Estimation of hourly near-surface air temperature in complex terrain: Influence of elevation, cold air pools and snow cover

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Fig. 3: iButtons for air (left) and ground temperature (right, before deployment) ***[4]***

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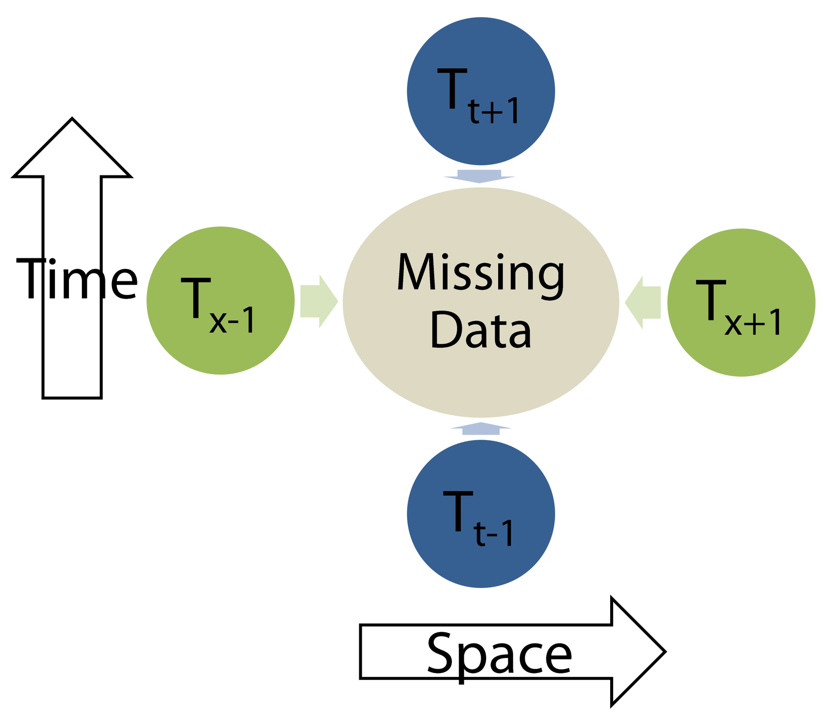
I. Introduction & Goals

For many applications, near-surface air temperature is needed at locations where it is not feasible to measure it due to mountainous terrain. Data may also be missing from observational records due to instruments failure or data transmission interruption.

Techniques for estimating temperature include elevation-based estimation using a lapse rate, temporal interpolation and empirical orthogonal function (EOF) reconstruction. These estimation methods rely on the relationship (either spatial, temporal, or both) between available and missing data (Fig.1).

This study tested method skill by randomly removing data and evaluating each technique's ability to reconstruct the gaps. We are interested in how the methods perform, and the impact of elevation difference, cold air pooling and snow cover on their accuracy.



Relationship	Methods
Spatial	*Lapse rates, kriging*
Temporal	*MicroMet*
Spatio-temporal	*EOF reconstruction*

Fig. 1: Conceptualization of estimating temperature from observations.

II. Methods

We compared the following methods:

- EOF reconstruction **[1]**
- Long-term lapse rate **[2]**
- Hourly lapse rate **[2]**
- Hourly lapse rate with kriging **[2]**
- Time series interpolation (MicroMet preprocessor) **[3]**

We tested the methods by removing data Monte Carlo-style and filling. We also tested for the effects of snow by comparing air temperature at snow-covered and snow-free locations. Snow cover was indicated by insulated ground temperatures near 0°C **[4]**.

III. Data

In order to cover a range of locations and spatial scales hourly temperature datasets from five regions were used. We collected distributed measurements using iButtons to measure air temperature and ground temperature for snow presence (Figs. 2, 3).

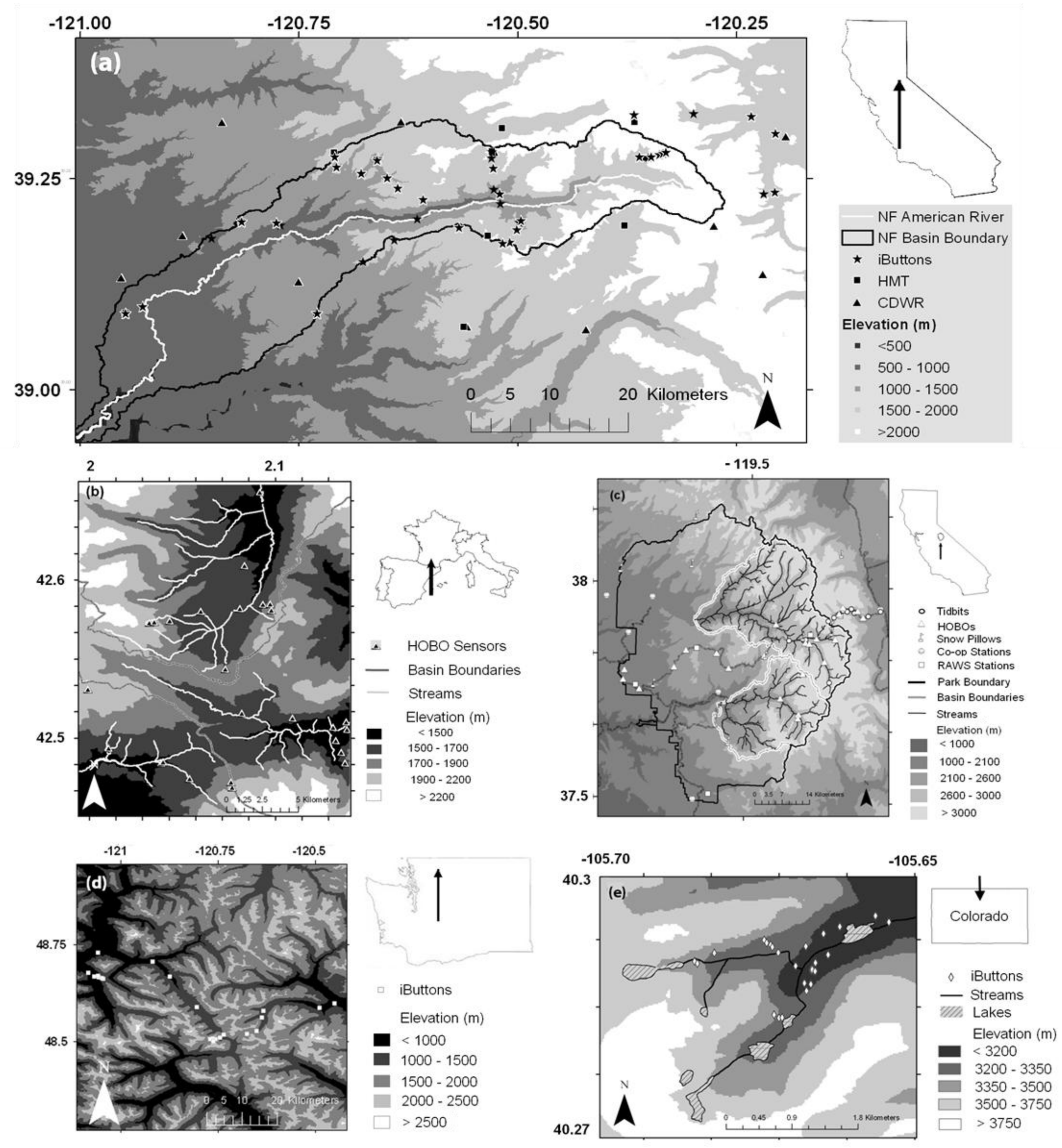


Fig. 2: Locations of five hourly temperature datasets: a) American River, Sierra Nevada, Calif. ***[5]****, b) Eastern French Pyrenees* ***[6]****, c) Yosemite National Park, Calif.* ***[7]****, d) North Cascades National Park, Wash.* ***[8]*** *and e) Loch Vale in Rocky Mountain National Park, Colo.* ***[9]****.*

IV. Results

Comparing the five methods, we found:

- EOF and lapse rate methods were sensitive to the number of stations
- MicroMet was sensitive to the length of the gap
- Vertical distance between stations increased error (e.g., Yosemite had large vertical range)

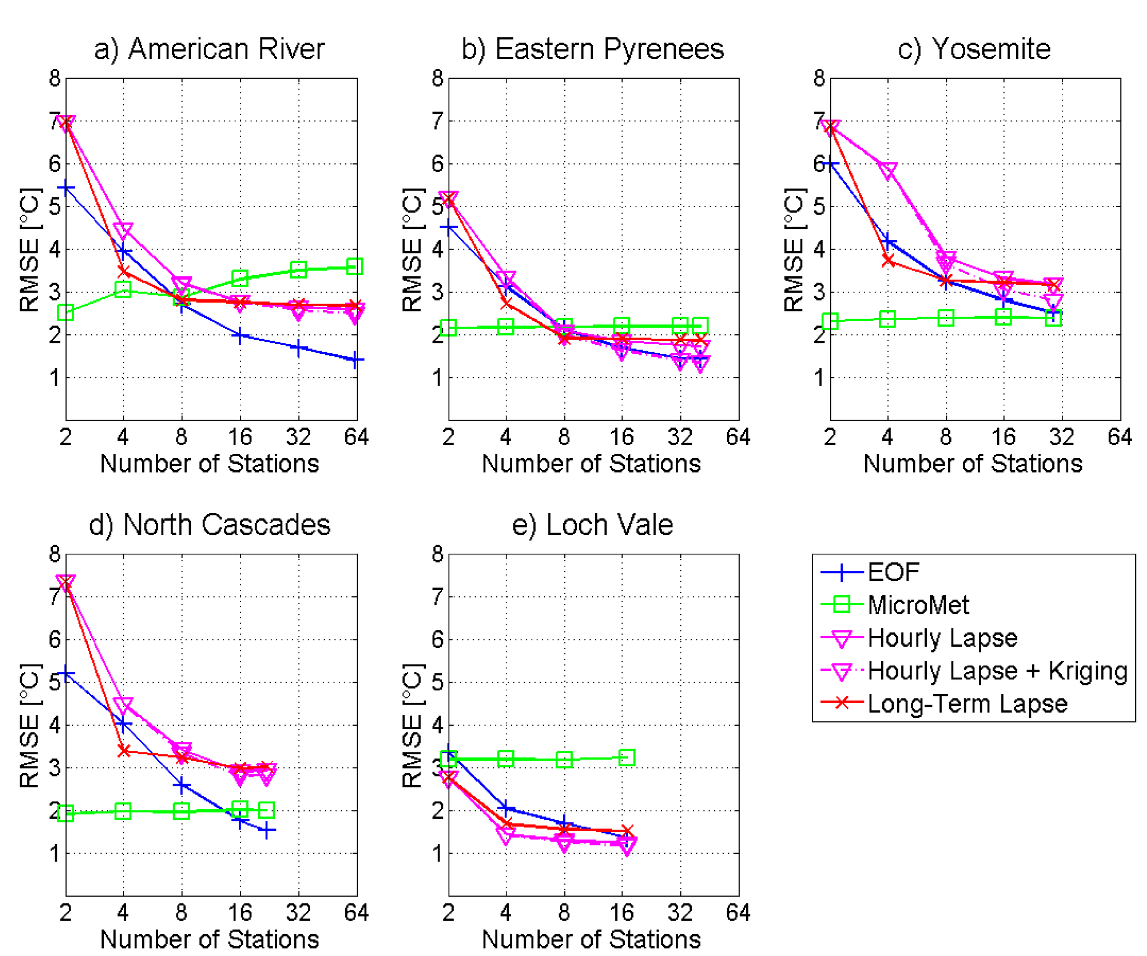


Fig. 4: RMSE for all methods and datasets.

IV. Results (cont.)

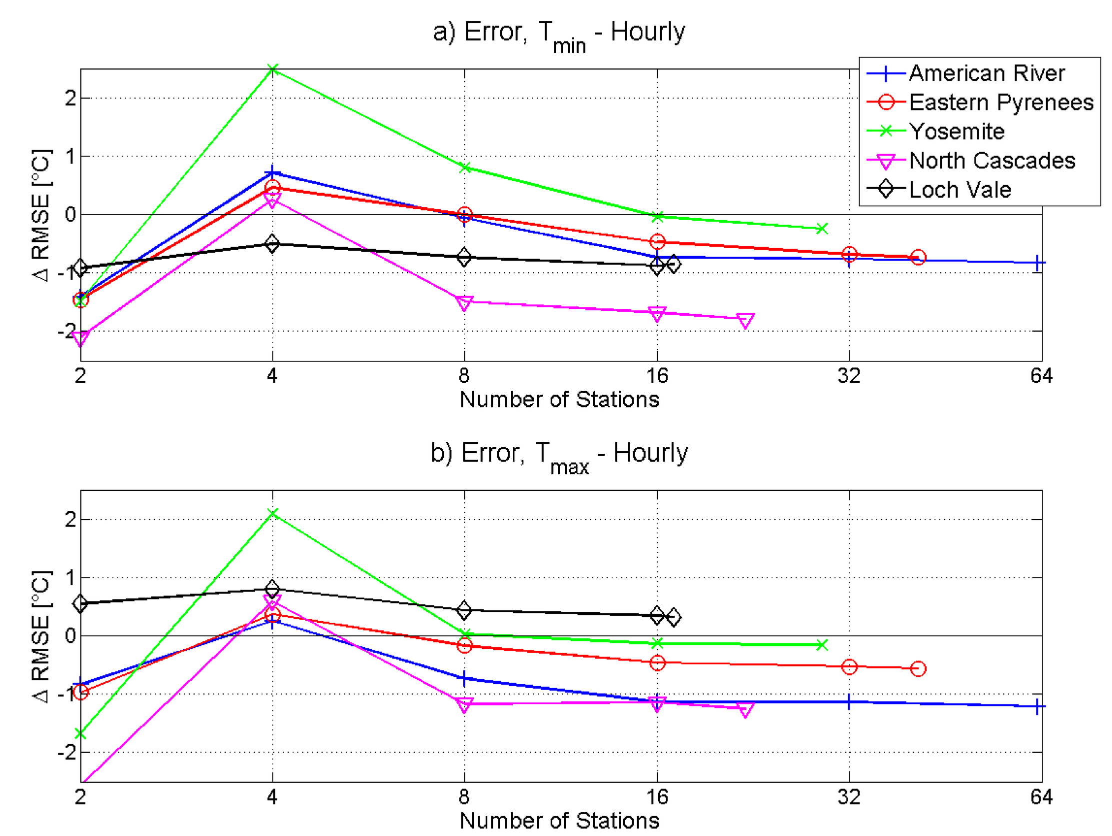


Fig. 5: a) Difference in RMSE between T_{min} and all hours, and b) difference in RMSE between T_{max} and all hours. Both are for the long-term lapse rate method.

By comparing hourly error to the T_{min} and T_{max} error, we found:

- Greater T_{min} error in Yosemite, probably due to cold air pools **[8]**
- Greater T_{max} error in Yosemite and Loch Vale (more solar radiation?)
- Lower T_{min} and T_{max} error in North Cascades (less solar radiation?)

We compared American River snow-covered and snow-free areas, after correcting for elevation:

- Snow-covered sites had colder deviations from the lapse rate profile, by about 1°C
- Difference consistent across 3 water years

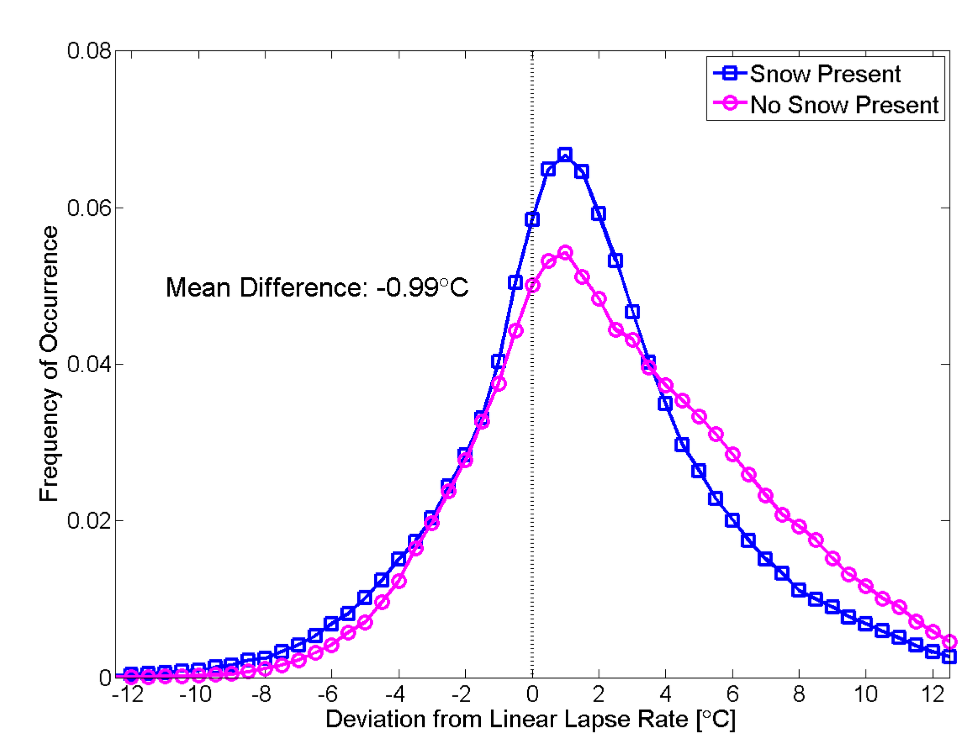


Fig. 6: Frequency of deviations from a fitted temperature-elevation profile, sorted into snow-covered and snow-free areas.

V. Conclusions

The study demonstrated that the most accurate method depends on the length of the gap and the number of stations. The methods' performance depended on the characteristics of the datasets such as vertical separation and cold air pooling. Considering snow cover can improve the lapse rate method accuracy by about 1°C.

Sources and Acknowledgements

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