Utilizing Meteorological Data with Supervised Learning to Predict Snowfall Amounts at Copper Mountain Ski Resort

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Introduction

› Prognostic models have difficulty predicting snowfall for specific mountains and slopes
› More accurate site specific snowfall forecasts could potentially improve ski resort operations
› Copper Mountain unique as multiple official meteorological stations are near or onsite, each with freely available data
› Could Supervied Learning be used to site specific snowfall?

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Overview

› Outline
  – Data Utilized
  – Modeling Methodology
  – Feature Selection
  – Model Performance
  – Model Diagnostics
  – Recommendations

› GOAL:
  – Given knowledge that a snowfall event is going to occur, goal of this assessment is to:
    › 1.) Determine how well an Ordinary Least Squares model might perform at predicting how much snowfall will fall over 12 hours given meteorological observations at the start of those 12 hours
    › 2.) Make recommendations regarding improving model performance

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Surface Data

Station ID	Station Type	Location	Elevation	Meteorological Measurements Utilized	Temporal Resolution
SNOTEL 415	NRCS SNOTEL	Popular Ski Runs midway up Copper Mtn	10550'	• Temperature • Snow Depth	Hourly
KLXV	NWS ASOS	~25 mi SW of Copper Mtn	9938'	• Temperature • Dewpoint • Wind Speed • Wind Direction • Pressure • 12-hr Pressure Changes*	Hourly
KCCU	CDOT AWOS	Near top of Copper Mtn	12075'	• Temperature • Dewpoint • Wind Speed • Wind Direction	Hourly

*Calculated feature

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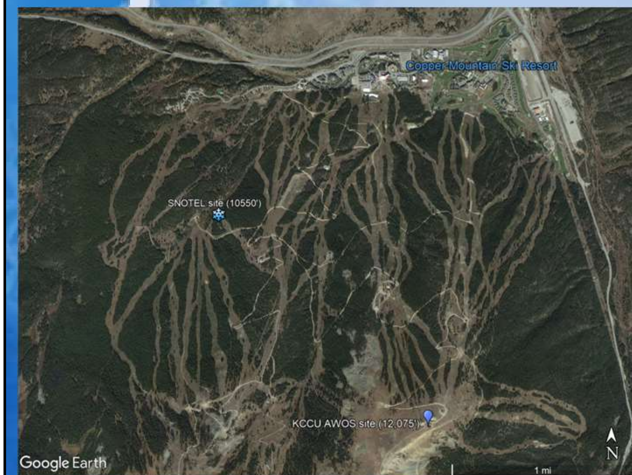
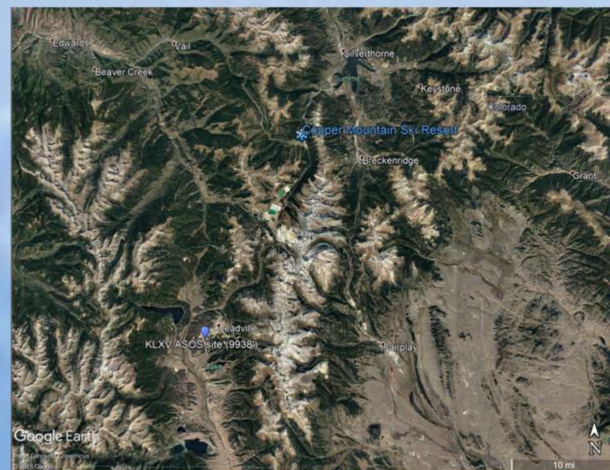
Surface Data Monitor Locations





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Additional Upper Air Data

› Snowfall is highly dependent on physics of crystal development, which is affected by upper air physics. Therefore, upper air data was also included

Station ID	Location	Pressure Levels	Measurements at each Level	Temporal Location
KJCT	Grand Junction, CO	200mb, 250mb, 300mb, 400mb, 500mb, 700mb, & 850mb	• Height • Temperature • Dewpoint • Wind Speed • Wind Direction	12 hour

› Differences in meteorological measurements between Pressure Levels are common considerations when forecasting snowaffall so were also calculated and included (e.g. 500mb Dewpoint minus 400mb Dewpoint) as additional features

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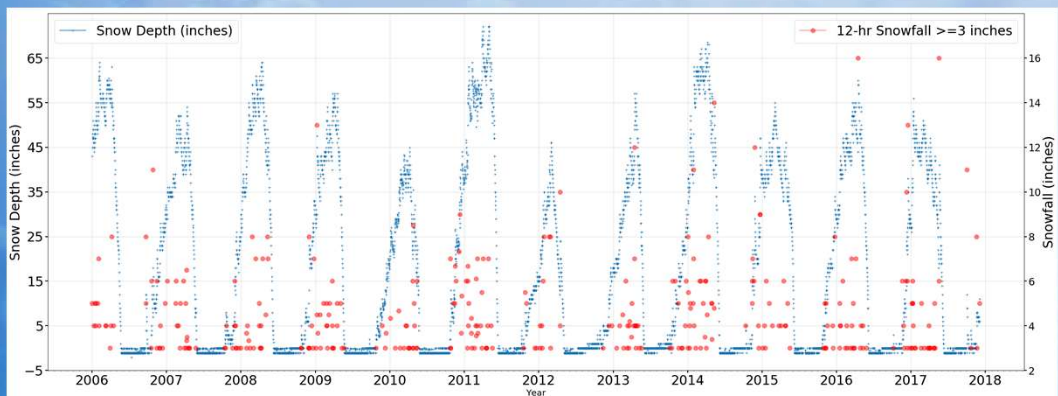
Snowfall vs Snow Depth

- SNOTEL stations report *snow depth*. Snowfall was calculated.
- 12-hr snowfall only. Events >=3” due to noise in data.



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Modeling Methodology

- Ordinary Least Squares (OLS) model
- Linear Regression Analysis performed for all features
- Datasets divided into two Training/Test partitions
- Features for use in model chosen using forward stepwise approach
- Two model runs were fit on each of the two training partitions:
  - Surface Data Feature Only
  - Surface Data plus Upper Air Data Features
- Fitted models were then tested on respective test datasets to assess snowfall prediction

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Test/Training Partitions

- Partition A:
  - Test set: Years 2006 and 2017
  - Train Set: Remaining Years 2007-2016
- Partition B
  - Test Set: Year 2014
  - Train Set: Remaining years - 2006-2013, 2015-2017

  - Each of the these divisions resulted in ~80% Training/~20% Test Datasets

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Feature Selection

- Statsmodel using forward stepwise approach on Training Datasets
- Adjusted R^2 used as metric
- Optimized such that individual feature t-statistic confidence intervals (p values) were minimized
- Upper Air Data did improve Adjusted R^2

Partition A – Best Combination of Features

Dataset	Adj. R-squared:	F-statistic:	Prob (F-statistic):
Surface Data Only	0.044	3.765	0.0118
Surface+Upper Air Data	0.129	3.087	0.000606

Partition B – Best Combination of Features

Dataset	Adj. R-squared:	F-statistic:	Prob (F-statistic):
Surface Data Only	0.063	4.166	0.00297
Surface+Upper Air Data	0.142	3.236	0.000229

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Model Performance of Snowfall Predictions

Model	Sci-kit R2 Score	RMSE (inches)
Partition A (Surface Data Features only)	0.046	2.6
Partition A (Surface+Upper Air Data Features)	0.128	2.487
Partition B (Surface Data Features only)	-0.174	2.785
Partition B Surface+Upper Air Data Features)	-0.412	3.055

- Partition A model performed better then Partition B model
- The Partition B models performed very poorly by all metrics
- Upper Air Data did improve performance in the Partition A cases.
- Why such bad performance for Partition B??

Much room for improvement! But many opportunities..

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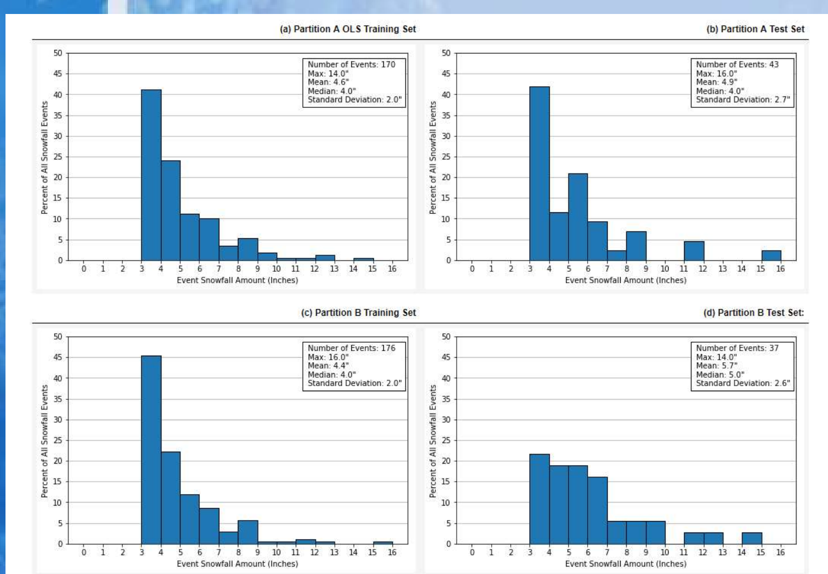
Snowfall Distributions between Training and Test Set



- Partition B Test and Training set snowfall distributions very different, likely causing poor performance
- Both Partition A Test/Train sets are heavily weighted by lighter snowfall – may tend to underpredict higher snowfall events.

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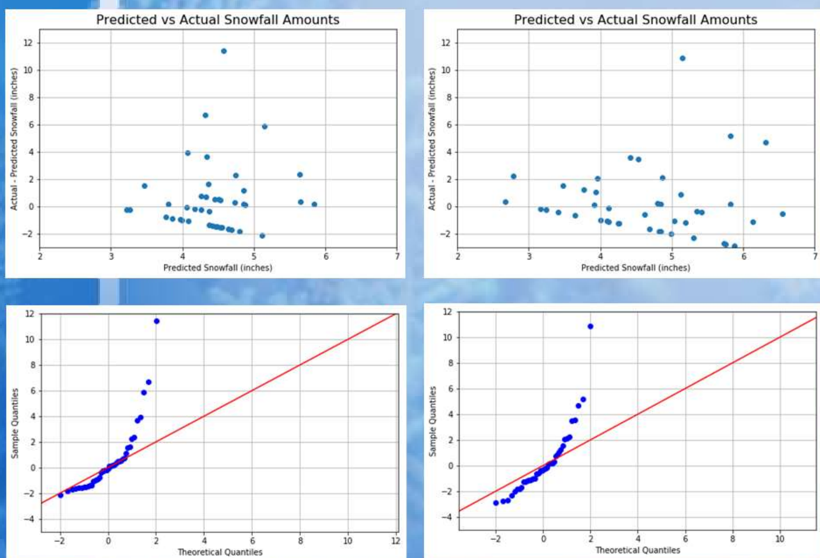
Upper Air Data Inclusion (Partition A)



- Large number of smaller snowfall events in training set caused lower underpredictions in higher snowfalls
- Despite large number of small snowfall events, upper air data did improve predictions of these events

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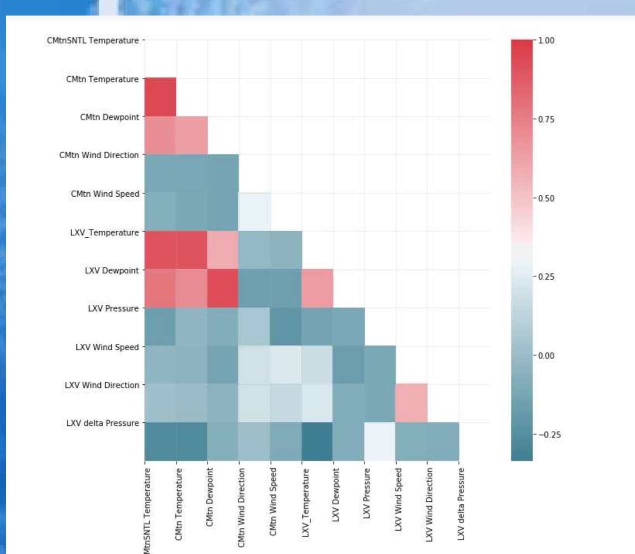
Multicollinearity and Non-linear features



- Multicollinearity
  - Due to proximity, temperature trends between sites were similar
  - In upper air data, heights were strongly correlated.
- Non-linear features
  - Though there was found to be predictive capability, Wind Direction is by nature not a linear variable and may not be beneficial in all cases, especially when winds are more northerly.
- Likely negatively influencing model

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Non-linearity considerations

› Sometimes 1" of melted can equate up to a foot of snow. Finer snow could result in two feet or more

› Snowfall must consider temperatures where the snow develops (upper air), as well as amount of moisture available.

- Breaking model down into finer components (e.g. try to predict amount of moisture to fall vs snowfall) may be better approach

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Recommendations

The initial model results did indicate poor performance. However, there are several opportunities to optimize predictive capabilities. These include:

1. While the Partition B model runs did indicate that Upper Air data would not improve performance, the Partition B Test and Training snowfall distributions were much different. Partition A modeling is likely a better gauge of performance, and upper air data did show potential to better predict the more extreme events in that model Therefore, upper air data should be utilized with surface data in future assessments.
2. Investigate collinear features more, and consider eliminating some of the strongly collinear features which may be negatively influencing the model's ability to predict.
3. If some collinear features are retained, the Ridge Regression may be a more appropriate method
4. Work to balance the distribution of large and smaller size snowfall events in the training to improve prediction of larger snowfall events. As shown, the training data set was heavily influenced by smaller, more inconsequential snowfall events. This led to the model to bias its prediction to only small snowfalls to reduce sum of squared errors.
5. Investigate whether wind direction (a rotational feature by nature) should be transformed in someway to allow it to work better with a linear model
6. Other supervised model types should be considered as non-linear relationships may be occurring.
7. As snowfall events are dependent on both crystal nature of snow as well as amount of precipitation, consider using model to just predict amount of moisture that is expected to fall at first - then add additional complexity of snow depth. Snow water equivalent is another measurement which is measured at the SNOTEL site.
8. The snowdepth dataset contains both information in increases in snowdepth and well as decreases in snowdepth. This model may be extended to identify days of rapid snowmelt.

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Acknowledgements

- Thanks to Dr. Guy Maskall of Springboard for mentorship during the preparation of this analysis

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