Assessing Mongolian snow disaster risk using livestock and satellite data

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A B S T R A C T

In Mongolia, several record-breaking disastrous dzuds (mass livestock loss directly induced by harsh winter conditions but often influenced by drought in the previous summer) occurred from 1999 to 2003. To understand the mechanism of this climatic disaster, we conducted a tree regression analysis. The predictor variables included two indices developed from remote sensing data— the Normalized Difference Vegetation Index (NDVI) and the Snow Water Equivalent (SWE)— as well as the previous year’s livestock numbers and mortality rates. According to the model, serious livestock mortality was associated with low NDVI values (i.e., poor vegetation) in August of the previous year, high SWE values (i.e., significant snow accumulation) in December of the previous year, a high previous year’s mortality, and high previous year’s livestock population. This result suggests that for dzud risk assessment, we need to monitor snowfall in winter, the vegetation condition in the previous summer, and the density and health condition of the livestock. The tree-based model developed in this study is effective only for a white dzud (deep snow), the most common type of dzud. The large cross-validation error indicates that more data are needed before using the model in order to make predictions.

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1. Introduction

The most widely felt climatic disaster in arid regions is drought; it has been identified as the world’s most hazardous natural disaster (e.g., Bryant, 1991; Obasi, 1994; Wilhite, 2000). In particular, rural populations dependent on agriculture or livestock farming are significantly impacted by droughts, and since droughts inevitably occur, rural populations are always exposed to the risk of this type of disaster. However, in dry and cold (and in many cases, high latitude and inland) regions, such as Mongolia, people living in rural areas are subjected not only to drought in the summer but also to another natural disaster in the winter. Harsh winter conditions can prevent livestock from accessing pastures and can result in a large number of livestock deaths. Even when winter conditions are comparatively moderate, if the pasture conditions are inadequate due to poor conditions (e.g., drought) in the previous growing season, livestock may not survive the winter.

In Mongolia, this type of disaster—a mass livestock loss directly induced by a harsh winter climate but often influenced by drought in the previous summer—is called a dzud (sometimes spelled zud). Dzud is experienced throughout central
Asia. For example, winter conditions, not drought, have historically controlled livestock numbers in Kazakhstan and winter disasters, including heavy snow and the refreezing of melted snow, are collectively called dzhuut there (Robinson and Milner-Gulland, 2003). The United Nations and Government of Mongolia (2001) described a dzud as a winter disaster that involves the mass debilitation, starvation, and death of livestock that seriously damages the livelihoods of the herder households who depend upon them.

Previous studies of this climatic disaster have been limited to simple analyses of the historic data and classification of the conditions. Begzsuren et al. (2004), in their study in southern Mongolia, concluded that dzud (noting that they use the term dzud to mean severe winter weather in general) resulted in higher livestock mortality than drought. They also found that the average livestock mortality resulting from drought combined with dzud is 18.8%, the mortality rate associated with dzud by itself is 13.3%, drought only is 11%, and the mortality rate attributable to neither drought nor dzud is 8.8%. Thus, a disastrous situation for the livestock sector in Mongolia is likely to occur when a summer drought is followed by severe winter conditions. In the United Nations Development Programme’s (UNDP) report on natural disasters in Mongolia, dzud was found to dominate in terms of the severity of damage (as measured by livestock loss), although wildfire was the most commonly occurring natural disaster in Mongolia (UNDPa). According to Templer et al. (1993), there were 24 dzuds in Mongolia between 1944 and 1993, with the most disastrous one occurring in 1944 (a nationwide dzud that caused 37% livestock mortality).

Begzsuren et al. (2004) reported that Mongolian researchers classified dzuds into five types: white dzud (caused by deep snow), black dzud (no accumulated snow), combined dzud (deep snow and sudden temperature drop), storm dzud (increased wind speed and heavy snow), and iron dzud (impenetrable ice cover over pastureland). Begzsuren et al. (2004) concluded that, among all types of dzud, white dzud combined with drought (unfortunately, the timing of the drought is not clearly stated in their paper) resulted in the highest rates of livestock mortality (32% and 24.1%, including natural mortality, in 1962 and 1983, respectively). Morinaga and Shinoda (2005) refined the concept of the combined dzud, calling it a cold dzud (sudden temperature drop), and they added a sixth category, hoof dzud (overgrazing). Morinaga and Shinoda (2005) observed that all six dzud types can be explained using three factors: snow or ice cover, stormy weather, and lack of pasture.

The recent historic dzud in 1999–2003, however, was beyond our conventional understanding of this type of climatic disaster. Severeininghaus (2001) identified the 1999–2000 dzud as the most severe one in the past 50 years. The International Federation of Red Cross and Red Crescent Societies (2004) determined that about 8.5 million or 25% of Mongolia’s herd perished from 1999 to 2003. The International Monetary Fund (2003) reported that droughts and dzuds between 1999 and 2002 killed 8.2 million livestock and that 3.0 million female livestock miscarried. It estimated that, if there were no droughts or dzuds during this period, Mongolia’s annual economic growth rate would have reached about 8%, which is about 4–7% higher than the actual economic growth rate of 1–4%. Additionally, Natsuagdorj (2003) observed that, in the 3 years from 2000 to 2002, more than 100 counties (soums) were affected by drought for the first time since 1989, and for the first time in the same period, more than 100 counties were also affected by dzud. The dzuds that occurred in 1999–2002 were described as “multiple dzuds” by the United Nations and Government of Mongolia (2001), a combination of multiple types of dzuds over the years; we classified the dzuds as a combined dzud using the classification of Begzsuren et al. (2004).

Lotsch et al. (2005), using a vegetation index derived from remote sensing data, observed that between 1999 and 2002 a large and geographically extensive decrease in vegetation activity that coincided with below normal rainfall in the Northern Hemisphere, and they associated that decrease with synchronous patterns of ocean circulation anomalies in the Pacific, Atlantic, and Indo-Pacific oceans. The possibility exists that the abnormal climate in Mongolia during this period was part of this larger scale phenomenon.

The significant impact of the dzuds of 1999–2003 prompted a need to better understand this type of climatic disaster, knowledge that would assist in the development of an early warning system (EWS) for Mongolia. In addition to summarizing historical records and classifying the nature of the dzud, a major objective of this study was to further our understanding of dzud, particularly when it starts and how it temporally progresses, and how drought and/or other effects contribute to this process.

The results of this study were considered in a drought/dzud EWS developed as part of an international co-operation project that was launched to strengthen the systems used to track droughts and dzuds in Mongolia (Shinoda and Morinaga, 2005).

In the following sections as this study focuses on the social impact of this climatic disaster, the term dzud refers to abnormally large livestock mortality in winter–spring that occurs as a result of drought and a harsh winter–spring climate (e.g., significant snowfall). Our primary focus was on the white dzud, the most serious type.

2. Study area and data used

2.1. Study area

The study area encompasses all of Mongolia, which has 21 provinces (aimag), three of which are significantly smaller than the others, and the capital (Ulaanbaatar), which forms an independent jurisdiction (Fig. 1a). Templer et al. (1993)
identified the dzud risk for each aimag by summarizing the historical frequency of dzuds. Provinces in the eastern region have the lowest risk (no more than one major dzud in 14 years), whereas provinces in the other regions have medium and high levels of risk.

The majority of Mongolia is considered to be highlands, particularly the western part (Fig. 1b). The northern region has a higher average annual rainfall (about 400 mm) than the southern region (about 100 mm), part of which lies within the Gobi Desert. As such, the northern provinces have, on average, better vegetation cover, whereas the southern provinces have, on average, poorer vegetation cover (Fig. 1c). With respect to the snow pack, the mountainous areas have, on average, a heavier snow cover in winter (Fig. 1d), whereas the low-lying eastern region has lower snow cover. Using remote sensing data, Suzuki et al. (2003) identified the peak level of vegetation cover as occurring around the beginning of August; observation data from the National Agency of Meteorology, Hydrology and Environmental Management (NAMHEM) identified it as occurring in late August. The heaviest snow is typically observed in January (Morinaga et al., 2003).

Agriculture, which is dominated by the livestock sector, combined with hunting and forestry accounted for 43.8% of the national GDP in 1996; this contribution has since decreased to 21.7% in 2005 (National Statistical Office of Mongolia, 2004, 2006).

2.2. Data used

2.2.1. Overview

We used two datasets derived from satellite imagery in our analyses. The first relates to vegetation condition, and it is estimated using the Normalized Difference Vegetation Index (NDVI). The second relates to snow conditions, which are estimated using the Snow Water Equivalent (SWE), an index that can be calculated by multiplying snow depth by its density. Monitoring vegetation cover (NDVI) is useful for detecting the effects of drought, while SWE is useful for monitoring snow conditions. In addition, we used the livestock mortality data published by the Mongolian government as the indicator of dzud damage. The aimag boundary map, the base map for all the data in this study, was provided by the GIS Section of the Information and Computer Center, NAMHEM, Mongolia. The following sections contain more detailed explanations of the NDVI, SWE, and livestock data used in the study.

2.2.2. NDVI

For the vegetation cover data, we used the Global Inventory Modeling and Mapping Studies dataset (GIMMS, http://glcf.umiacs.umd.edu/data/gimms/) provided by the Global Land Cover Facility, University of Maryland (College Park, MD,
USA). The Global Mosaic of GIMMS provides semimonthly NDVI data derived from National Oceanic and Atmospheric Administration/Advanced Very High Resolution Radiometer (NOAA/AVHRR) data from 1981 to 2003. The original cell size of this data is 0.073° by 0.073°.

2.2.3. SWE

For the SWE data, we used the Global Monthly EASE-Grid Snow Water Equivalent Climatology dataset (version 1) provided by the National Snow and Ice Data Center (NSIDC) of the United States (http://nsidc.org/). This dataset presents global monthly SWE data from November 1978 through June 2003. These data, available in Northern and Southern 25-km Equal-Area Scalable Earth Grids (EASE-Grids), are derived from Scanning Multichannel Microwave Radiometer (SMMR) data from 1978 to 1987 and from selected Special Sensor Microwave/Imagers (SSM/I) data from 1987 to 2003. SSM/I is carried onboard the Defense Meteorological Satellite Program (DMSP) series of polar orbiting satellites. The original data were converted from a Lambert Azimuthal Equal Area Projection (25-km grid) to geographical coordinates to match the NDVI data and resampled into 0.25° grids.

2.2.4. Livestock data

In this study, we assumed that the intensity of the dzud is reflected in the livestock loss rate, which was obtained by dividing livestock deaths (as of December) by the previous year’s total livestock numbers. Livestock mortality data, in which deaths resulting from drought/dzud are included, are collected by the National Statistical Office of Mongolia. The Ministry of Livestock Husbandry collects the mortality data each December, and the National Statistical Office of Mongolia (2004, 2006) has total livestock numbers for each aimag (also as of December). Combining these data sources, we produced a livestock loss rate dataset for 1991–2002 for each aimag. For the dzud of 1999–2003, supplemental data were also obtained from reports produced by international organizations (e.g., UNDPb).

3. Methods

3.1. Data preprocessing

Although the results are not presented, models initially were developed using simple differences but they resulted in poorer performance than models using anomalous ratios (normalized by the long-term average).

Two NDVI values were used for each month from April to September. We used these semimonthly values to calculate the ratio of each NDVI value to the 1981–2003 (1982–2003 for April, May, and June) average for each aimag.

To maximize the amount of NDVI data available for our analysis, the following process was carried out on the independent variables. If the average value for a given period was less than 0.1, a shift was carried out to prevent “division by zero” as well as to preclude negative values from being derived. Thus, the ratio, \( \text{NDVI}_r \), was calculated as follows (note that in case of NDVI\(_a\) < 0.1, \([0.1 – \text{NDVI}_a]\) was added to both the denominator and the numerator so that the denominator is never less than 0.1):

\[
\text{NDVI}_r = \begin{cases} 
\frac{(\text{NDVI}_i)}{(\text{NDVI}_a)} & \text{(if NDVI}_a \geq 0.1) \\
\frac{(\text{NDVI}_i + 0.1 – \text{NDVI}_a)}{0.1} & \text{(if NDVI}_a < 0.1)}
\end{cases}
\]

where \( \text{NDVI}_i \) is the NDVI value in the period of concern and \( \text{NDVI}_a \) is the average value (1981 or 1982–2003). \( \text{NDVI}_a \) was calculated for every half-month from April to September; thus, there are 12 ratios for each year.

The final step was to take the average within each aimag of the adjusted ratio of NDVI values obtained by the above-mentioned processes and to subtract 1 so that the average values were shifted from 1 to 0.

Monthly SWE values from October to April were used as the snow-related variables. In calculating the average values, only grid cells containing data for at least eight of the 16 years the dataset covers (i.e., from October 1987 to April 2003) were considered. If either the average value or the monthly value for a grid cell had no data (i.e., the SWE values within a grid cell were not measured by the NSIDC), the pixels were not used in the analysis. The SWE ratio was determined for every grid cell (for which data were available) for every month from October through April. To prevent the division-by-zero problem, a value of 1 mm was added to both the overall average and to the monthly SWE values, only grid cells containing data for at least eight of the 16 years the dataset covers (i.e., from October 1987 to April 2002).

Small aimags were integrated with an adjacent larger one in order to produce more stable rates: the data for the aimags of Erdenet, Darkhan-Uul, and Govi-Sumber were combined with the data for Selenge, Bulgan, and Dornogovi, respectively (see Fig. 1a). Similarly, Ulaanbaatar’s data were combined with Tuv’s, the aimag that surrounds the capital. Consequently, given that there were 18 combined aimags and 11 years of livestock mortality data, there are 198 observations available. Because data from the previous year is used as an independent factor, our analysis only covers livestock losses from 1992 to 2002.
3.2. Methods of analysis

In addition to using the NDVI and SWE values as predictors, we also included the previous year's livestock numbers (as a ratio to the total livestock within that aimag in 1990, just before the study period) and livestock loss rates (Table 1). Including the previous year's livestock numbers enabled us to investigate the effect of density on livestock mortality (i.e., the impact of carrying capacity on mortality), and including the livestock loss rate enabled us to consider the cumulative impact of previous disasters on mortality.

Table 1
Variables used in the study

<table>
<thead>
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<th>NDVI</th>
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<th>Year</th>
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<td>May</td>
<td></td>
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<tr>
<td></td>
<td>May2_0</td>
<td>2nd</td>
<td></td>
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<tr>
<td></td>
<td>Jun1_0</td>
<td>1st</td>
<td>June</td>
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<td>2nd</td>
<td></td>
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<tr>
<td></td>
<td>Jul1_0</td>
<td>1st</td>
<td>July</td>
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<tr>
<td></td>
<td>Jul2_0</td>
<td>2nd</td>
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<td>August</td>
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<td>Previous year</td>
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<table>
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<tr>
<td></td>
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<tr>
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<tbody>
<tr>
<td></td>
<td>Loss1</td>
<td>Previous year's livestock loss rate</td>
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The last digit in a variable name indicates the year (i.e., 0 refers to the current season and 1 to the previous season), while for the NDVI data the second last digit represents the 1st or 2nd half of the month. For SWE, in order to respect seasonal continuity, the same last digit is used throughout one winter from October to the next April.
After reviewing and checking the data, we first considered a linear regression approach using the variables described above (after removing some of the variables as a result of high intercorrelations amongst some of them), but the results (Fig. 2) demonstrated that a linear model could not adequately represent the strongly nonlinear data. After considering the alternatives, and in light of the need to use the results of our analysis in the development of an EWS, a tree-based model approach was selected in order to predict dzud damage. All analyses, including data assessment and tree-based modeling, were carried out using R (Venables et al., 2006).

Tree-based models are a relatively new method of analysis that provides an alternative to linear and additive models for regression problems (regression trees) and to linear logistic and additive logistic models for classification trees. Tree-based models employ binary recursive partitioning, whereby a dataset is successively split into increasingly homogeneous subsets until it is infeasible to continue (Clark and Pregibon, 1992). The following explanation is an overview of this methodology summarized from Hastie et al. (2001).

The model can be described as a binary tree. The full dataset sits at the top of the tree and observations satisfying the stated condition at each junction are assigned to the left branch; all others are assigned to the right branch. The terminal nodes, or leaves, of the tree correspond to the regions having a single predicted value. For each leaf, the average (which can be derived from the minimization of the sum of squares) is normally chosen as the representative value (if the absolute value is selected as the error function, the predicted value of each leaf will be the median). For every step or branch of the tree, a splitting variable and a splitting point are determined so that the result minimizes the sum of the squared error (or an alternative error function).

In order to limit the tree size (i.e., the number of branches) and to prevent over-fitting (i.e., having too many parameters, which may decrease the training error but increase the validation error), additional parameters are used to limit the tree’s size (i.e., we could reduce the total error of the model to zero by using as many nodes as there are observations). A preferred method is, first, to grow a large tree $T_0$, stopping the splitting process only when some a priori minimum node size (given in advance considering the application of the model output) is reached, and then to prune the tree by using a complexity parameter. The complexity criterion is

$$C_\alpha(T) = \sum_{m=1}^{[T]} N_m Q_m(T) + \alpha |T|,$$

where $\alpha$, $|T|$, $N_m$, and $Q_m(T)$ are the complex parameter, number of leaves, number of data points in leaf $m$, and the error function for leaf $m$, respectively. The error function is expressed here as

$$Q_m(T) = \frac{1}{R_m} \sum_{i \in R_m} (x_i - c_m)^2,$$

where $c_m$, $R_m$, and $x_i$ are the representative value of the leaf, the space covered by leaf $m$, and the observed data included in leaf $m$, respectively. Starting from $T_0$ (i.e., $\alpha = 0$), we increase $\alpha$ continuously and successively delete the internal node so that $C_\alpha(T)$ is minimized. This process ends when we reach a one-leaf (no split) tree. As $\alpha$ is increased, a smaller tree is selected as the best model. Thus, we obtain a set of candidate trees for varied $\alpha$ (the weight for the simplicity).

![Fig. 2. Scatterplot of the output of the linear regression model and observed loss rate.](image-url)
From a set of candidate sub-trees, the best model is chosen through five- or 10-fold cross validation (CV, Breiman et al., 1984). This process is called pruning. We carried out five- and 10-fold CVs 10 times each and used the average error values to help select the best model. We used the minimum validation error method to select the best model because the difference in error between each model was too small to consider applying the alternative 1 S.E. method (although 1 S.D. would seem to be a more appropriate name for the method, we decided to follow the conventional naming in the literature) that is, taking the smallest tree that has an error within 1 S.D. of the minimum (Venables and Ripley, 2002).

An \( n \)-fold CV error for the tree-based model was assessed for \( \frac{1}{n} \) of the data through comparison with the tree derived from \( \frac{(n-1)}{n} \) of the data (Breiman et al., 1984). The resultant CV error (relative deviance) for tree regression is typically reported to be about 0.6–0.7 (Deconinck et al., 2005; Laaha and Blöschl, 2006; Negron, 1998) or greater (Nerini et al., 2000). Nirel and Dayan’s (2001) model had a training error of about 0.7, which indicates that the (unreported) CV error was larger.

In this study, the \textit{rpart} (which stands for Recursive PARTitioning) package of \textit{R} was used to develop the tree-based model. Upon developing the initial tree, the minimum number of observations for each terminal node \((m_1)\) and the minimum number of observations a parent node must possess prior to being split \((m_2; \text{obviously } m_2 \geq 2m_1)\) were determined as follows: considering the dataset size, we concluded that an \( m_1 \) of about 5 is suitable, and several values of such an \( m_1 \) (3, 4, 5, 6, 10) and typical \( m_2 \) (2\( m_1 \) and 3\( m_1 \)) were tested to select the best combination. The test results demonstrated that, in general, (1) smaller \( m_1 \) values result in a larger CV error, although they also produce smaller training errors (i.e., over-fitting); (2) setting \( m_2 = 3m_1 \) results in a smaller cross-validation error as compared with \( m_2 = 2m_1 \) for our data; and (3) if \( m_1 > 5 \), the leaves become too heterogeneous (i.e., the model is over constrained). After considering the results, a setting of \((m_1, m_2) = (5, 15)\) was identified as producing the best results.

In order to strengthen the robustness of the tree-based model (e.g., Schröder, 2006), the dependent data were first converted to ordinal (ordered categorical) data. By this transformation, the nonlinear relation between the livestock mortality and potential explaining variables is significantly moderated, and it was confirmed through observation that the resultant leaves become more homogeneous. This transformation is based on the concept that a loss rate less than a certain

\[\text{Fig. 3. Histogram of livestock loss rate.}\]

\[\text{Fig. 4. Distribution of livestock loss rate per year.}\]
value can be considered to be normal, whereas loss rates beyond a certain threshold can be thought to be out of the ordinary (eventually being classified as “emergency” rates). The following classification was determined on the basis of the distribution of the livestock loss rates ($L$, presented in Figs. 3 and 4): 1 is for $L < 0.05$ (131 cases), 2 is for $0.05 \leq L < 0.11$ (42 cases), 3 is for $0.11 \leq L < 0.17$ (12 cases), 4 is for $0.17 \leq L < 0.23$ (7 cases), and 5 is for $0.23 \leq L$ (6 cases).

Although the transformed data are ordered categorically, the classification was specified such that it is roughly possible to consider the distance between category 1 and category 3 as twice that between category 1 and category 2; as such, the classes to some degree can be considered to be on an interval scale (i.e., the concept of root mean square errors (RMSEs) works as an error evaluation). Kramer et al. (2001) concluded, although noting future work is needed, that using the regression tree methodology with ordinal data results in reasonable performance in RMSE and the Spearman’s rank correlation coefficient.

4. Results

4.1. Overview of the 2000–2003 dzud

The distribution of cases with a loss rate of less than 10% is close to a normal distribution. However, when the cases with loss rates above 10% are included, there is an obvious non-normal distribution (Fig. 3). Furthermore, it is apparent that almost all of the high loss rate cases were observed in the period from 2000 to 2002 (Fig. 4; note that data for 2003 are unavailable).

The spatial distribution of dzud damage for 2000 through 2002 is presented in Fig. 5. In 2000, the most serious damage was observed in the center of the country. All aimags recorded some dzud damage in 2001, with the northern aimags exhibiting the highest livestock loss rates. In 2002, the dzud occurred principally in the southwestern region and the northeast region was not impacted. On average, the aimag of Bayankhongor experienced the most serious dzud damage, and, basically, the further away from this aimag, the more moderate the dzud damage.

4.2. Tree-based model

The final tree regression model (Fig. 6) has an estimated RMSE of 0.441. The first node uses Aug1_1 as the branching condition (i.e., NDVI in early August in the previous year). Thus, if the NDVI in this period is greater than normal ($X/C0_0.0065$) (note that in this section, references to NDVI and SWE values refer to the transformed values used in the analysis), the cases branch to the left. This branch contains comparatively moderate livestock loss rates. On the other hand, if the NDVI is below this threshold, the cases are assigned to the right branch that contains the higher livestock loss rates. A similar methodology was used for the remaining branches: if the data satisfies the condition given as an inequality, the cases are assigned to the left branch, and if the data does not match the condition, the cases are assigned to the right branch. In this tree, the most severe losses are assigned to the leaf that contains cases in which NDVI for Aug1_1 $\leq -0.0065$, Loss1 (the previous year’s loss rate) $\geq 0.0595$, SWE for Dec1 $\geq -0.6315$, and NDVI for Aug2_1 $\leq -0.0635$. There are two
leaves that contain the next most severe set of cases: when the same conditions as above are met except for Aug2_1 $\geq$ 0.0635, and when NDVI Aug1_1 $< -0.0065$, Loss1 $< 0.0595$, and the previous year’s livestock population $\geq 0.397$.

That is, if NDVI in the first-half of August in the previous year is equal to or above $-0.0065$ (i.e., 99.35% of the average), the resultant livestock loss rate is generally low, at worst being in category 3 (i.e., a livestock loss rate between 11% and 17%).

It should be noted that in the model the main predictors, except for Loss1 and Pop1, are the previous summer’s NDVI and the previous winter’s SWE. Only two predictors (Jun2_0 and Nov0) that reflect conditions after Apr1 (April of the current year) are included, neither of which is associated with significant impact to the values finally predicted.

There is only one case wherein smaller SWE values result in higher livestock mortality; that is, if Nov0 $< -0.485$ (i.e., approximately smaller than half of the average SWE value for that month), leaf (9) branches from leaves (7) and (8). This case may be related to the occurrence of a black dzud. Approximately, equal numbers of NDVI (7 out of 24 in all) and SWE (5/14) predictors are used as conditions in the final model (Fig. 6).

The correspondence between the actual and the predicted category (by the model in Fig. 6) is presented in Appendix 1 (see Appendix A) (electronic version only). The condition column in Appendix 1 (see Appendix A) was determined as follows: (1) leaf nodes containing a majority of category 1 cases and no cases 3 or higher are called normal; (2) leaf nodes with only one case of 3 (or higher), or having a majority of cases higher than category 1, are labeled cautious; (3) leaf nodes with no category 1 cases and an average of less than 3 are called moderate dzud; (4) leaf nodes with an average of 3 are called intense dzud; and (5) leaf nodes with an average above 4, in which all cases are 4 or 5, are identified as emergency dzud.

The plot of total deviance (training error) for all the candidate trees obtained when we increase the complex parameter ($\alpha$) shows that later splits make smaller improvements (Fig. 7). All the candidate sub-trees are presented in Appendix 2 (see Appendix A) (electronic version only).

The average of 10 times the 5- and 10-fold CV error is 0.96.

5. Discussion

The significant contribution of Pop1 and Loss1 in the tree regression model (Fig. 6) should be noted. The positive contribution of Pop1 in the model indicates that there is an inherent carrying capacity of livestock numbers and, if it is exceeded, more livestock are prone to abnormal deaths and dzuds control the livestock number. On the other hand, the positive contribution of Loss1 suggests that a dzud’s effect sometimes extends into the following year; that is, livestock weakened in the first year fail to survive through the following year if stressful conditions are experienced.
Although the final regression tree model (Fig. 6) provides a convincing view of dzud (e.g., the environmental conditions included in the model are consistent with the seasonal livestock mortality trend; Batjargal et al., 2000), the large total CV error (a CV error of 0.96 means there is only a 4% improvement over a mean [constant] model) and the inapplicability of the 1 S.E. method to choose the best tree indicates that the results presented may not represent the best “global” solution. The main reason for the large CV error is our data’s strongly biased distribution (Figs. 2 and 3). Because the average of our data is 1.56, taking the average value as the “best” predictor results in a small error for categories 1 and 2 (the majority of the cases), but it results in a large error for categories 3–5. These characteristics result in our model producing a large relative deviance for categories 1 and 2, and a relatively small deviance for categories 3–5 (the significant categories in disaster management). For 10-fold CV, for example, the average relative deviance for high mortality categories (3–5) is improved to 0.65, in line with the results of previous studies. Additional data should be obtained that would improve the reliability of the tree-based model.

The split associated with Nov0, wherein a relatively small amount of snow resulted in a relatively larger livestock loss, is the only case in the model that cannot be explained by the white dzud mechanism. This split may be related to a black dzud.

Although the white dzud was the main target of our study, other abrupt abnormal climatic events occur in winter and spring. These include serious snowstorms in late March or April (i.e., after sheering), which sometimes result in large livestock losses, as reported in 1993 (15 March–15 May, Templer et al., 1993), 2001 (5–9 April, UNDPe), and 2002 (18–22 March, UNDPd, and 5–9 April, UNDPe). In particular, a snowstorm on 5–9 April 2001 (UNDPe) resulted in damage in at least 12 aimags; 20 people and 150,000 livestock were killed. Storm dzuds, which occur rapidly and are difficult to predict in advance, are beyond the scope of this study, but they should also be considered in the future, given the significant impact they can have on people and livestock. Although some of these effects are considered in our model (i.e., SWE in March and April), the compounding effect of wind, in particular, has not been considered.

In the future, a model using absolute physical values, as opposed to relative ones, should be attempted. It should consider the relation between snow depth, snow density, and the availability of pasture (e.g., Tuvaansuren, 1986). Incorporating such relations in conjunction with an animal biology model (e.g., Hobbs, 1989) integrated with a plant growth model and a climatic model may be possible in the future, but the development of such a complex model is still several years away, so our tree-based model is appropriate for now.

Another important consideration revealed in Tuvaansuren’s (1986) study was the different impacts that snow conditions have with respect to each type of livestock. In Mongolia, associated with the regional vegetation and climatic conditions, each region has a unique composition of livestock types. For example, in the southern region, goats are more common than sheep, whereas sheep are more common in the other regions. The regional differences in livestock composition and the morphological differences associated with each livestock type in the different regions result in different resistances to snow and drought. According to data from the National Statistical Office of Mongolia, a higher level of camel mortality is found in the northern region, whereas other livestock mortality is higher in the southern region. Significant levels of goat mortality are evident in Zavkhan, Bayankhongor, and Govi-Altai (which also have the highest mortality in total livestock as well). This factor is implicitly considered in our analysis since livestock holders have adapted over time to the average regional climate and abnormalities from the average will impact the livestock regardless of the type of livestock common to that region.
Some error is expected in estimating SWE and vegetation conditions from satellite imagery. A comparison of observed SWE (the product of snow depth and its density observed by NAMHEM) and estimated SWE values indicates that there is a spatial variation in the ratio of remotely sensed and observed SWE values. Existing studies (e.g., Tedesco et al., 2004) concluded that the inversion of the emission model can include significant bias dependent upon snow grain size, stratification, and snow pack; thus, even the empirical SWE detection method, such as that applied in the dataset used in this study, results in some bias. However, using ratios of the data (to the average), as we did in our analyses, should moderate any effect that uncertainty in the values has on our results. In general, SWE indices derived from remote sensing data are insensitive to SWE conditions above about 100 mm (e.g., Tedesco et al., 2004). Fortunately, according to Tuvaansuren (1986), this threshold is high enough to avoid serious problems when evaluating livestock’s accessibility to snow-covered pasture.

The timing of the collection of livestock numbers by the Mongolian government should also be considered. A dzud ends in spring, so the current timing of the data collection (in December) is not best for dzud assessment. The government points out that it is easier to count livestock when the livestock population is stable. It would be best if the livestock numbers could be determined after a dzud has ended, if the numbers are to be used in monitoring the impacts of dzud, although this may not be technically feasible.

Finally, the effects of changes in social conditions after 1990 and how those changes affect the impact that disasters have on society should be considered. Mears (2004) pointed out that herd sizes had increased until the last dzud, due in part to the shift from socialism to a market economy that was triggered by the collapse of the Soviet Union in 1991. Siurua and Swift (2002) stated that one reason for the most recent dzud’s significant toll on livestock was emergence of the market system, which resulted in a large number of unemployed people becoming inexperienced nomads. They reported that the self-security system in the local Mongolian community (i.e., normal winter preparations, such as preparing frozen meat and flour, and a traditional mutual assistance system) endured until 2001 (resulting in almost no human deaths), but that system started to decline in 2002. Bedunah and Schmidt (2004) concluded that governmental policy to protect some areas from overgrazing had inadvertently produced negative side effects. Furthermore, dzuds also affect the structure of society. For example, in 2001 after 2 consecutive years of dzuds, the Mongolian prime minister publicly stated that Mongolians should stop being nomads and suggested intensive urbanization of Mongolia (Finch, 2002).

6. Conclusion

In this study, motivated by the serious consequences of a recent historic dzud, and the desire to moderate future dzud damage in Mongolia, we used datasets readily derived from remote sensing data as well as census data of livestock numbers and mortality rates in a regression tree analysis in order to develop an understanding of the conditions that lead to dzud. With the development of an effective EWS in mind, we particularly focused on the need to identify which factors, selecting from amongst the (semi)monthly vegetation and snow conditions observed in the preceding period, and the

![Fig. 8. Conceptual diagram of the results of this study.](image-url)
recent livestock population/mortality rates, have the greatest explanatory potential with respect to predicting a potential winter disaster (i.e., a dzud).

The regression tree analysis was used after we confirmed that linear regression models failed to adequately predict livestock mortality because the relationship between the predictor and the predicted variables exhibited significant nonlinearity. The regression tree method demonstrated that it is robust enough to deal with problematic (i.e., nonlinear and non-normal) data and produce results that are easy to interpret.

The regression tree model results are summarized in Fig. 8. In the model, only two predictors (Jun2_0 and Nov0) after Apr1 (April of the current year) are included, neither of which is associated with significant impacts. The minimal contribution by the current season’s NDVI indicates that drought weakens but does not kill the livestock in many cases. The large contribution of NDVI values from the previous summer and SWE values from the previous winter means that livestock weakened by a drought in the previous year are likely killed by deep snow in the previous winter. That is, as the animals typically die in the latter half of winter—January or later—they are not included in the December count for the winter in which they died. Their deaths are thereby counted by the government almost a full year after the events that led to that mortality. The model provides satisfactory results in understanding the dzud mechanism, although the large CV error indicates that we should be cautious when applying the model to actual monitoring. The tree-based model developed in this study is effective only for a white dzud. Although the model includes one split which may be related to a black dzud, detailed consideration of other types of dzud remains as a future work.

Spatial variation in the parameters should also be considered in extending our analyses, although significantly more data will be needed in order to use spatial regression techniques. Ultimately, recent progress in modeling may enable us to create advanced models that connect numerical predictions of climate and physical processes to animal and plant ecological models. However, until then, the model presented in this study should be of significant help to government officials trying to prepare for dzuds.

Appendix A. Supplementary materials

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jaridenv.2008.06.015.

References


