

Abstract

The understanding of how human activities impact the region's climate and ultimately the Lake Champlain basin is pivotal in conservation efforts. The Integrated Assessment Model (IAM) requires climate data as inputs. Currently the climate team is using a non-parametric nearest-neighbor weather estimator to provide daily values of weather variables. This work presents the results of a sensitivity analysis for the parameter "Date Range", which controls the seasonal cycles of estimated weather.

Introduction

Climate projections are limited by general circulation models' (GCM's) ability to provide only temperature (T) and precipitation (P) values. Therefore a weather estimator was developed to generate the complete set of weather variables necessary to run the IAM lake model and obtain water quality predictions. The set includes temperature, precipitation, evaporation, incoming radiation, cloud cover, wind speed and direction. The scope of this project is to test the sensitivity of the overall weather estimator to three separate parameters.

1. Sampling time window (*date range*),
2. Number of Nearest Neighbors (*NN*),
3. P and T weights for weighted Euclidean distance (*w*).

Methods

Weather estimator: daily GCMs projections of T and P are the independent variables used as a link to sample from historical data. The North American Regional Reanalysis (NARR) provides the historical data (1979/1/1 to 2014/12/31) with the complete set of variables. The algorithm searches the most similar historical P and T pair and draws along the rest of the weather variables.

Analysis steps:

1. Vary the values of the parameters controlling the sampling:

Tested Parameter Values

Date range (# of days)	3, 5, 7, 14, 21, 42, 63, 84, 100, 130, 175
NN	10
Weights (T:P)	1:1

Date range
The neighbor T and P pair bound within a time window for consistent seasonality.

NN
Number of potentially good neighbors for selection

Weights (T:P)
Relative influence T and P in-weighting the neighbor distance.

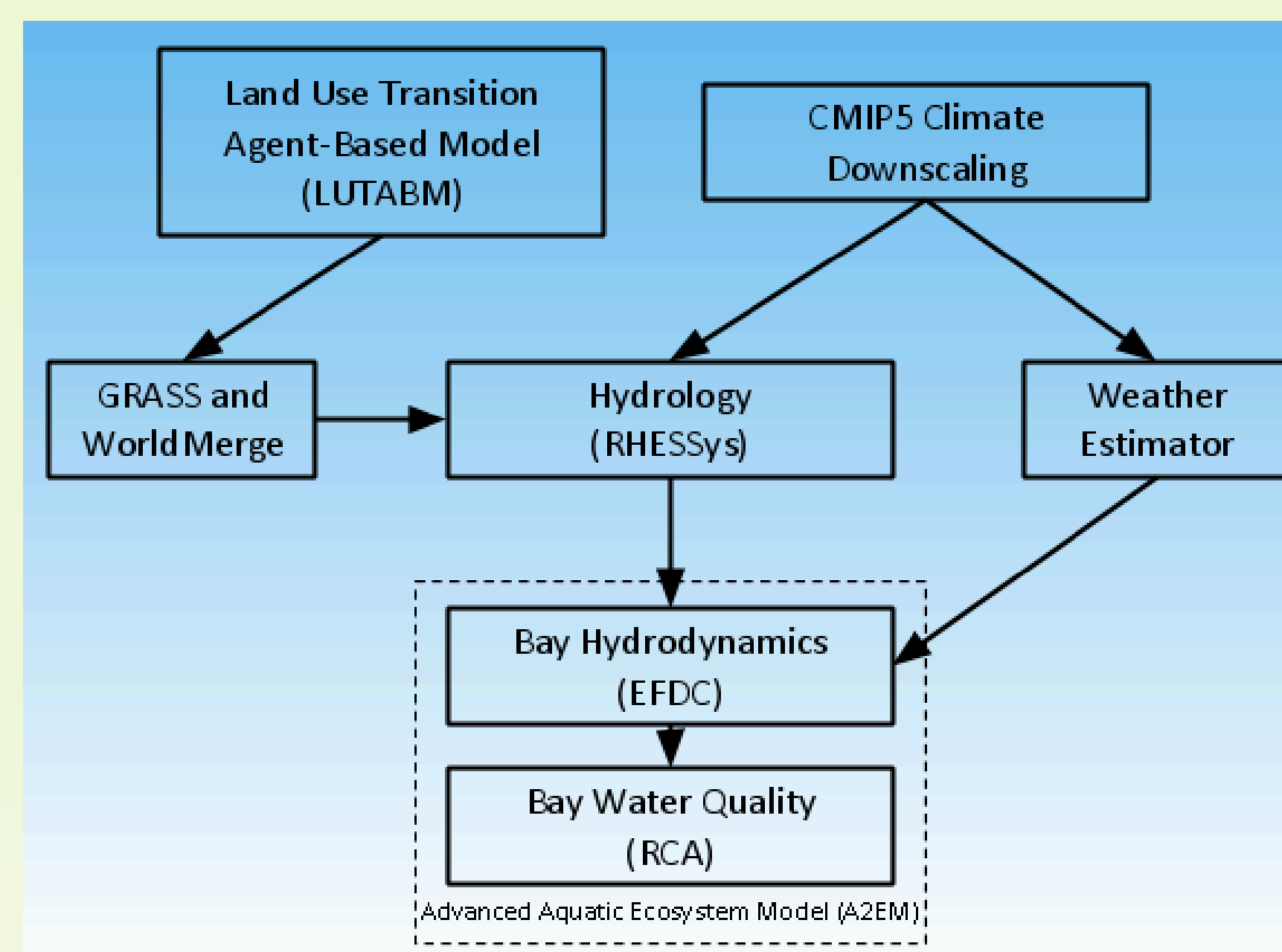
2. Sensitivity to Date Range variability is quantified based on a **Perkins skill score** (Perkins et al., 2007). Definition:

$$S_{score} = \sum_{i=1}^n \text{minimum}(Z_1, Z_2)$$

Where *n* is the number of the bins used to calculate the probability density function (PDF), *Z*₁ is the frequency of values in a given bin for the dataset 1 and *Z*₂ the frequency of values in the same given bin for the dataset 2.

- Each parameter combination was run 20 times to ensure viable results.
- The skill score mean and variance were calculated and plotted

Context



- The Integrated Assessment Model (IAM) developed by the Vermont EPSCoR RACC team simulates the effects of climate change and resource management policy on water quality.
- An important function of the IAM is to investigate possible future scenarios of water quality for the Lake Champlain basin.
- The IAM requires climate data as inputs. Currently the climate team is utilizing the weather estimator described here to provide daily values of weather variables for lake models.

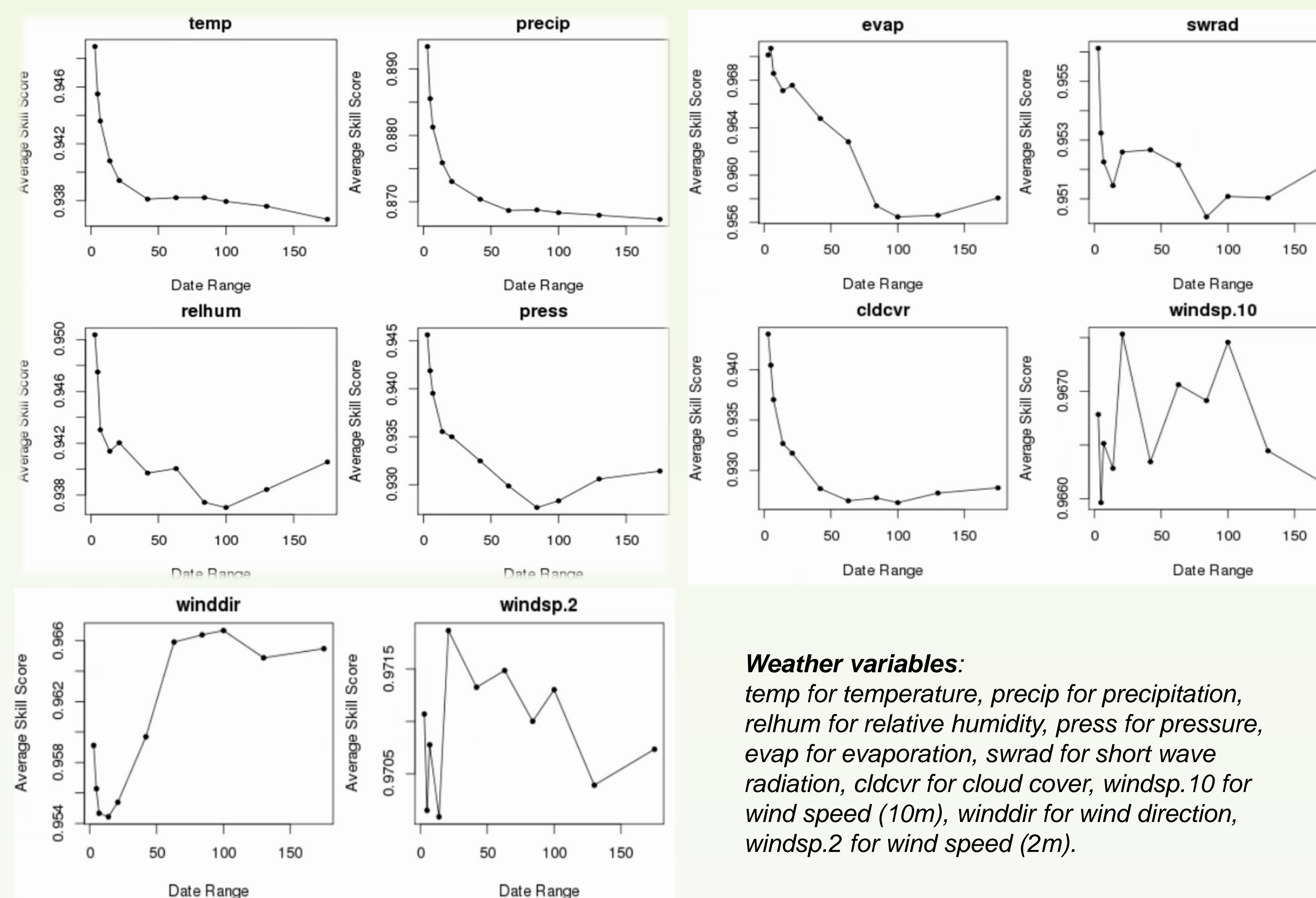
Conclusion

Our objective was to test the sensitivity of the overall weather estimator to three separate parameters, sampling time window (date range), Number of Nearest Neighbors (NN), and relative weights of P and T in the weighted Euclidean distance. The full analysis was not conducted for all three parameters due to time. An in depth analysis of date range was completed and is presented in this poster.

The goal of the date range parameter in the weather estimator is to maintain seasonality patterns in the resampled data, an important aspect in a region with significant seasonal shifts such as The Lake Champlain basin.

- The sensitivity analysis for the date range produced results that were expected with only a few exceptions.
- We can conclude that the value selected for date range parameter to run the weather estimator plays an important role. Accurate results are obtained with a range of 21 days or less.
- Further research is needed to analyze the sensitivity of the algorithm to NN and T:P weights in the same fashion as date range. This will improve our understanding of the effects associated with each parameter on the weather estimator outputs.

Results



Weather variables:

temp for temperature, *precip* for precipitation, *relhum* for relative humidity, *press* for pressure, *evap* for evaporation, *swrad* for short wave radiation, *cldcvr* for cloud cover, *windsp.10* for wind speed (10m), *winddir* for wind direction, *windsp.2* for wind speed (2m).

The graphs display the relationship between skill score and date range for each of the 12 weather variables. X axis: date range values from 3 to 175 days. Y axis: skill score averages derived from averaging skill scores over the 20 runs.

The reference data set for the skill score calculation is the NARR dataset.

Variance bars are reported but not visible because their ranges are of the order of +/- 10 E-006.

Results suggest that:

- Date range < 21 returns accurate results. Temp, Precip, Rel Hum, Press, Evap, and Cldcvr all display a behavior supporting these findings
- Short wave radiation has a strong seasonal tie: higher date ranges were scoring as high as some lower ranges. This could be due to seasonal cycle in solar radiation or the influence of other weather variables such as cloud cover.
- Wind variables show no preference to any given date range. They might have little seasonal tie and therefore no relationship with a selected time window.

References

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