Review of the Utah Snow Load Study

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Outline

Introduction

The Snow Load Challenge

Proper consideration of snow loads in building design can be a delicate balancing act:

- Underestimates → structure failure
- Overestimates → increased construction costs

Figure 1: Minneapolis Metrodome, December 2010[8].

Introduction

The Snow Load Challenge

Proper consideration of snow loads in building design can be a delicate balancing act:

- Underestimates $\rightarrow$ structure failure
- Overestimates $\rightarrow$ increased construction costs

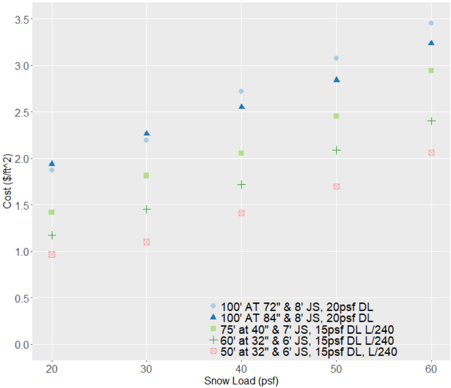


Figure 2: Cost of roof joists built for various snow loads. (Courtesy of Vulcraft).

Introduction

The Snow Load Challenge

The Challenge:

- Making accurate predictions of ground snow loads in a state as topographically complex as Utah.

Tradeoffs:

- Data quality vs data quantity
- Model accuracy vs model interpretability
- Individual exceptions vs objectivity
- conservative adjustments vs unbiasedness

Figure 3: Map of Utah (courtesy Google Earth Pro).

Introduction

Notation

- $p_g(\boldsymbol{u})$ - ground snow load at a location $\boldsymbol{u}$.
  - $p_g^*(\boldsymbol{u})$ - 50 year ground snow load at said location.
- $A(\boldsymbol{u})$ - location elevation.
- $\boldsymbol{u}_\alpha$ - location of a station $(\alpha = 1, \cdots, N)$
- $D(\boldsymbol{i}, \boldsymbol{j})$ - geographic distance between locations $\boldsymbol{i}$ and $\boldsymbol{j}$.

- Most recent Utah snow load report created in 1990 (updated in 1992) [12].
- Prediction equations intended to capture a near upper bound for ground snow loads at any given elevation within each county.

$$P_g(\boldsymbol{u}) = \begin{cases} \left(P_0^2 + S^2\left(A(\boldsymbol{u}) - A_0\right)^2\right)^{\frac{1}{2}} & A(\boldsymbol{u}) > A_0 \\ P_0 & A(\boldsymbol{u}) \leq A_0 \end{cases}$$

County specific parameters:

- P_0 - base ground snow load
- S - change in ground snow load with elevation
- A_0 - (base ground snow elevation)

Introduction

Utah ground snow loads: Example curves

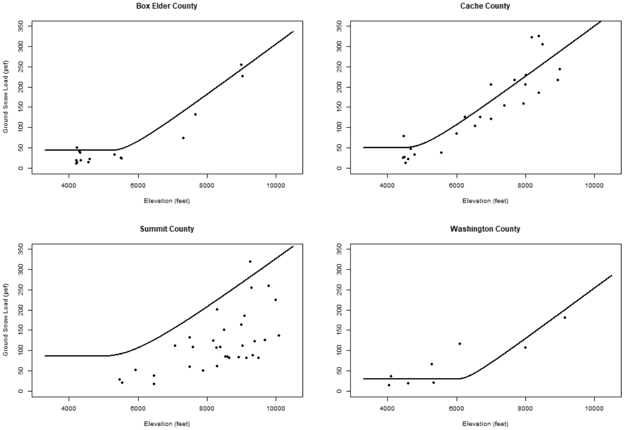


Figure 4: Example county snow load curves plotted against station values from the old Utah dataset.

Introduction

Utah ground snow loads: Discrepancies

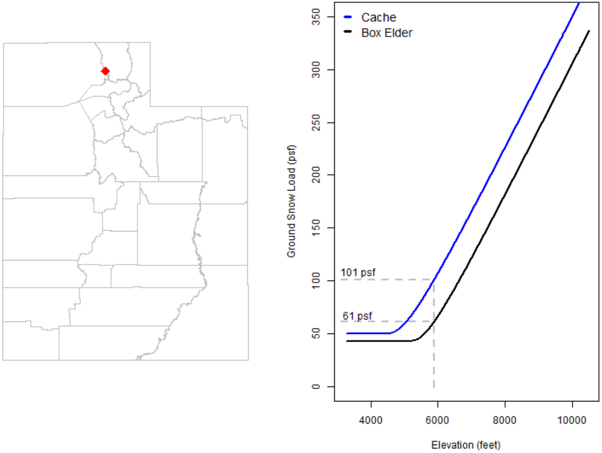


Figure 5: Illustration of the discrepancies in ground snow load requirements at the Box Elder/Cache County boundary near U.S. Highway 89.

Introduction

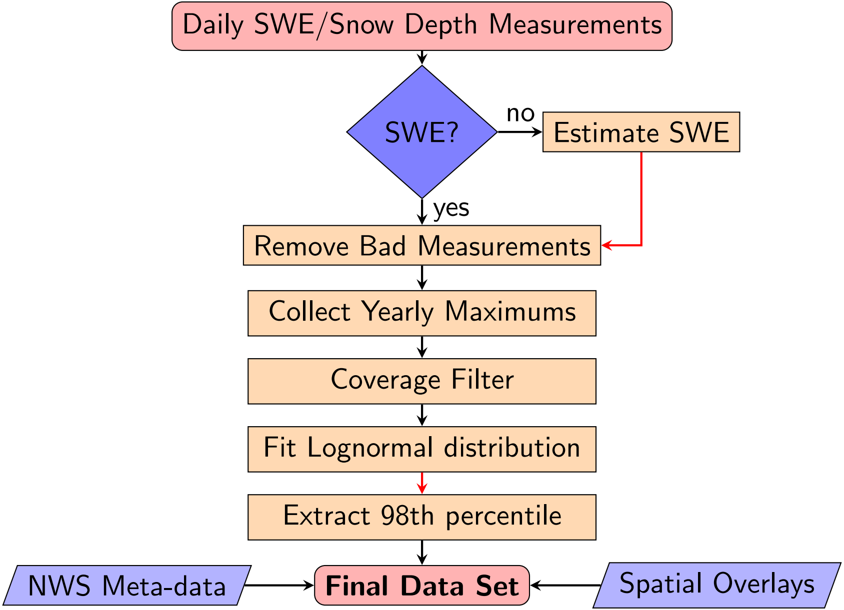
Utah ground snow loads: A need for an update.

- More than 25 years of additional snow data now available.
- Discrepancies along county borders.
- Method has since required city specific adjustments.

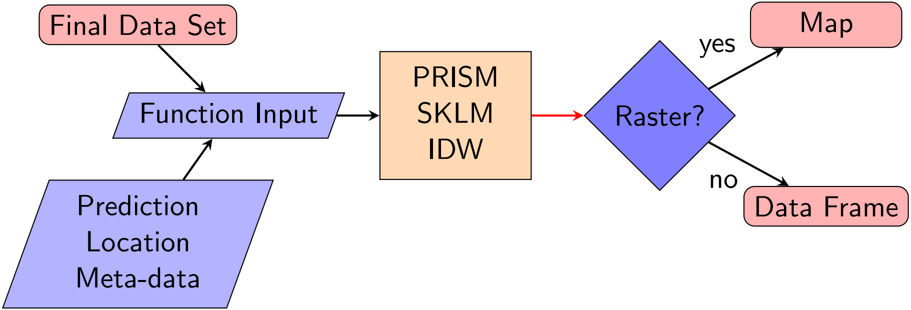
City	**Elevation** (feet)	**Law** (psf)	**Equation** (psf)
Laketown	6000	57	133
Randolph	6300	57	150
Woodruff	6315	57	151

Table 3 - Updated ground snow load requirements for Rich county, Utah (effective July 1, 2016).

Introduction



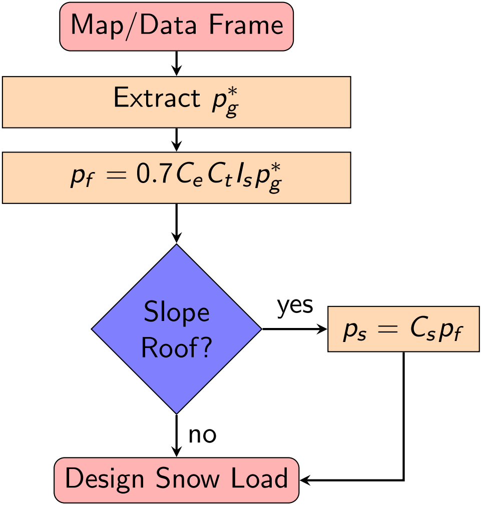
Introduction



Introduction

Variables [9]:

- p_g^* - 50 year ground snow load
- C_e - exposure coefficient
- C_t - thermal factor
- I_s - importance factor
- p_f - flat roof snow load
- p_s - sloped roof snow load



Data Set Development

Snow Measurements

- National Weather Service (NWS) provides convenient platform for collecting daily snow water equivalent (SWE) and snow depth measurements.
- Stations are a combination of Snowpack Telemetry (SNOTEL) stations and Cooperative-Observer Network (COOP) stations.
- Begin with 6.7 million daily observations at more than 1200 unique stations in an around Utah.

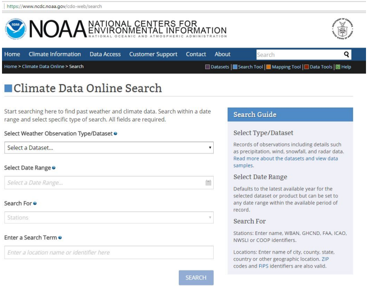


Figure 6: Snapshot of NWS Data download on-line platform.

Data Set Development

Estimate SWE

Rocky Mountain Conversion Density (English units)[11]:

$$p_g(\boldsymbol{u}) = \begin{cases} 0.9 h_g(\boldsymbol{u}) & h_g(\boldsymbol{u}) < 22\text{in} \\ 2.36 h_g(\boldsymbol{u}) - 31.9 & h_g(\boldsymbol{u}) \geq 22\text{in} \end{cases}$$

- $h_g(\boldsymbol{u})$ - depth of snow at location $\boldsymbol{u}$

Data Set Development

Estimate SWE

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Sturm's bulk density equation (metric units)[13]:

$$SWE = h_g(\boldsymbol{u}) \left[(p_{max}(\boldsymbol{u}) - p_0(\boldsymbol{u})) \left(1 - e^{(-k_1(\boldsymbol{u})h - k_2(\boldsymbol{u})D)} \right) + p_0(\boldsymbol{u}) \right]$$

- $p_0(\boldsymbol{u})$, $p_{max}(\boldsymbol{u})$ - base and maximum snow density for a particular climate class
- $k_1(\boldsymbol{u})$, $k_2(\boldsymbol{u})$ - climate specific classification parameters
- D - day of the snow year [-92 - October 1, 181 - June 30]

Data Set Development

Estimate SWE

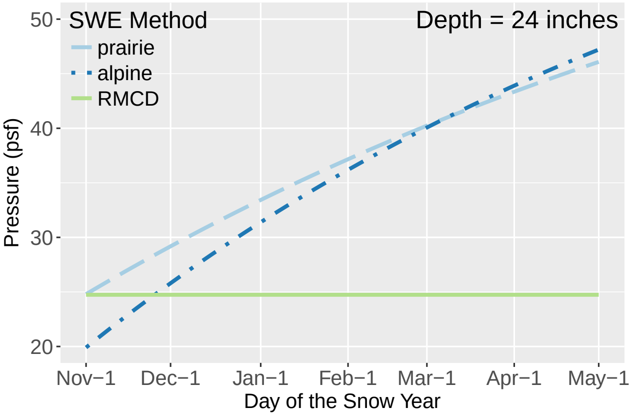


Figure 7: Comparison of RMCD to Sturm's equation for a set snow depth across time.

Data Set Development

Estimate SWE

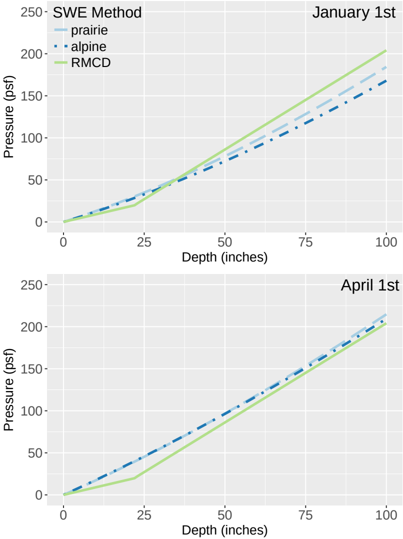


Figure 8: Comparison of RMCD to Sturm's equation for set days across snow depths.

Data Set Development

Remove Bad Measurements

- Most (but not all) faulty measurements are automatically flagged by the NWS.
- Candidate outlier points were flagged as two consecutive changes of at least 30 psf in any set of three sequential measurements in a ten day period.
- Removal of outliers, missing values, and "summertime" measurements leaves 1.9 million observations.

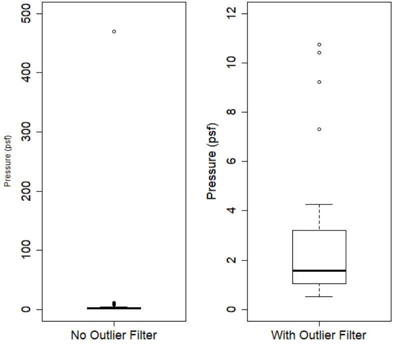


Figure 9: Comparison of 1990 non-zero snow pressure measurements at Ely Airport, NV.

Data Set Development

Collect Yearly Maximums

- For each unique station number, take the median value of the latitude, longitude, and elevation.

STATION NAME	STATION	LATITUDE	LONGITUDE	ELEVATION
CASTLE VALLEY UT US	USS0012M13S	37.66	-112.74	9580
CASTLE VALLEY UT US	USC00421241	38.651	-109.399	4725
CASTLE VALLEY UT US	USC00421241	38.651	-109.399	4720
CASTLE VALLEY UT US	USC00421241	38.65	-109.4	4719
CASTLE VALLEY UT US	USC00421241	38.65	-109.4	4720
CASTLE VALLEY UT US	USC00421241	38.65	-109.4	4699

- Merge station information for stations sharing identical location.

STATION NAME	STATION	LATITUDE	LONGITUDE	ELEVATION
HUNTSVILLE SNOW BSN UT US	USC00424140	41.217	-111.85	6562
SNOW BASIN UT US	USC00427924	41.217	-111.85	6424

- Maxes separated by water year not calendar year
  - 1998 water year: October 1997 - June 1998

Data Set Development

Apply Coverage Filter

- Distribution fitting technique assumes all maximums at location $\boldsymbol{u}$ come from the same log-normal distribution.
- Inadequate coverage of the snow season introduces low outliers to the distribution fitting process.
- Low outliers artificially inflate the standard deviation parameter of the log-normal distribution.
  - In this example, $\sigma_{\log} = 0.69$ vs $\sigma_{\log} = 0.33$.

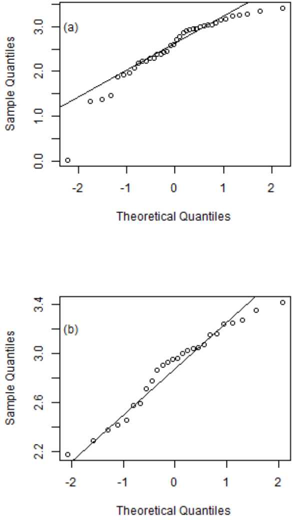


Figure 10: Theoretical log-normal distribution quantiles vs empirical (observed) quantiles for (a) raw yearly maximum snow loads and (b) yearly maximums with coverage filter applied in Levan, UT.

Data Set Development

Apply Coverage Filter

- Coverage filter designed to ensure measurements represent true yearly maximums.
  - Low Elevations - December to March
  - High Elevations - February to May
- Maximum only retained if there are measurements taken in all four months specified above OR maximum is in the upper half of all yearly maximums for that station.
- Throwing out bottom 10% of data for each station also guards against low outliers.

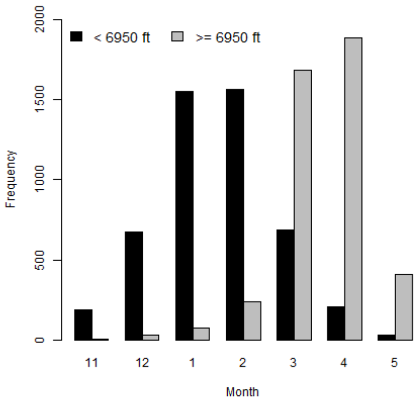


Figure 11: Month in which yearly maximum ground snow load occurred as separated by elevation.

Data Set Development

Log-normal Distribution and 98th Percentile Estimation

- Assume the non-zero yearly maximums at station location $\boldsymbol{u}_\alpha$ are *independent and identically distributed*[1] random variables $X_i(\boldsymbol{u}_\alpha) \quad (i = 1, \cdots, n = \text{station years})$ such that

$$\log(X_i(\boldsymbol{u}_\alpha)) \sim N(\mu_\alpha, \sigma^2_\alpha)$$

- Estimate the values of μ_α and σ^2_α via Maximum Likelihood Estimation in the *fitdistrplus* package [4],then

$$p^*_g(\boldsymbol{u}_\alpha) = e^{x_0} \text{ where } \frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{x_0} e^{-\frac{(x-\mu_\alpha)^2}{2\sigma^2_\alpha}}\,dx = 0.98.$$

- Only estimate 50 year ground snow loads at locations with at least 12 valid yearly maximums (and at least 5 nonzero yearly maximums).

[1] Measurements are most likely time dependent.

Data Set Development

Log-normal Distribution: Examples

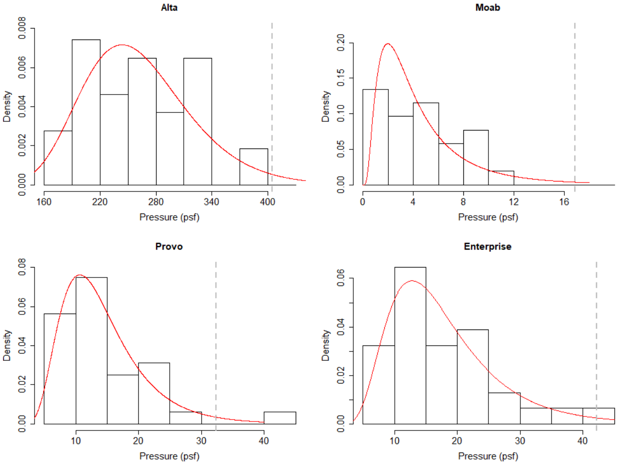


Figure 12: Log-normal distribution fitting examples for select cities in Utah.

Summary of Methods

Inverse Distance Weighting (IDW)

$$p_g^*(\boldsymbol{u}) = \frac{A(\boldsymbol{u})}{\sum_{\alpha=1}^{N} D\left(\boldsymbol{u}_\alpha, \boldsymbol{u}\right)} \sum_{\alpha=1}^{n} \left[\left(\frac{1}{D\left(\boldsymbol{u}_\alpha, \boldsymbol{u}\right)} \right)^c \frac{p_g^*(\boldsymbol{u}_\alpha)}{A(\boldsymbol{u}_\alpha)} \right].$$

- c - weighting exponent for distance weighting
- NGSL $= \frac{p_g^*(\boldsymbol{u}_\alpha)}{A(\boldsymbol{u}_\alpha)}$ is commonly used method to account for elevation in predictions
  - "reduce[s] the entire area to a common base elevation" [10].
  - Used in the current snow load reports of Idaho, Montana, and Washington [10].

Summary of Methods

Linear Triangulation Interpolation (TRI)

- Create a Delaunay triangulation of the convex hull.
- Predictions are a weighted average of the three measurements comprising the overlying triangle.
- Like IDW, relies on NGSL to account for elevation.
- Convex hull occasionally results in missing value predictions during cross validation.

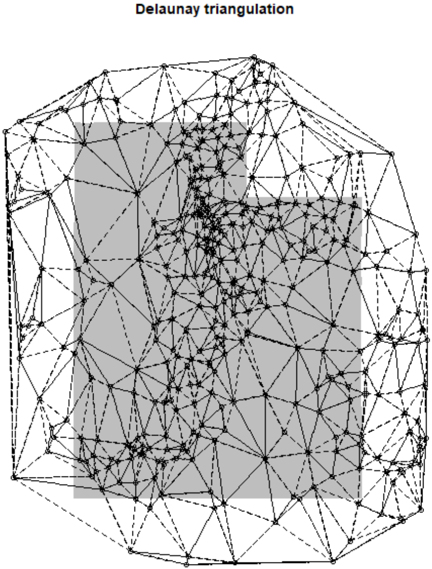


Figure 13: Delaunay triangulation using the new Utah dataset

Summary of Methods

Normalized Ground Snow Loads (NGSL)

- NGSL is highly correlated with elevation in Utah.
- This correlation violates the assumption that NGSL accounts for elevation when predicting ground snow loads.
- Consequences will be discussed in cross validation section.

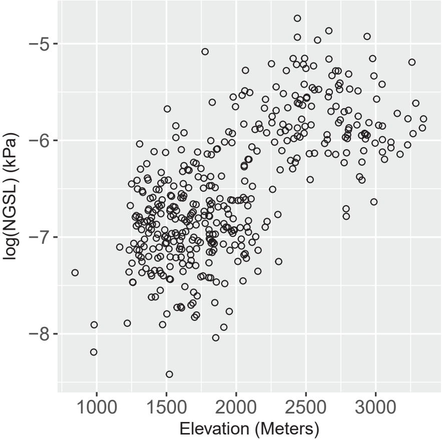


Figure 14: Station NGSL plotted against station elevation.

Summary of Methods

Least Squares Regression vs PRISM

Least squares regression:

$$\log(p_g^*(\boldsymbol{u})) = \beta_0 + \beta_1 A(\boldsymbol{u})$$

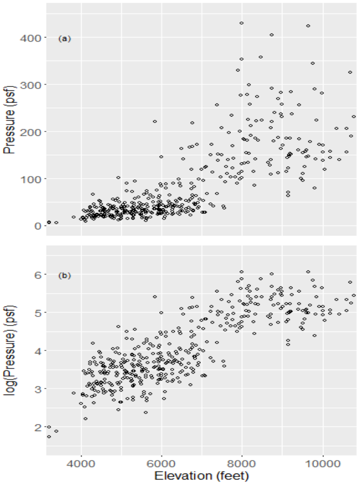


Figure 15: (a) Scatter plot of 50 yr ground snow load against elevation and (b) with log-transformation applied.

Summary of Methods

Least Squares Regression vs PRISM

Least squares regression:

$$\log(p_g^*(\boldsymbol{u})) = \beta_0 + \beta_1 A(\boldsymbol{u})$$

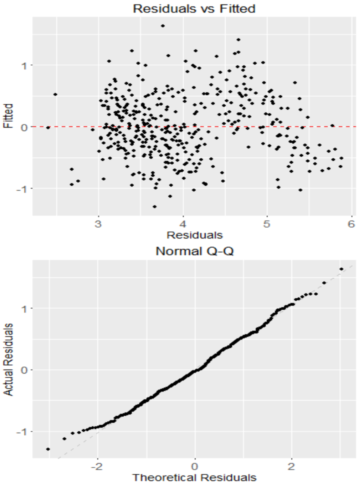


Figure 16: Residuals diagnostics of least squares regression on the new Utah dataset.

Summary of Methods

Least Squares Regression vs PRISM

Least squares regression:

$$\log(p_g^*(\boldsymbol{u})) = \beta_0 + \beta_1 A(\boldsymbol{u})$$

PRISM (Parameter-elevation Relationships on Independent Slopes Model) [2][3]:

$$\log(p_g^*(\boldsymbol{u})) = \beta_0(\boldsymbol{u}, \boldsymbol{X}) + \beta_1(\boldsymbol{u}, \boldsymbol{X})A(\boldsymbol{u})$$

where $\boldsymbol{X}$ is the matrix containing all station meta-data

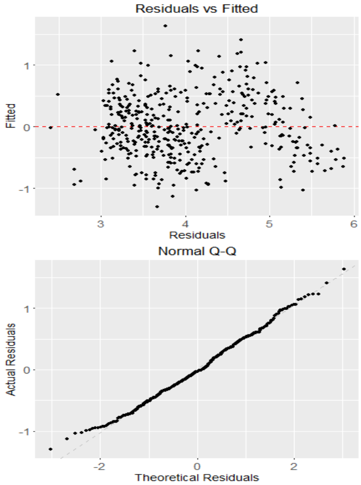


Figure 16: Residuals diagnostics of least squares regression on the new Utah dataset.

Summary of Methods

PRISM

$$\log(p_g^*(\boldsymbol{u})) = \beta_0(\boldsymbol{u}, \boldsymbol{X}) + \beta_1(\boldsymbol{u}, \boldsymbol{X})A(\boldsymbol{u})$$

Parameters originally estimated via weighted least squares regression using the matrix [3]:

$$W(\boldsymbol{u}, \boldsymbol{X}) = W_c \left[F_d W_d^2 + F_z W_z^2\right]^{\frac{1}{2}} W_p W_f W_l W_t W_e,$$

- W_c - cluster factor
- W_d W_z - distance and elevation weights
- F_d and F_Z - importance factors for distance and elevation weights
- W_p - coastal proximity
- W_f - topographic facet
- W_t - topographic position
- W_e - effective terrain weight

Summary of Methods

PRISM

$$\log(p_g^*(\boldsymbol{u})) = \beta_0(\boldsymbol{u}, \boldsymbol{X}) + \beta_1(\boldsymbol{u}, \boldsymbol{X})A(\boldsymbol{u})$$

Adaptation:

$$W(\boldsymbol{u}, \boldsymbol{X}) = W_c \left[F_d W_d^2 + F_z W_z^2\right]^{\frac{1}{2}} W_b,$$

- W_c - cluster factor
- W_d W_z - distance and elevation weights
- F_d and F_Z - importance factors for distance and elevation weights
- W_b - basin weight

Summary of Methods

PRISM - Distance Weighting

Distance weighting

- The closer a station resides to the area of interest, the more weight the station receives.

$$W_d = \begin{cases} 1 & D(\boldsymbol{u}, \boldsymbol{u}_\alpha) - r_m \leq 0 \\ \frac{1}{(D(\boldsymbol{u}, \boldsymbol{u}_\alpha) - r_m)^a} & D(\boldsymbol{u}, \boldsymbol{u}_\alpha) - r_m > 0 \end{cases}$$

- r_m - minimum radius of influence
- a - scaling factor

Summary of Methods

PRISM - Elevation Weighting

Elevation weighting

- Stations with similar elevations to the area of interest receive more weight

$$W_z = \begin{cases} \frac{1}{(\Delta z_m)^b} & \Delta z \leq \Delta z_m \\ \frac{1}{(\Delta z)^b} & \Delta z_m < \Delta z < \Delta z_x \\ 0 & \Delta z \geq \Delta z_x \end{cases}$$

- $\Delta z = |A(\boldsymbol{u}) - A(\boldsymbol{u}_\alpha)|$
- $\Delta z_m, \Delta z_x$ - minimum and maximum elevation differences (user specified).
- b - scaling factor

Summary of Methods

PRISM - Basin Weighting

Basin Weighting

- Use water catchments as a replacement for topographic facet.
- USGS Hydro-logic unit code (HUC) are 12-digit numbers, with every two digits representing a smaller water catchment (left to right).

$$W_b = \left(\frac{s_\alpha + 1}{5} \right)^c$$

- s_α - number of common watersheds (*four* levels ranging from HUC 2 through 8) shared by $\boldsymbol{u}_\alpha$ and $\boldsymbol{u}$
- c - scaling factor

Figure 17: Sample water basins in Utah [17].

Summary of Methods

PRISM - Cluster Weighting

Cluster Weighting

- Reduce weight of individual stations located in a cluster of similar stations (in both location and elevation).

$$W_c = \frac{1}{1 + S_c}, \text{ where } S_c = \sum_{j=1}^{n} h_{ij} v_{ij}$$

- h_{ij}, v_{ij} - horizontal and vertical cluster factors between station i and j

$$h_{ij} = \begin{cases} 0 & D(\boldsymbol{u}_i, \boldsymbol{u}_j) > .2r_m \\ \frac{.2r_m - D(\boldsymbol{u}_i, \boldsymbol{u}_j)}{.2r_m} & 0 \leq D(\boldsymbol{u}_i, \boldsymbol{u}_j) \leq .2r_m \end{cases}$$

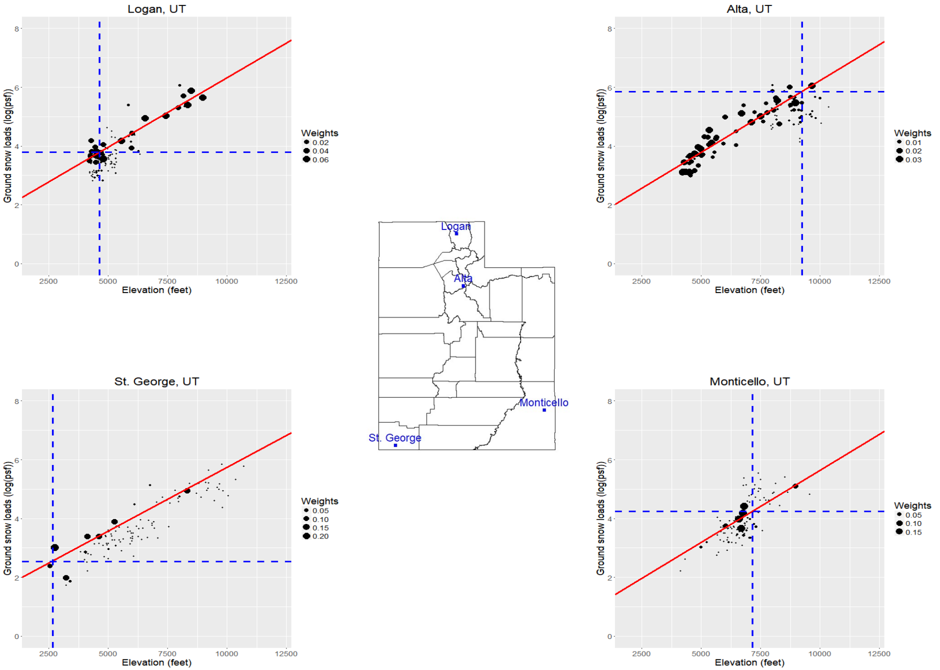
$$v_{ij} = \begin{cases} 0 & (\Delta z_{ij} - p) > 0 \\ \frac{2p - \Delta z_{ij}}{p} & (\Delta z_{ij} - p) \leq 0 \end{cases}$$

- p - (user defined) minimum elevation of influence

Summary of Methods

PRISM - Table of Parameters

Parameter	Description	Tuned Value PRISM (log-PRISM)	Typical Values
Fd	Distance weighting importance	.8 (.8)	.8
rm	Minimum radius of influence	20mi (10mi)	20-60mi
a	Distance weighting exponent	2.5 (3)	2
b	Elevation weighting exponent	2 (2)	1
zm	Minimum elevation threshold	330ft (330ft)	330-985ft
zx	Maximum elevation threshold	8200ft (4920ft)	1640-8200ft
p	Elevation precision	330ft (165ft)	n/a
d	Basin weighting exponent	2 (2)	n/a


Logan, UT
Ground snow loads (log(psf))
Elevation (feet)
Weights
0.02
0.04
0.06
Alta, UT
Ground snow loads (log(psf))
Elevation (feet)
Weights
0.01
0.02
0.03
St. George, UT
Ground snow loads (log(psf))
Elevation (feet)
Weights
0.05
0.10
0.15
0.20
Monticello, UT
Ground snow loads (log(psf))
Elevation (feet)
Weights
0.05
0.10
0.15
Logan
Alta
Monticello
St. George

Summary of Methods

Kriging

Considering the random function $Z(\boldsymbol{u})$, all kriging estimators have the form[1]

$$\hat{Z}(\boldsymbol{u}^*) = \sum_{\alpha=1}^{N} \lambda_\alpha Z(\boldsymbol{u}_\alpha), \quad \lambda_\alpha \in \mathbb{R},$$

where the $\lambda_i's$ form the unbiased estimator of $Z(\boldsymbol{u})$ that minimizes $Q(\boldsymbol{\lambda}) = E\left(\hat{Z}(\boldsymbol{u}^*) - Z(\boldsymbol{u}^*)\right)^2$ i.e.

$$\sum_{\alpha}\sum_{\beta} \lambda_\alpha \lambda_\beta C_Z(\boldsymbol{u}_\alpha - \boldsymbol{u}_\beta) - 2\sum_{\alpha} \lambda_\alpha C_Z(\boldsymbol{u}_\alpha - \boldsymbol{u}^*) + C_Z(\mathbf{0})$$

where $C_Z(\boldsymbol{u}_i - \boldsymbol{u}_j) = Cov(Z(\boldsymbol{u_i}), Z(\boldsymbol{u}_j))$.

[1] references [5] and [7] motivate this notation

Summary of Methods

Simple Kriging

We can minimize $Q(\boldsymbol{u})$ by $\nabla Q(\boldsymbol{\lambda}) = 0$ i.e.

$$\sum_{\alpha} \lambda_\alpha C_Z(\boldsymbol{u}_\alpha - \boldsymbol{u}_\beta) = C_Z(\boldsymbol{u}_\beta - \boldsymbol{u}^*) \quad \beta = 1, \cdots, n.$$

When the following conditions are met:

1. $E\left(Z(\boldsymbol{u})\right) = m$ is constant over the entire region of interest.
2. $C(\boldsymbol{h}) = Cov\left(Z(\boldsymbol{u} + \boldsymbol{h}), Z(\boldsymbol{u})\right)$ is independent of location $\boldsymbol{u}$.

Summary of Methods

Variograms

Define

$$\gamma(\boldsymbol{h}) = \frac{1}{2} Var\left[Z(\boldsymbol{u}+\boldsymbol{h}) - Z(\boldsymbol{u})\right]$$

Estimated by

$$\hat{\gamma}(\boldsymbol{h}) = \frac{1}{2N_{\boldsymbol{h}}} \sum_{\alpha_{\boldsymbol{h}}=1}^{N_{\boldsymbol{h}}} \left[Z(\boldsymbol{u}_{\alpha_{\boldsymbol{h}}}+\boldsymbol{h}) - Z(\boldsymbol{u}_{\alpha_{\boldsymbol{h}}})\right]^2$$

where $N_{\boldsymbol{h}}$ is the number of stations $\boldsymbol{h}$ distance apart from each other.

- Under certain conditions: $\gamma(\boldsymbol{h}) = C(\boldsymbol{0}) - C(\boldsymbol{h})$

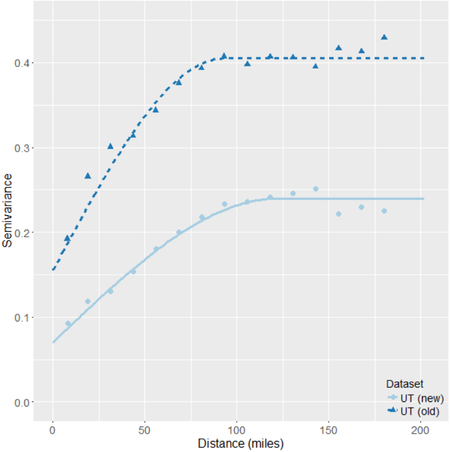


Figure 18: Empirical semi-variances for the residuals of station ground snow loads resulting from Ordinary Least Squares Regression (OLS).

Summary of Methods

Simple Kriging with Varying Local Means (SKLM)

- Simple Kriging with varying local means (SKLM) [6].

$$\log(p_g^*(\boldsymbol{u})) = \beta_0 + \beta_1 A(\boldsymbol{u}) + \sum_{\alpha=1}^{N} \lambda_\alpha(\boldsymbol{u}) r(\boldsymbol{u}_\alpha)$$

  - β_0 and β_1 - calculated via ordinary least squares regression (OLS).
  - $r(\boldsymbol{u}_\alpha)$ - residual at station location α resulting from the regression.
  - $\lambda_\alpha(\boldsymbol{u})$ - determined via simple kriging.

Steps of SKLM

- Step 1 - Fit linear model
- Step 2 - Perform simple kriging on residuals.
- Step 3 - Update linear model predictions with simple kriging residual predictions.

Summary of Methods

Universal Kriging (UK)

- Calculates the coefficients of the trend implicitly.
- When trend is only dependent on elevation, universal kriging is simply

$$\log(p_g^*(\boldsymbol{u})) = \beta_0^* + \beta_1^* A(\boldsymbol{u}) + \sum_{\alpha=1}^{N} \lambda_\alpha(\boldsymbol{u}) r(\boldsymbol{u}_\alpha)$$

where β_0^* and β_0^* are calculated using generalized least squares regression (GLS).

Summary of Methods

OLS vs GLS

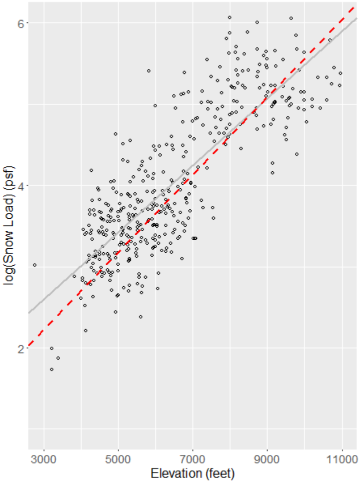


Figure 19: Regression curve estimates for (a) the new Utah dataset and (b) the old Utah dataset.

Visual Comparisons

Digital Elevation Models

- Use spatial overlays to create gridded inputs to spatial estimators
    - Digital Elevation Models (DEM) [15]
    - National Hydrography Dataset [16]
    - County and State Boundary Shapefiles [1]

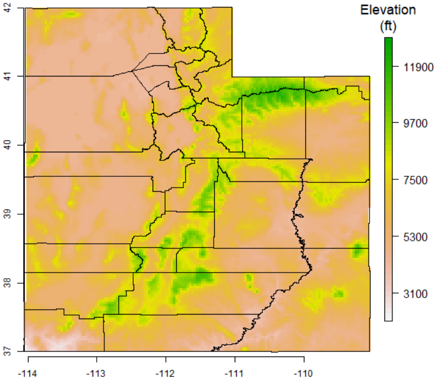


Figure 20: Utah DEM at a 3.6km by 3.6km resolution.

Visual Comparisons

Practical Prediction Constraints

- Predictions for final map were not allowed to go below 21 psf.
- To prevent Kriging and PRISM from extrapolating the elevation snow load relationship:
    - Predictions were not allowed to go beyond the highest 50 year snow load from the dataset (approximately 430 psf).
    - Estimate of the Kriging trend was not allowed to go beyond the predicted trend for the highest elevation station.

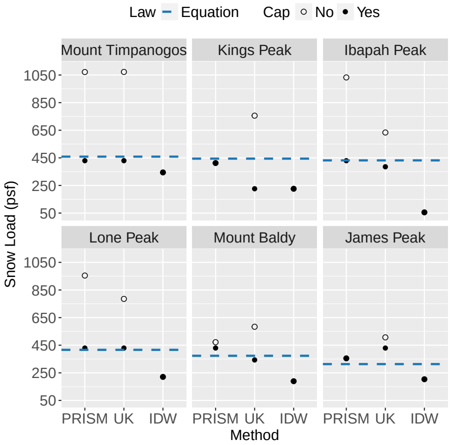


Figure 21: Comparison of predictions with and without constraints applied at select mountain peaks in Utah.

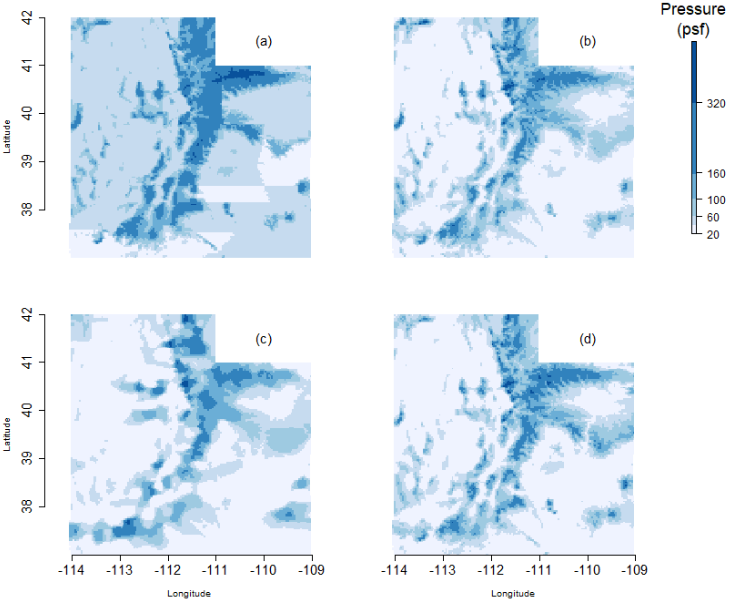


Figure 22: (a) Current law, (b) PRISM, (c) IDW, and (d) SKLM.

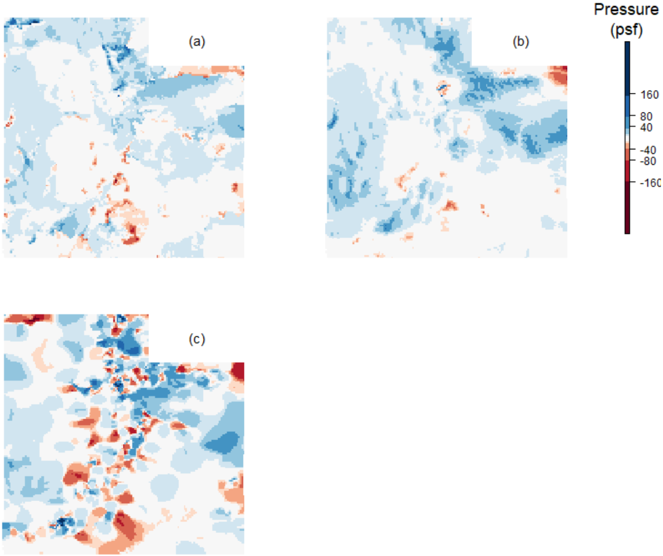


Figure 23: Predictions for (a) PRISM, (b) IDW, and (c) UK where blue represents areas where new Utah dataset leads to higher predictions than the old Utah dataset

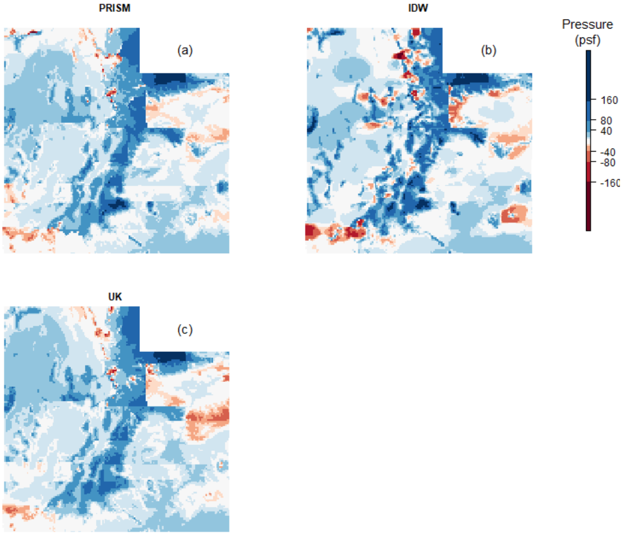


Figure 24: (a-c) Comparisons to current snow law where blue represents areas where the current law predicts higher snow loads than the respective methods.

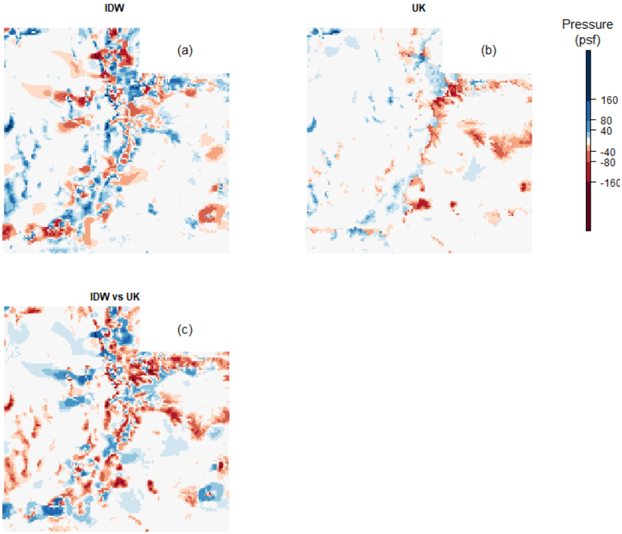


Figure 25: (a-b) Comparisons to PRISM where blue represents areas where PRISM predicts higher snow loads than the respective methods. (c) Blue represents areas where IDW predicts higher than UK.

Cross Validation

Comparison Data Sets

- New Utah Dataset
  - 284 (197 COOP, 87 SNOTEL) Utah stations and 129 (96 COOP, 33 SNOTEL) surrounding stations
- Old Utah Dataset
  - 413 (203 COOP, 210 Snow Course (SC)) Utah stations

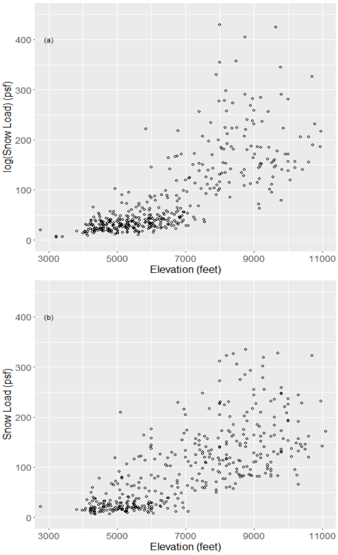


Figure 26: Scatter-plots for (a) the new and (b) old Utah data sets.

Cross Validation

Definitions

Let

$$e(\boldsymbol{u}_\alpha) = \hat{p}^*_g(\boldsymbol{u}_\alpha) - p^*_g(\boldsymbol{u}_\alpha)$$

and define mean absolute error (MAE) and mean error (ME) as

$$\text{MAE} = \frac{1}{N}\sum_{\alpha=1}^{N} |e(\boldsymbol{u}_\alpha)|$$

$$\text{ME} = \frac{1}{N}\sum_{\alpha=1}^{N} e(\boldsymbol{u}_\alpha)$$

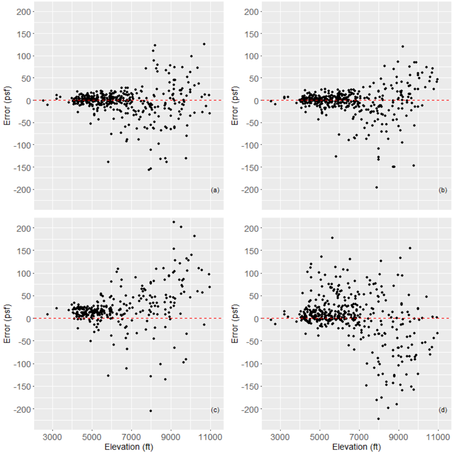


Figure 27: Scatter plot of cross validated errors for (a) PRISM, (b) SKLM, (c) SNLW, and (d) IDW on the new Utah dataset.

Cross Validation

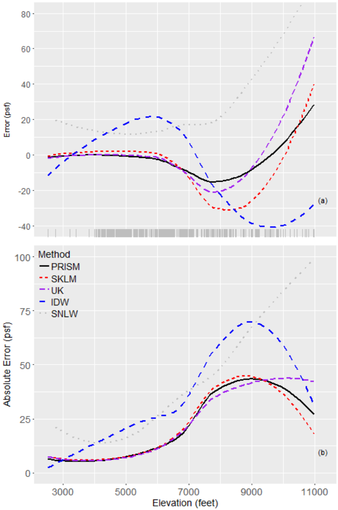


Figure 28: (a) smoothed errors and (b) smoothed absolute errors for the new Utah dataset.

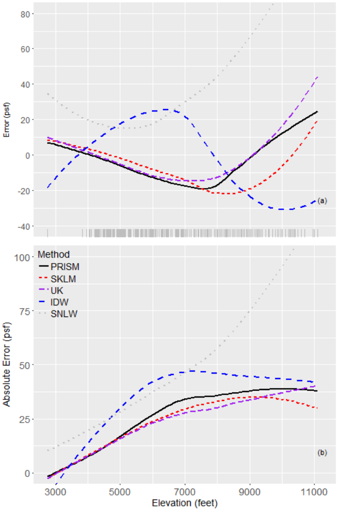


Figure 29: (a) smoothed errors and (b) smoothed absolute errors for the old Utah dataset.

Cross Validation

Method Comparison: New Utah Dataset

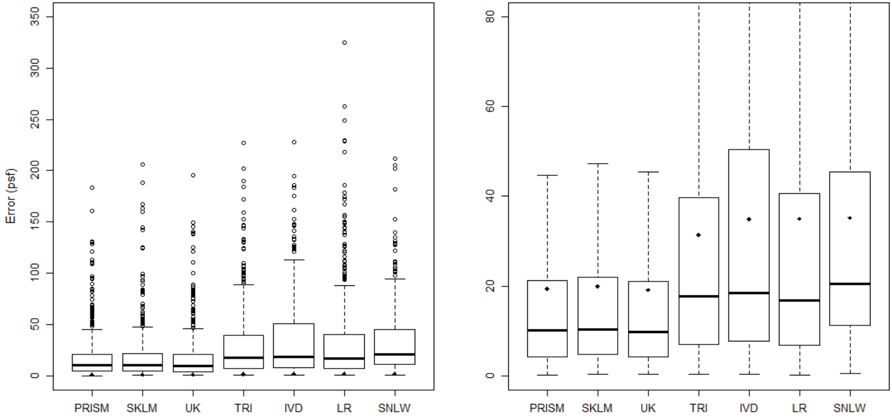


Figure 30: Mean cross validated error at each station location for the new Utah dataset (100 iterations).

Cross Validation

Method Comparison: Old Utah Dataset

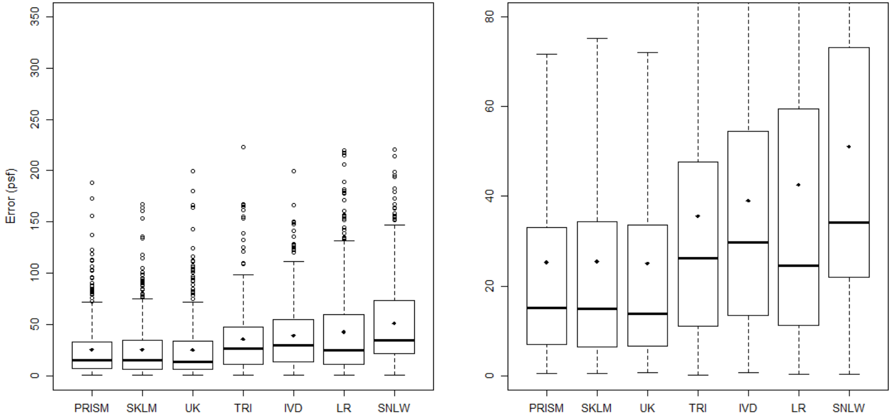


Figure 31: Mean cross validated error at each station location for the old Utah dataset (100 iterations).

Cross Validation

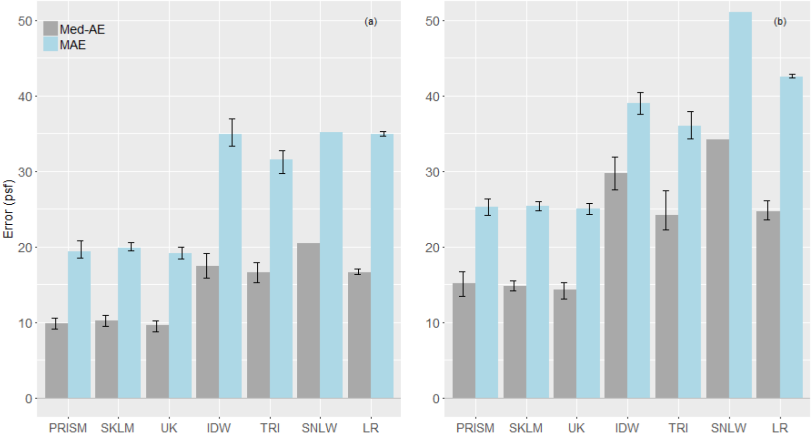


Figure 32: Cross validated errors for (a) the new Utah dataset and (b) the old Utah dataset. Bar heights represent the mean of means (or mean of medians) of the 100 iterations of cross validation. Whiskers represent maximum and minimum cross validated mean and medians respectively.

Conclusions

- The current Utah ground snow load equations have a tendency to over-predict ground snow loads, particularly at high elevations.
- Considerable data processing is required to estimate 50 year ground snow loads.
- Superior spatial prediction methods model the log-linear relationship between ground snow loads and elevation.
- SKLM and UK are preferred methods given their simplicity and comparable accuracy to PRISM.

City by City Comparisons

Figure 33: Comparison of new prediction methods to the current Utah for cities with amended snow load requirements.

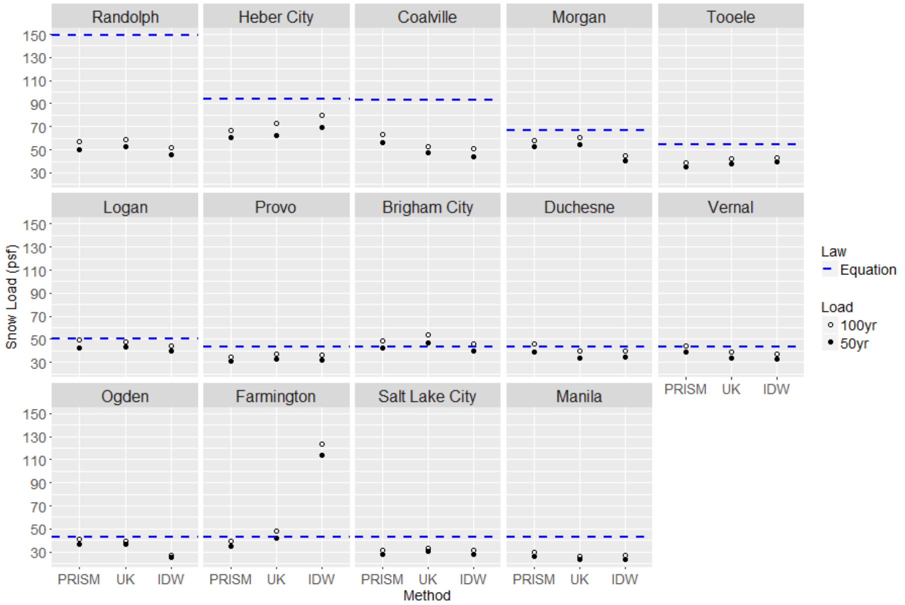


Figure 34: Comparison of new prediction methods at northern county seats.

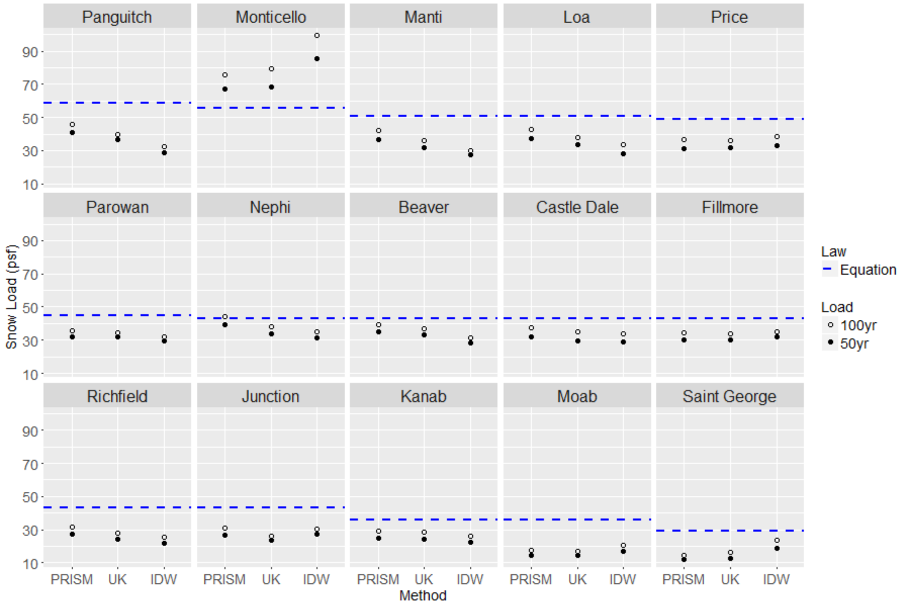


Figure 35: Comparison of new prediction methods at southern county seats.

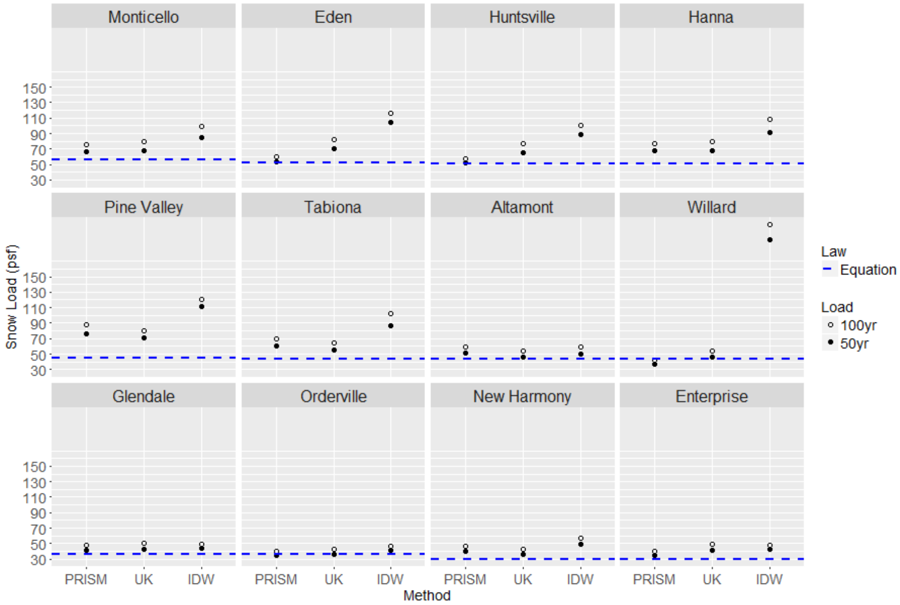


Figure 36: Comparison of new prediction methods at locations where predictions are notably higher than current law.

County Specific Comparisons

Duchesne County

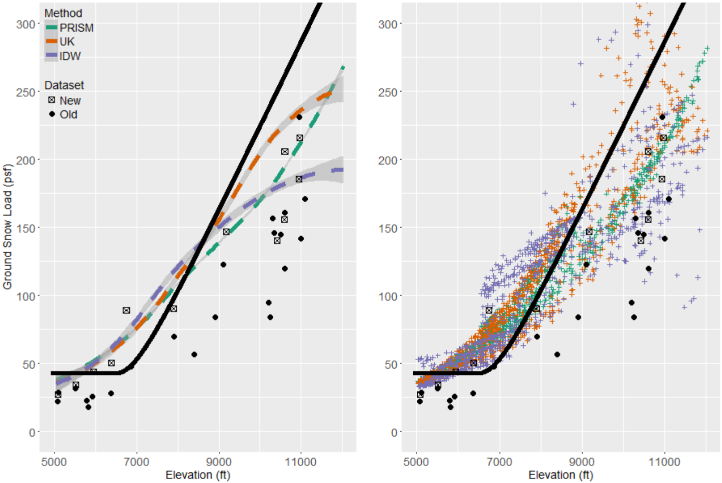


Figure 37: Comparison of new prediction methods at grid cells located in Duchesne County, Utah.

Duchesne County

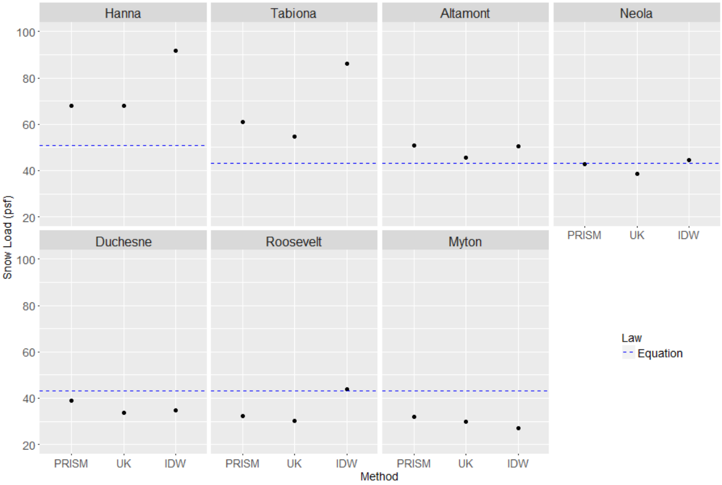


Figure 38: Comparison of new prediction methods post office locations in Duchesne County, Utah.

Summit County

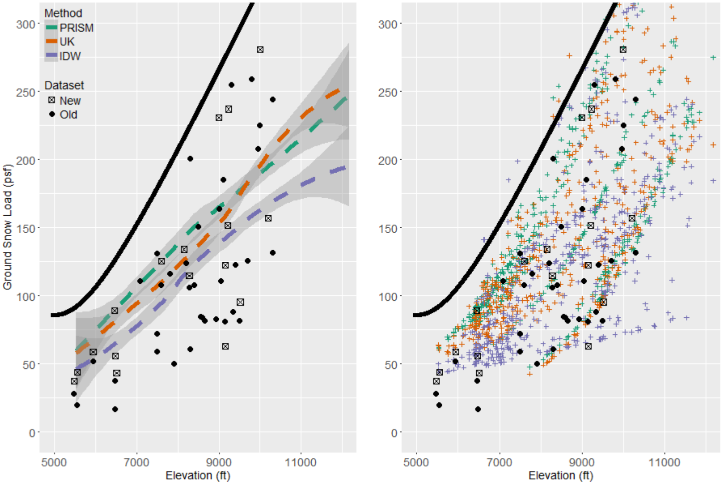


Figure 39: Comparison of new prediction methods at grid cells located in Summit County, Utah.

Summit County

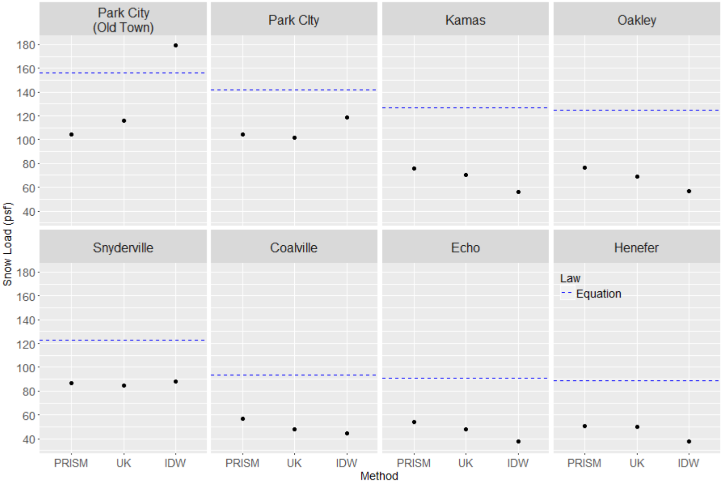


Figure 40: Comparison of new prediction methods post office locations in Summit County, Utah.

Border Comparisons

Applications

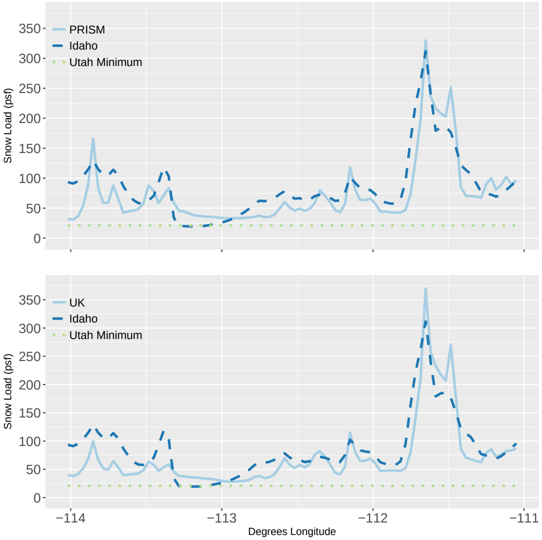


Figure 41: Ground snow load predictions along 42.02 degrees latitude with 3.6 by 3.6 km resolution.

Applications

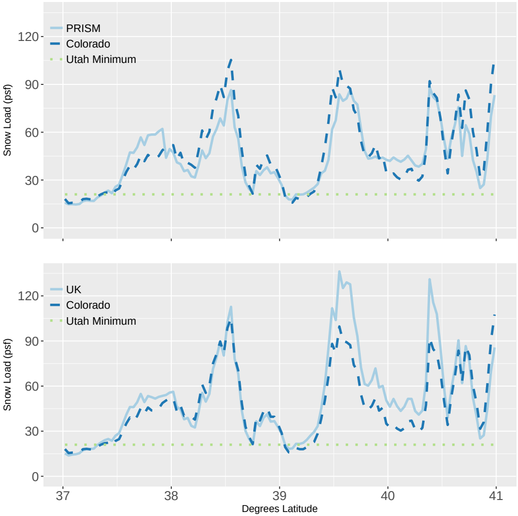
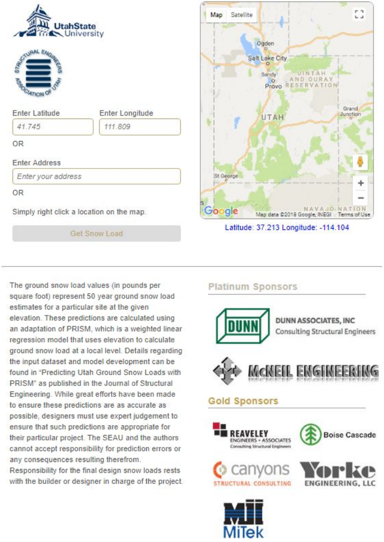


Figure 42: Ground snow load predictions along -109.06 degrees longitude with 3.6 by 3.6 km resolution. (Colorado Equation: $p_g(\boldsymbol{u}) = \max\left[\frac{K(\boldsymbol{u})}{100}A(\boldsymbol{u})^3, 25\right]$) [14]

Website Demonstration

- Predictions made on a 0.6 mi by 0.6 mi grid of Utah.
- Website returns design ground snow load and elevation of the grid cell containing the user specified coordinates.



Thank You

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Questions

Figure 43: Caribou-Targhee National Forest, Idaho

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