Introduction

The Russian River basin in northern California is susceptible to devastating flooding events associated with winter rainfall. Soil moisture content, streamflow, and surface runoff can be simulated using a model known as the Sacramento Soil Moisture Accounting Model. This model is a part of a larger model framework called the Hydro Lab Research Distributed Hydrological Model (HL-RDHM), a key component of the National Weather Service (NWS) flood forecasting system. As part of the NOAA Hydrometeorology Testbed (HMT), seven soil moisture observing stations have been deployed across the basin. The goal of this project was to find whether or not HMT soil moisture observations can be used in data assimilation techniques that can improve HL-RDHM soil moisture simulations and NWS flood forecasts.

Methods

Data assimilation techniques use observations to update model simulated forecasts. Before they can be applied to HMT data and the HL-RDHM, it must first be determined that spatial and temporal patterns exist within the soil moisture observations collected at each station. To do this, three statistical tests were run on each network data set.

1. Using Autocorrelation for Temporal Analysis
   - Can future events be predicted from past events?
   - For how long do the data hold memory of their past values?
   - Tells us how slowly the soil moisture field is evolving
     a. Plot the correlation of individual soil moisture observations with previous values gathered by that station
     b. Index soil moisture autocorrelation from -1 to +1 for every successive time lag
     c. Extract the time lag values at which correlation falls to zero

2. Pearson’s Correlation for Spatial Analysis
   - Are the soil moisture observations related in space as well as time?
   - Determines whether there are spatial patterns in the data
     a. Calculate the correlation between soil moisture data for every possible station pair within the Russian River’s HMT network
     b. Use Pearson’s coefficient to index station pair correlations on a scale of 0 to 1

3. Covariance of the Model-Observation Differences
   - Can the difference between HMT observations and RDHM simulations be minimized?
   - The answer determines whether or not HMT data can be assimilated to improve forecasts
     a. Calculate the differences for each station
     b. Create a covariance matrix to index how these differences vary together
     c. Test if the matrix is positive definite: YES or NO

Results

1. Autocorrelation (AC) Analysis Results
   - AC in the observations is highly persistent during the summer and fall when precipitation is limited.
   - The AC periods are shortened in the spring where the variability in soil moisture is high.
   - The winter AC analysis cannot be validated because of the lack of stationary data during that period. We expect a lower AC period similar to the spring’s because of the dry season. The winter ACF’s do not show this.

2. Pearson’s Correlation Results
   - Data between station pairs are highly correlated during the summer and the fall.
   - Correlation is low between many station pairs during the spring, and some during the winter. Many winter correlations are still quite high.
   - Observational problems are highlighted for the station at Hopland (HLD), especially in the spring.
   - The correlation between several station pairs are high, likely due to their closeness in proximity.

3. Positive Definite Matrix Test Result
   The covariance matrix for the differences between HL-RDHM simulations and the HMT observations is positive definite. (YES) The difference can be absolutely minimized.

Discussion

The data generally capture the temporal nature of the soil moisture quite well. We expect to see increased evolution during wet seasons, and slow evolution during dry-down periods. This is shown in both the AC results and the observation time series below. It would be useful to compare the soil moisture data with corresponding precipitation records from Russian River basin.

Spatial patterns are represented well during the summer and fall when the entire basin is drying down. For flood forecasting, it is more important that these patterns are well captured during precipitation events. Unfortunately, it is harder to resolve these patterns, as shown in the spring and winter analyses. An improved analysis would factor in a spatial model based on station coordinates and their relative positions in the basin.

Conclusions

The data reflect the spatial and temporal behavior of the soil moisture field during much of the year. Representativeness error increases during periods when the soil moisture field is quickly evolving. Data assimilation techniques can and will be explored since it is possible to minimize the difference between the observations and the model outputs.

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References