Cause and Effect: Temporal Variability in Climate Forcing and Ecological Responses at East River Watershed, Colorado

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Motivation and Objectives

Motivation:

- Water and energy balances under gradual climate change reshapes hydrologic dynamics and ecological responses in vulnerable mountainous watersheds
- Long term and large scale predictive tools for hydrologic dynamics and ecological functioning are needed for ungaged sites

Objectives:

- Identify cause and effect linkages among climate forcing, soil moisture (SM) and ET dynamics in mountainous watersheds.
- Determine the inter-annual variability of SM and ET and corresponding hydrological and ecological effects
- Develop long term large scale hybrid predictive model for watershed and ecosystem monitoring

Research Sites

In this study, our modeling focus on three locations within the SNOTEL network (Fig 1 & 2): Butte, Schofield Pass (SP) and Porphyry Creek (PK).

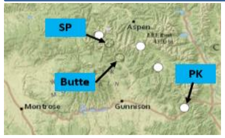

Fig 1: Focused SNOTEL station

Fig 2. Butte station from SNOTEL monitoring network

Data and Community Land Model (CLM)

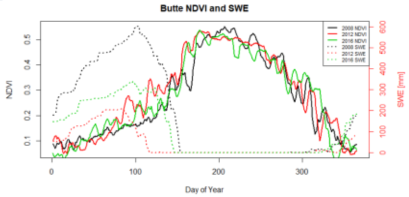

Fig 3: NDVI (LANDSAT) and SWE (SNOTEL) measurements at Butte

Fig 4: LANDSAT satellite images

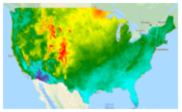

Fig 5: Daymet dataset distributed by ORNL DCCA project

Methodology

Hidden Markov Model (HMM)

- ET dynamics are controlled by different hydrological regimes.
- HMM is capable of determination hydrological regimes.
- HMM is able to quantify temporal variation of regimes.
- Hidden Variable S represent dominant hydrological regime at any given time t.

$$P(S_t|S_1, S_2, \dots, S_{t-1}) = P(S_t|S_{t-1}), t = 2, 3, \dots, T \quad \text{Eq1}$$

$$P(X_t|X_1, X_2, \dots, X_{t-1}, S_1, S_2, \dots, S_t) = P(X_t|S_t), t \in N \quad \text{Eq2}$$

Fig 6: simple illustration of HMM

Hybrid Predictive Model (HPM)

Long Short Term Memory Recurrent Neural Network (LSTM-RNN)

- Significant autocorrelation
- Seasonality and inter-annual variability
- Cross correlation among climate forcing and Ecological/Hydrological responses

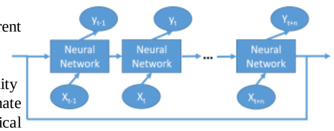

Fig 7: information path in a LSTM-RNN framework

HPM Structure

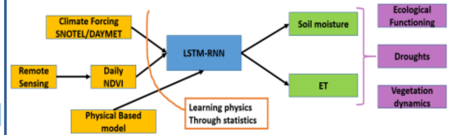

Fig 8: HPM flowchart

Training:
- CLM model

Inputs:
- Climate Forcing
- NDVI

Outputs:
- ET
- Soil Moisture

HPM Performance

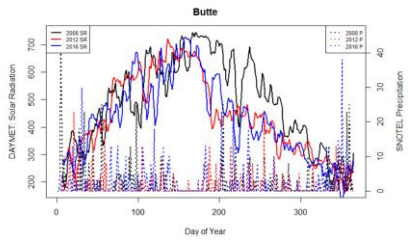

Fig 9: Inter-annual variability of climate

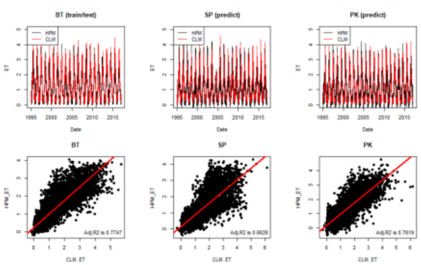

Fig 10: HPM model validation. Butte station is used for model training; SP and PK results are predictions independent from CLM model

Cause and Effect linkages

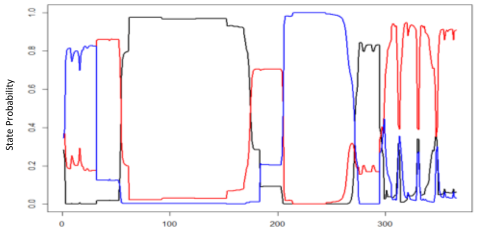

Fig 11: 3-stage HMM result of year 2008

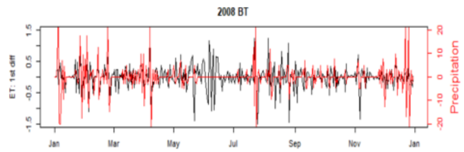

Fig 12: Correlation between first order difference of ET and Precipitation

ET and SM dynamics are controlled by different hydrological regimes:

- Black line: representing low soil moisture time periods. Snow covering and post snowmelt drought condition. Energy limiting condition.
- Blue line: representing decreasing soil moisture and increasing ET (drying after precipitation events. Water limiting condition.
- Red line: representing low soil moisture and high ET. Abundant soil moisture with ample energy. Associated with high plant yields.
- Small temporal variation of ET dynamics after summer controlled by monsoon activities.

Implications from HPM

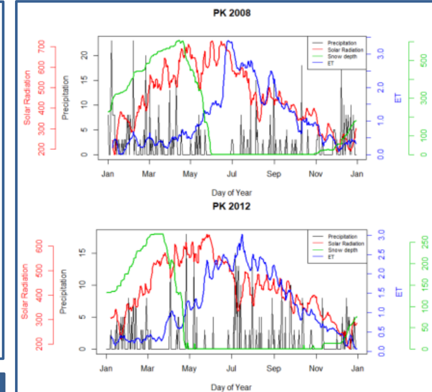

Fig 13: ET and climate forcing dynamics at PK in 2008 and 2012

Preliminary Explanation:

- Snowmelt triggers greatest ET increasing gradient
- Fore-summer drought leads to ET decreasing due to water limiting condition
- ET follows solar radiation trends (energy limiting condition)
- Small scale ET fluctuation follows precipitation pattern
- Inter-annual variability of ET dynamics as a result of climate variation in precipitation patterns and energy inputs

Conclusions

1. HPM is capable of incorporating information from a well developed physically based model. This has significant potential for long term and large scale simulation for ET, soil moisture and other environmental attributes at ungagged sites or sites with limited information.
2. HPM is also computationally efficient as it only needs to solve physical equations once.
3. HMM and correlation analysis indicate dynamics of snow, and drying/wetting processes during monsoon season are important for shaping ET dynamics.
4. Greatest increasing gradient of ET follows rapid snowmelt. Fast growth in plants trigger the high level of ET dynamics.

Future Work

We will apply the HPM model for a watershed scale estimation of ET. Through a better understanding of cause-effect linkages, we could provide more accurate HPM for long term and large scale estimation.

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Acknowledgements

Funding: Jane-Lewis Fellowship, LBNL-SFA project

Support: Lawrence Berkeley National Laboratory's Watershed Science Focus Area (SFA).

Data Source: DAYMET, LANDSAT, NCRA SNOTEL