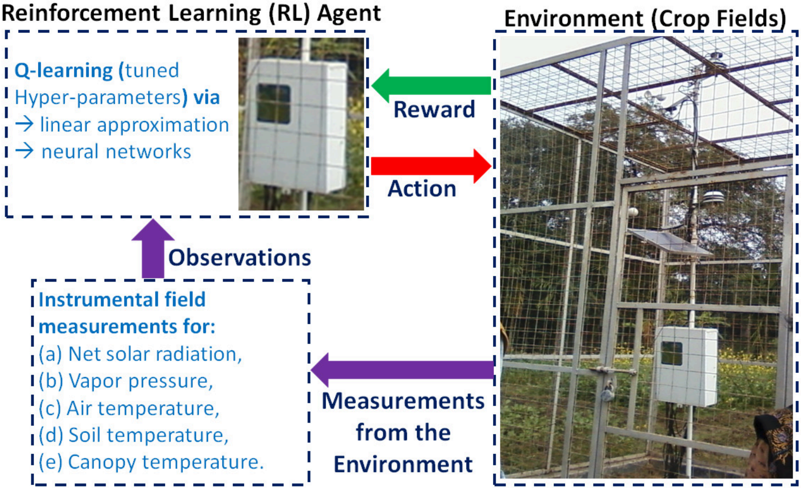

Figure: Workflow of the proposed methodology

Meteorological Data Collection

- **Study Area and Field Experiment Details:**
  The experimental farm area is located in the **Bidhan Chandra Krishi Viswavidyalaya (BCKV), State Agricultural University, Kalyani, West Bengal (WB), India,** located near the **Tropic of Cancer** (Latitude: $22°57'N$, **Longitude:** $88°20'E$). The cropland lies in the **sub-tropical climate zone** and receives an **average annual rainfall** of **1467.5mm**, with a mean temperature ranging from $15.5°C$ **to** $21.3°C$ **in winter**, and a maximum of **(**$27.6°$ **to** $31.7°C$**) during May**. Three important non-rice crops of the region, namely the **yellow Sarson (mustard), potato, and green-gram**, owing to **similar energy balance partitioning patterns**, are considered for analysis in the present study.

Meteorological Data Collection (contd..)

- **Meteorological Parameters & Data Collection:**
  The **ISR** is measured with the help of a **net Pyrradiometer** (*Make National Instrument and Calibrated by IMD, Pune*).
- The **canopy temperature** is measured with the help of an **infrared thermometer** (*Model No. TES 1326/1327*).
- The **soil temperature** is measured at hourly intervals in between the two rows of the crops with two **soil thermometers** inserted into the soil at an angle of 60°, and taken from a height of **5cm and 15cm**, respectively, from the ground surface.
- The **Assmann psychrometer** is used to measure the **air temperature & vapor pressure deficit** at a height of **5cm and 15cm**, respectively.
- The **wind speed** is measured with a **hand-held anemometer**.

Meteorological Data Collection (contd..)

Figure: Micro-MP measuring instrument setup from the study area.

Meteorological Data Collection (contd..)

Measured meteorological parameters	Range	Mean $\pm$ Std
f_1 = Net solar radiation (W/m^2)	2.2 to 606.83	233.89 ± 138.42
f_2 = Air temperature (°C)	0 to 34.20	25.91 ± 3.78
f_3 = Actual vapour pressure $(N.m^2)$	0 to 50.86	24.52 ± 7.38
f_4 = Wind speed at a height of 2m (m/sec)	0 to 9.95	1.64 ± 1.55
f_5 = Soil temperature at a height of 5cm (°C)	0 to 32.50	22.02 ± 4.26
f_6 = Soil temperature at a height of 15cm (°C)	0 to 30.61	21.24 ± 3.78
f_7 = Canopy temperature (°C)	0 to 34.93	22.79 ± 4.50

Figure: Statistics of the acquired meteorological parameters.

Problem Definition via Reinforcement Learning

- As it can be seen from the previous slide, where the different micro-MP feature values are designated as $f_i \in F = f_1, ..., f_6$.
- Let us define $y \in Y$, which is the output response variable denoting the LHF trend, which may be either positive or negative.
- A vector $x = [x_1 \ x_2 \ x_3 \ x_4 \ x_5 \ x_6 \ x_7]^T$, where x_i is a value of the meteorological parameter f_i.
- Thus $(x, y) \in D$ together constitute a sample being drawn from a data distribution (D). This D contains the measured LHF (y) and the predictor variable (x).
- A function mapping, $c : F \rightarrow R$ is defined which associates a feature f with a real-valued cost $c(f)$, and a cost scaling factor λ is defined, where $\lambda \in [0, 1]$.

RL for LHF Trend Estimation (Contd..)

- The classification model encompasses a set of coupled parametric functions and the aim is to learn the model parameters θ, which minimizes the mean classification error, and a corresponding λ scaled expected feature cost.
- Here, $y_\theta : X \rightarrow Y$, where y_θ is the misclassification cost, and $z_\theta : X \rightarrow \wp(F)$ denotes the used features in the process. The overall problem can be expressed as:

$$\underset{\theta}{argmin} = \frac{1}{D} \sum_{(x,y)\in D} \left[l(y_\theta(x), y) + \lambda \sum_{f \in z_\theta(x)} c(f) \right] \tag{1}$$

- For our deep-RL methodology, we have followed the strategy as given in [1] and followed its implementation from [2].

[1] Janisch, Jaromír, Tomáš Pevný, and Viliam Lisý. "Classification with costly features using deep reinforcement learning." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 33. 2019.

[2] https://github.com/jaromiru/cwcf

RL for LHF Trend Estimation (Contd..)

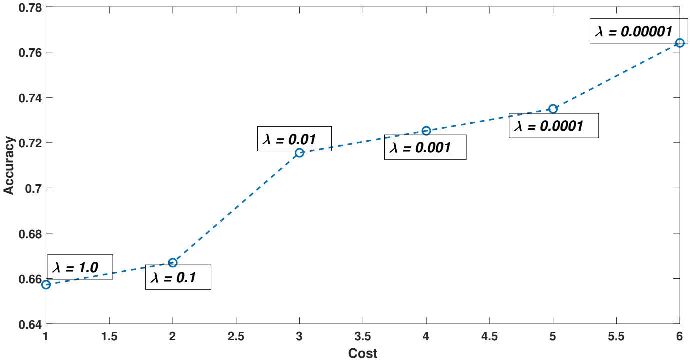

Figure: The dependence of trend estimation accuracy for different λ values.

RL for LHF Trend Estimation (Contd..)

- The above problem statement can be reformulated as a sequential decision-making problem, where an agent analyze a feature at each step to estimate the trend output.
- For a conventional RL setting, an agent explores its environment through a series of actions and observes the relative change in the environment states at each step, which in turn gives a reward based on the action taken.
- In our case, this environment is considered as a partially observable Markov decision process (POMDP) due to its state-transition dynamics representation.
- A sample classification from the experimentally collected dataset concludes each episode.

Q-learning

In Q-learning, we try to optimize an optimal function Q^*, which characterizes the anticipated discounted reward and action a pair in the state s via some optimal policy update. This is achieved via Bellman equation as discussed below:

$$Q*(s,a) = \underset{s' \sim t(s,a)}{E}\left[r(s,a,s') + \gamma \underset{a'}{max} Q^*(s',a')\right] \qquad (2)$$

Where, $r(s,a,s')$ signifies the expected reward, and $\gamma \leq 1$ denotes the discount factor. By joint optimization, for all the actions a, a neural network characterized by the parameters θ and taking a state s gives an estimate of $Q^\theta(s,a)$. Deep Q-learning algorithms include a discrete target network having parameters ϕ, and it follows with a delay. More details on Q-learning and deep Q-learning can be found from the references given at the end.

- Proposed method envisages an adaptive micro-MP selection strategy.
- Dataset normalization via mean & standard deviation of the MPs.
- The split-ratio of the dataset for training, validation, and testing sets is **0.6:0.2:0.2**. Each algorithm is repeatedly run 100 times, and the mean performance accuracy is depicted in the figure below.
- Prediction accuracy of 73.51% using Q-learning (linear approximation).

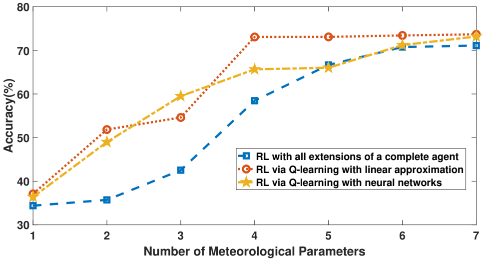

Figure: Comparison of the 3 explored RL models for the LHF trend estimation.

Experimental Result and Discussion (contd..)

- All the three non-rice crops have similar energy balance partitioning patterns and therefore clubbed together for the presented analysis.
- Relative change in daily micro-MP values and the corresponding change in the ground measurements of LHF are used for RL model training.
- The estimated LHF trends are in good agreement over the studied cropland monitoring sites, signifying the potency of the proposed methods for evaluating the cropland LHF over diverse climatic conditions.
- Not all micro-MPs are important for LHF prediction.
- Comparative evaluation with other RL variants: **(i)** RL with a complete agent, and **(ii)** Q-learning with neural networks.
- The utility of data-driven deep RL as a trade-off between the prediction error and reduce the input micro-MPs acquisition cost holds economical significance over physics-based and empirical models.
- Our approach is model-free and uses fewer micro-MPs as input and thus minimizes the effect of uncertainties caused by the underlying model and inherent input parameters.

Conclusion

Problem reformulation as a sequential decision making problem, where each of the low-cost MPs is acquired for a cost.

Objective: Short-term LHF variability forecasting via joint minimization of the LHF trend prediction error and the relative MP measurement cost.

We explore the following Deep RL variants:

- RL with all the extensions of a complete agent.
- RL via Q-learning with linear approximation.
- RL via Q-learning with neural networks.

Concluding Remark: Domain-independent prediction for continual adaptation of the profoundly changing non-stationary environments like atmosphere and cropland ecosystem.

Futuristic scope: We are expanding our dataset to include other crops and exploring state-of-the-art machine learning and deep learning-based regression methods.

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[3] https://github.com/jaromiru/cwcf