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Review of the Utah Snow Load Study

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Review of the Utah Snow Load Study

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Utah State University

February 21th, 2018
Outline

1 Introduction
2 Data Set Development
3 Spatial Methods
   • Inverse Distance Weighting (IDW)
   • Linear Triangulation Interpolation (TRI)
   • PRISM
   • Kriging
4 Visual Comparisons
5 Cross Validation
6 Applications
7 Acknowledgements and References
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 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

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

- 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.

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

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.
More than 25 years of additional snow data now available.

Discrepancies along county borders.

Method has since required city specific adjustments.

<table>
<thead>
<tr>
<th>City</th>
<th>Elevation (feet)</th>
<th>Law (psf)</th>
<th>Equation (psf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laketown</td>
<td>6000</td>
<td>57</td>
<td>133</td>
</tr>
<tr>
<td>Randolph</td>
<td>6300</td>
<td>57</td>
<td>150</td>
</tr>
<tr>
<td>Woodruff</td>
<td>6315</td>
<td>57</td>
<td>151</td>
</tr>
</tbody>
</table>

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

Daily SWE/Snow Depth Measurements

SWE?

no → Estimate SWE

yes → Remove Bad Measurements

Collect Yearly Maximums

Coverage Filter

Fit Lognormal distribution

Extract 98th percentile

NWS Meta-data → Final Data Set → Spatial Overlays
Variables [9]:
- $p_g^*$ - 50 year ground snow load
- $C_e$ - exposure coefficient
- $C_t$ - thermal factor
- $l_s$ - importance factor
- $p_f$ - flat roof snow load
- $p_s$ - sloped roof snow load
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]:

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

- \( h_g(u) \) - depth of snow at location \( u \)
Data Set Development

Estimate SWE

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

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

- \(h_g(u)\) - depth of snow at location \(u\)

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

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

- \(p_0(u), p_{\text{max}}(u)\) - base and maximum snow density for a particular climate class
- \(k_1(u), k_2(u)\) - 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.

<table>
<thead>
<tr>
<th>STATION NAME</th>
<th>STATION</th>
<th>LATITUDE</th>
<th>LONGITUDE</th>
<th>ELEVATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASTLE VALLEY UT US USS0012M13S</td>
<td>37.66</td>
<td>-112.74</td>
<td>9580</td>
<td></td>
</tr>
<tr>
<td>CASTLE VALLEY UT US USC00421241</td>
<td>38.651</td>
<td>-109.399</td>
<td>4725</td>
<td></td>
</tr>
<tr>
<td>CASTLE VALLEY UT US USC00421241</td>
<td>38.651</td>
<td>-109.399</td>
<td>4720</td>
<td></td>
</tr>
<tr>
<td>CASTLE VALLEY UT US USC00421241</td>
<td>38.65</td>
<td>-109.4</td>
<td>4719</td>
<td></td>
</tr>
<tr>
<td>CASTLE VALLEY UT US USC00421241</td>
<td>38.65</td>
<td>-109.4</td>
<td>4720</td>
<td></td>
</tr>
<tr>
<td>CASTLE VALLEY UT US USC00421241</td>
<td>38.65</td>
<td>-109.4</td>
<td>4699</td>
<td></td>
</tr>
</tbody>
</table>

- Merge station information for stations sharing identical location.

<table>
<thead>
<tr>
<th>STATION NAME</th>
<th>STATION</th>
<th>LATITUDE</th>
<th>LONGITUDE</th>
<th>ELEVATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>HUNTSVILLE SNOW BSN UT US USC00424140</td>
<td>41.217</td>
<td>-111.85</td>
<td>6562</td>
<td></td>
</tr>
<tr>
<td>SNOW BASIN UT US USC00427924</td>
<td>41.217</td>
<td>-111.85</td>
<td>6424</td>
<td></td>
</tr>
</tbody>
</table>

- Maxes separated by water year not calendar year
Data Set Development
Apply Coverage Filter

- Distribution fitting technique assumes all maximums at location $u$ 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 $u_\alpha$ are independent and identically distributed\(^1\) random variables $X_i(u_\alpha)$ ($i = 1, \cdots, n = \text{station years}$) such that
  \[
  \log(X_i(u_\alpha)) \sim N(\mu_\alpha, \sigma^2_\alpha)
  \]

- Estimate the values of $\mu_\alpha$ and $\sigma^2_\alpha$ via Maximum Likelihood Estimation in the `fitdistrplus` package [4], then
  \[
  p_g^*(u_\alpha) = e^{x_0} \text{ where } \frac{1}{\sqrt{2\pi\sigma}} \int_{-\infty}^{x_0} e^{-\frac{(x-\mu_\alpha)^2}{2\sigma^2_\alpha}} \, dx = 0.98.
  \]

- 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.
Figure 12: Log-normal distribution fitting examples for select cities in Utah.
Summary of Methods
Inverse Distance Weighting (IDW)

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

- \( c \) - weighting exponent for distance weighting
- NGSL = \( \frac{p_g^*(\mathbf{u}_{\alpha})}{A(\mathbf{u}_{\alpha})} \) 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.
Least squares regression:

\[ \log(p_g^*(u)) = \beta_0 + \beta_1 A(u) \]

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:

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

Figure 16: Residuals diagnostics of least squares regression on the new Utah dataset.
Summary of Methods
Least Squares Regression vs PRISM

Least squares regression:

$$\log(p^*_g(u)) = \beta_0 + \beta_1 A(u)$$

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

$$\log(p^*_g(u)) = \beta_0(u, X) + \beta_1(u, X) A(u)$$

where \(X\) 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

\[
\log(p_g^*(u)) = \beta_0(u, X) + \beta_1(u, X)A(u)
\]

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

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

- \(W_c\) - cluster factor
- \(W_d\) and \(W_z\) - 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

\[
\log(p^*_g(u)) = \beta_0(u, X) + \beta_1(u, X)A(u)
\]

Adaptation:

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

- \(W_c\) - cluster factor
- \(W_d, W_z\) - distance and elevation weights
- \(F_d, F_Z\) - 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.

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

- \( r_m \) - 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

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

- \( \Delta z = |A(u) - A(u_\alpha)| \)
- \( \Delta z_m, \Delta z_x \) - 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).

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

- \( s_\alpha \) - number of common watersheds (four levels ranging from HUC 2 through 8) shared by \( u_\alpha \) and \( u \)
- \( c \) - 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 \( j \)

\[ h_{ij} = \begin{cases} 
0 & D(u_i, u_j) > .2r_m \\
\frac{.2r_m - D(u_i, u_j)}{.2r_m} & 0 \leq D(u_i, u_j) \leq .2r_m 
\end{cases} \]

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

- \( p \) - (user defined) minimum elevation of influence
### Summary of Methods

**PRISM - Table of Parameters**

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

Kriging

Considering the random function $Z(u)$, all kriging estimators have the form\(^1\)

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

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

$$
\sum_{\alpha} \sum_{\beta} \lambda_{\alpha} \lambda_{\beta} C_{Z}(u_{\alpha} - u_{\beta}) - 2 \sum_{\alpha} \lambda_{\alpha} C_{Z}(u_{\alpha} - u^*) + C_{Z}(0)
$$

where $C_{Z}(u_i - u_j) = \text{Cov}(Z(u_i), Z(u_j))$.

---

\(^1\)references [5] and [7] motivate this notation
Summary of Methods
Simple Kriging

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

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

When the following conditions are met:

1. $E(Z(u)) = m$ is constant over the entire region of interest.
2. $C(h) = Cov(Z(u + h), Z(u))$ is independent of location $u$. 
Summary of Methods

Variograms

Define

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

Estimated by

$$
\hat{\gamma}(h) = \frac{1}{2N_h} \sum_{\alpha_h=1}^{N_h} [Z(u_{\alpha_h} + h) - Z(u_{\alpha_h})]^2
$$

where $N_h$ is the number of stations $h$ distance apart from each other.

- Under certain conditions:

  $$
  \gamma(h) = C(0) - C(h)
  $$

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].

$$\log(p^*_g(u)) = \beta_0 + \beta_1 A(u) + \sum_{\alpha=1}^{N} \lambda_\alpha(u) r(u_\alpha)$$

- $\beta_0$ and $\beta_1$ - calculated via ordinary least squares regression (OLS).
- $r(u_\alpha)$ - residual at station location $\alpha$ resulting from the regression.
- $\lambda_\alpha(u)$ - 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

\[
\log(p_g^*(u)) = \beta_0^* + \beta_1^* A(u) + \sum_{\alpha=1}^{N} \lambda_\alpha(u) r(u_\alpha)
\]

where $\beta_0^*$ and $\beta_1^*$ 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.
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

\[ e(u_\alpha) = \hat{p}_g^*(u_\alpha) - p_g^*(u_\alpha) \]

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

\[ \text{MAE} = \frac{1}{N} \sum_{\alpha=1}^{N} |e(u_\alpha)| \]

\[ \text{ME} = \frac{1}{N} \sum_{\alpha=1}^{N} e(u_\alpha) \]

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.
Applications

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.
Applications

County Specific Comparisons
Figure 37: Comparison of new prediction methods at grid cells located in Duchesne County, Utah.
Figure 38: Comparison of new prediction methods post office locations in Duchesne County, Utah.
Figure 39: Comparison of new prediction methods at grid cells located in Summit County, Utah.
Figure 40: Comparison of new prediction methods post office locations in Summit County, Utah.
Applications

Border Comparisons
Figure 41: Ground snow load predictions along 42.02 degrees latitude with 3.6 by 3.6 km resolution.
Figure 42: Ground snow load predictions along -109.06 degrees longitude with 3.6 by 3.6 km resolution. (Colorado Equation: $p_g(u) = \max \left[ \frac{K(u)}{100} A(u)^3, 25 \right]$) [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

In addition to the SEAU, the authors would like to thank the following sponsors.

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- McNeil Engineering

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- Boise Cascade

- Canyons Structural Consulting

- Yorke Engineering, LLC

- MiTek
Questions

Figure 43: Caribou-Targhee National Forest, Idaho
References


References II


References III

