

Exploratory Analysis of Spatial and Temporal Dynamics of Dzud Development in Mongolia, 1993-2004

Ninel Shestakovich

A thesis submitted
in partial fulfillment of the requirements
for the degree of
Master of Science in the School of Natural Resources & Environment
of the University of Michigan
November 2010

Thesis Committee:
Dr. Kathleen Bergen
Dr. Dan Brown

Table of Contents

Abstract	8
List of Abbreviations	9
Introduction	10
Background	11
Study Area and Data	14
Methods	20
Results	29
Discussion.....	45
Conclusion.....	50
Bibliography	86

List of Tables

Table 1: Source datasets.....	18
Table 2: 1993 Descriptive statistics.....	29
Table 3: 1996 Descriptive statistics.....	32
Table 4: 2000 Descriptive statistics.....	34
Table 5: 2001 Descriptive statistics.....	36
Table 6: 2002 Descriptive statistics.....	39
Table 7: 2003 Descriptive statistics.....	41
Table 8: 2004 Descriptive statistics.....	43
Table A1: 1993 OLS Regression output.....	53
Table A2: 1993 GWR model report.....	54
Table B1: 1996 OLS Regression output.....	57
Table B2: 1996 GWR model report.....	58
Table C1: 2000 OLS Regression output.....	62
Table C2: 2000 SAR Regression output.....	63
Table D1: 2001 OLS Regression output.....	67
Table D2: 2001 SAR Regression output.....	68
Table E1: 2002 OLS Regression output.....	72
Table E2: 2002 SAR Regression output.....	73
Table F1: 2003 OLS Regression output.....	77
Table F2: 2003 SAR Regression output.....	78
Table G1: 2004 OLS Regression output.....	82
Table G2: 2004 SAR Regression output.....	83

List of Figures

Figure 1: Topographic Map of Mongolia.	14
Figure 2: Ecological Zones of Mongolia.	15
Figure 3: Landscape ecological zones	16
Figure 4: Livestock production zones based.	16
Figure 5: A map of January long-term mean air temperature.....	17
Figure 6: The time-series plot of livestock mortality rate.....	24
Figure 7: 1993 Regression tree.	31
Figure 8: 1996 Regression tree.	33
Figure 9: 2000 Regression tree.	35
Figure 10: 2001 Regression tree.	38
Figure 11: 2002 Regression tree.	40
Figure 12: 2003 Regression tree.	42
Figure 13: 2004 Regression tree.	44
Figure A1: Spatial distribution of variables in 1993.	52
Figure A2: 1993 Cross-validation results.	55
Figure A3: Map of 1993 Regression tree.	55
Figure B1: Spatial distribution of variables in 1996.	56
Figure B2: 1996 Cross-validation results.....	59
Figure B3: Map of 1996 Regression tree.....	60
Figure C1: Spatial distribution of variables in 2000.	61
Figure C2: 2000 Cross-validation results.....	64
Figure C3: Map of 2000 Regression tree.....	65
Figure D1: Spatial distribution of variables in 2001.....	66
Figure D2: 2001 Cross-validation results.	69
Figure D3: Map of 2001 Regression tree.	70

Figure E1: Spatial distribution of variables in 2002.	71
Figure E2: 2002 Cross-validation results.	74
Figure E3: Map of 2002 Regression tree.	75
Figure F1: Spatial distribution of variables in 2003.	76
Figure F2: 2003 Cross-validation results.	79
Figure F3: Map of 2003 Regression tree.	80
Figure G1: Spatial distribution of variables in 2004.	81
Figure G2: 2004 Cross-validation results.	84
Figure G3: Map of 2004 Regression tree.	85

List of Appendices

Appendix A: 1993 data and models.....	52
Appendix B: 1996 data and models.....	56
Appendix C: 2000 data and models.....	61
Appendix D: 2001 data and models.....	66
Appendix E: 2002 data and models.....	71
Appendix F: 2003 data and models.....	76
Appendix G: 2004 data and models.....	81

Abstract

Dzud is a natural disaster endemic to parts of Central Asia and fairly unknown outside of the region. During spells of severe winter weather, livestock population suffers debilitating death from starvation and cold, which exacts enormous economic losses to nomadic herders and the society at large. Focusing on dzud outbreaks between 1993 and 2004 in Mongolia, I explored environmental and anthropogenic factors that contribute to geographic distribution of dzud impact and evaluate success of classical and spatial regression models to predict dzud mortality. Four regression methods were tested including ordinary least squares regression, spatial autoregressive models, geographically weighted regression, and recursive partitioning.

Regional heterogeneity in patterns of livestock mortality and contributing factors, as well as low efficiency of regression models, suggest that a single-model framework of analysis and non-normalized explanatory variables tend to perform poorly. The recursive-partitioning results demonstrate that the presence of several distinct ecological biomes within the territory of Mongolia create non-stationary and non-linear relationships between factors and livestock mortality. Diversity of ecological conditions drives regional predisposition for different types of dzud, most notably white dzud in mountainous and northern parts of Mongolia and black dzud in the Gobi desert.

The comparison of dzud episodes of 1993 and 2000-2003 revealed that an additional contributing factor unaccounted in previous modeling exercises of dzud is the long-distance mobility of herders as a main strategy for risk mitigation. While it is a necessary adaptation for livestock management in arid grasslands, under contemporary conditions of high livestock density it has an unexpected effect of spreading dzud vulnerability into unaffected areas, which may have contributed to development of multi-annual dzud episodes such as the one that occurred in 2000-2003. Since the transition of Mongolia to free-market economy, the vulnerability of herders to dzud has increased against a backdrop of exploding livestock population, a dysfunctional system of rangeland management, and withdrawal of government-run disaster preparedness programs.

List of Abbreviations

AIC – Akaike Information Criterion
AVHRR – Advanced Very High Resolution Radiometer
CART – Classification and Regression Tree Analysis
CMLP – percent camel of the total herd
CTLP – percent cattle of the total herd
ELEV – mean elevation, meters
GIMMS – Global Inventory Modeling and Mapping Studies
GTP – percent goat of the total herd
GWR – geographically weighted regression
HRSP – percent horses of the total herd
LD – livestock density, animals/unit area
LM – Lagrange Multiplier
LMR – livestock mortality rate expressed in percentage
LR – Likelihood Ratio Test
ML – maximum likelihood
MODIS – Moderate Resolution Imaging Spectroradiometer
MVC – multiple value composite
NAMHEM – National Agency of Meteorology, Hydrology and Environmental Management
NDVI – normalized difference vegetation index
NGIC - National Geo-Information Center
NOAA – National Oceanic and Atmospheric Administration
OLS – ordinary least square
PRLMR – livestock mortality from a previous year
SAR - spatial autoregressive model
SASWE – seasonally averaged snow water equivalent, mm
SATMP – seasonally averaged monthly temperatures, C°
SHPP – percent sheep of the total herd
SINDVI – seasonally integrated normalized difference vegetation index, unit less
SWE – snow water equivalent

Introduction

Human societies have always been in a process of perpetual adaptation to their surrounding environments, which provides the natural resource base available to people for preservation of life and sustaining economic activity. Natural hazards, as extreme manifestations of climate variability, put the quality of that adaptation to the test and highlight vulnerabilities inherent in the capacity of human systems to manage environmental risk. When the resilience of an affected population cannot withstand the impact of a natural hazard, a disaster occurs with a catastrophic economic, environmental, and human losses (Singh 2006). Owing to their disruption of human life, natural disasters attract a fair share of scientific research with the purpose of developing a body of knowledge that can guide disaster management efforts. Despite the attention of the scientific community to these phenomena, the interactions between natural phenomena and human societies that produce some natural disasters are poorly understood. Mongolia has been known to suffer from a natural disaster, termed dzud, which is endemic to Central Asia and has been poorly understood outside of the region.

Dzud is a meteorological disaster that causes mass mortality and debilitation of livestock due to starvation and prolonged exposure to extreme winter weather. It can be caused by one or a combination of the following environmental factors: heavy snowfall, extremely low temperatures, wind and low productivity of pasture (Morinaga, Tian et al. 2003; Shinoda 2005). Often called an evolving disaster, this natural phenomenon dynamically progresses simultaneously on several different spatial and temporal scales. As the disaster unfolds over the course of a season, livestock resilience is undermined from the early onset of winter by spells of bitter cold accompanied by snowfalls that can blanket pasture for weeks and make it inaccessible to grazers. While thousands of animals can perish overnight in a spell of a severe blizzard, the overall impact culminates in peak mortality in the early spring when animals are at their weakest. In addition to physical stress, survivability of animals depends directly on the quality of pasture available for grazing; therefore, the disaster's intensity can be influenced by drought conditions from a preceding summer.

Livestock is the backbone of rural Mongolian economy and often the only means of income, food and fuel for a rural household. Animal raw products provide food, fuel for cooking and heating, clothing, transportation, and currency for paying for services and education. Currently one third of the Mongolian population resides in the countryside and is either directly involved in a pastoral semi-nomadic lifestyle or employed in processing or trade of animal products (Bedunah and Schmidt 2004). The livestock sector accounts for 20 % of economic output in the Mongolian economy and translates directly into a source of employment and livelihood for at least 40% of the population. To fully appreciate the extent of dzud consequences on the Mongolian society, it is necessary to consider, in addition to meteorological factors, the role of livestock production in shaping the demographic and economic structure of the country.

Key studies by Shinoda et al (2005) and Tachiiri et al (2008) have described the complexity of the dzud phenomenon and our fragmented understanding of it. The two distinct dzud episodes of 1993 and 2000 – 2003 represent an important set of natural disaster events to analyze, and form the cases for this study. I hypothesize that the contributing factors to dzud have changed over the course of 7 years,

reflecting changes in the socio-economic system and in herding practices. Therefore, the overall goal of the study is to improve our understanding of dzud causality and find an appropriate methodology to analyze its spatial and temporal dynamics. There seems to be strong evidence to believe that there is regional variation in dzud causation that can be teased out at the finer spatial scale of analysis. Building on Tachiiri's methodology and findings, I will evaluate the ability of spatial regression models and recursive partitioning to explain geographic variation in dzud. The results of this study will contribute to advancing our knowledge of appropriate methods for dzud forecasting and development of an integrated early warning system. Understanding of spatial and temporal dynamics of dzud will facilitate crafting informed and effective policy measures aimed at improving livelihood and reducing long-term vulnerabilities of the rural population of Mongolia as well as enhancing the efficiency of disaster relief interventions undertaken by international donor organizations.

The following sections of this paper include a review of dzud and its effect on the Mongolian people, description of the study area, data acquisition and processing methods, and methods of analysis. The second half is dedicated to the discussion of the results and limitations of the analysis with the directions for future research.

Background

Characteristics of Dzud Events

Depending on its environmental causes, several types of dzud are currently recognized. *White dzud* is the most devastating and common type, which is characterized by deep snowdrifts that prevent livestock from accessing pasture. *Black dzud* denotes lack of drinkable water for both livestock and people. The latter condition may occur when the absence of snow and subzero temperatures make all surface water resources unavailable by freezing. Black dzud is not very common and is usually highly localized. *Storm dzud* consists of prolonged blizzard condition during which animals are driven by the wind for many miles and die of exhaustion (Suttie 2005). Extremely low temperatures and freezing winds constitute *cold dzud*, which prevents livestock from free grazing. *Iron dzud* happens when fluctuating temperatures turn snow cover into an ice sheet. It is possible that different types of dzud can follow each other or happen simultaneously in different parts of the country (Tachiiri, Shinoda et al. 2008). Landscape heterogeneity and the presence of several biomes within the territory of Mongolia underlie the diverse nature of the phenomenon and are thought to explain regional predispositions to certain types of dzud. For example, black dzud is thought to occur mostly in the desert while white and cold dzuds are more common in mountainous regions and the north (Tachiiri, Shinoda et al. 2008).

The role of drought in dzud occurrence deserves a special mention. Several instances in scientific literature define dzud as a combined effect of a summer drought and a severe winter (Tachiiri, Shinoda et al. 2008), but it should be noted that drought is not a prerequisite for dzud. Sternberg's (2009) research in the South Gobi province demonstrated that drought and dzud are not coincidental and work independently of each other. Occasionally they occur in tandem and create interactions that can exacerbate both events. In the last decade, summer droughts have affected a general condition of vegetation over a large part of Mongolia and thus controlled the amount of forage available to livestock

yearlong. Droughts increase livestock vulnerability to dzud by reducing the amount of fodder available to attain a necessary body weight for winter survival, and thus contribute to dzud incidence and intensity. Dzud and drought independently can inflict significant mortality of livestock and control stock numbers (Suttie 2005). Mortality due to drought is usually lower than to dzud; however, when drought and dzud follow in sequence, the results can be more than additive.

Vulnerability of Mongolian Herders to Dzud

While dzud is triggered by meteorological conditions, it is defined for the purpose of planning relief efforts by the magnitude of livestock losses incurred by the Mongolian herders who continue practicing a traditional semi-nomadic pastoral lifestyle in a climate that offers practically no other opportunities for agricultural production (Suttie 2005). Such an open-grazing system requires minimal external inputs but demands hard labor and extensive mobility of herders and their animals due to variability and unpredictability of forage conditions in any particular place. Dzud represents an inherent risk of the socio-ecological system predicated on a unique geography, the cold arid climate, and a transhumant pastoral lifestyle, and herders' work revolves around minimizing and avoiding that risk. The tradition of nomadic herding has persisted for centuries, testifying to the success of this livelihood, but severe economic and social ramifications of recent outbreaks of dzud force us to take a closer look at vulnerability of modern pastoral livestock production in Mongolia.

When in 1990 Mongolia chose to transition to a market economy, it followed a "shock therapy" style of economic reform, a principal component of which was privatization of state-owned assets and services. This included a transfer of livestock and livestock-related assets to private ownership (Nixon and Walters 2006). Prior to the 1990s, animal husbandry was organized around negdels, a collective management unit for livestock production that geographically coincided with a soum (an administrative unit equivalent to a county). The negdels were responsible for output of predetermined quotas of livestock products and provision of grazing management, supply of inputs, consumer goods and services to its members. The collective farms relied heavily on government subsidies and support services, such as the State Emergency Fodder Fund whose responsibility was to prepare and distribute emergency fodder supplies during the time of disaster (Suttie, 2005). The first phase of privatization of the livestock sector took place between 1991 and 1993, when negdels were disbanded and their livestock and assets, such as water wells and animal shelters, were transferred to their members and supporting staff in soum centers. The responsibility for emergency preparedness passed on to herders, and the fodder production under the State Emergency program was ceased. Privatization coincided with a big rise in unemployment in government-subsidized sectors. These newly unemployed were absorbed largely by a livestock sector (Mearns, 2004). Influx of new herders, who lacked experience in grazing management and marketing, together with stagnant levels of economic activity in the countryside resulted in unbridled growth of livestock numbers and by 2000 the national herd had reached 33 million animals.

Following a net migration from urban centers to the countryside, the number of herders had doubled by 1997 (Mearns 2004) but the productivity of rangelands remained the same or even diminished due to increased informal gold mining and desertification (Murray 2003). A herd size is one of the indicators of economic security and households with a herd size of 100 animals or fewer are officially considered to

be below poverty level. It is estimated that in 1998, 36% of the population was classified as poor and 20% as extremely poor (Mongolia 2001). Of these groups, 43% resided in the countryside. By 2000, 30% of all herder households in the country had fewer than 50 animals (Mearns 2004) and this demographic group proved to be the most vulnerable. During the disaster events of 1999-2001, approximately 9400 herder households (Mongolia 2001; Finch 2002) lost their entire herds and were forced to migrate to provincial centers or Ulaanbaatar and become urban poor. A massive migration of newly impoverished herders to urban centers created a “dzud” imprint on demographic structure of the nation, with a ballooning urban population against contracting rural population. Already strained and limited urban infrastructure was not capable of accommodating the population influx and migrating herders ended up living in spontaneous ger (a Mongolian name for yurt) districts in abject poverty.

One of the worst dzud episodes in Mongolian recent history happened in winter 2000. The confluence of bad winter conditions and summer droughts plagued the country for three years in a row and resulted in an unprecedented occurrence of four consecutive dzuds from 2000 – 2003. During this period, 12 million head of livestock perished, which reduced the size of a national herd from 33.6 mil in 1999 to 25.4 mil. in 2003 (Mongolia 2008). Severe losses in the livestock sector slashed economic growth to a mere 1.0 % in 2001 and a moderate 3.9 % in 2002, but in the absence of dzud impact the gross domestic product (GDP) was estimated to amount to 8% growth over the period of 1999 – 2002 (Mearns 2004).

The environmental and economic insecurities that grew during the previous two decades suggest the possibility that the dzud events of 2000 – 2003 resulted from a combination of natural and anthropogenic causes. It is unclear whether the extent of damage of the dzud of 2000-2002 was due to unpreparedness of herders and the collapse of the government subsidized emergency preparedness programs, to the severity of climatic conditions, or both (Suttie 2005). Understanding causes, dynamics and consequences of dzud is of enormous importance to Mongolian society and to the international development community. Studies to date have only probed the surface of dzud dynamics, and more research is needed to investigate the contributions of environmental drivers and socio-economic vulnerabilities to dzud mortality.

The chain of disaster events in 2000 – 2003 has attracted attention of the global scientific community to the dzud phenomenon and several multi-disciplinary studies had followed in its wake. Morinaga et al (2003) investigated the role of atmospheric circulation patterns in development of snow anomalies in Mongolia. His study showed that if snow anomalies are present in the early winter, they tend to persist through the entire winter season until March. The 4-5 year cycle of interannual anomaly in snow depth is related to El Nino Southern Oscillation (ENSO), which governs the precipitation patterns in the southern central Siberia north of Mongolia. Superimposed on that is the influence of All-Indian Monsoon Rainfall, which affects dzud cycle on a decadal time scale (Morinaga, Tian et al. 2003). Taichirii (2008) compared provincial stock mortality over the period of 2000-2003 with vegetation condition, snow water equivalent, livestock population and its mortality. His findings suggest that poor vegetation conditions at the end of summer and high snowfall in December determined the high rate of mortality in the following year. In addition, high previous year mortality and high previous year’s livestock population were also related to dzud losses. Bergzuren (2004) and Sternberg (2009) investigated

livestock mortality induced by environmental risk factors in Gurvan Saikhan National Park in South Gobi Province. Bergzuren (2004) showed that in the desert, dzud occurs once every two or three years and associates stronger with severe winter conditions than with drought. Sternberg (2009) investigated a coupled relationship between dzud and drought in the South Gobi province and found no evidence that drought in summer 1999 affected livestock mortality in the following winter. Bedunah (2004), Mearns (2004), and Nixon (2006) investigated the current trends in methods of livestock production and the effect of political and economic changes on herders' livelihood and vulnerability to natural hazards. Their conclusions agree that since transition of Mongolia to a free-market economy, rising poverty, neglect of livestock industry in the governmental development programs, and competition for rangeland has increased vulnerability of Mongolian herders to drought and dzud.

Study Area and Data

Mongolia is a landlocked country in the Northern Asia, bordered by Russia and China. It occupies approximately 1.56 million km², and much of the country is underlain by the vast Mongolian Plateau that positions most of its territory higher than 1500 meters above sea level. The elevation ranges from 800 to over 4000 meters with marked differences between the east and west, and climate and topography organize the terrain into three pronounced longitudinal zones: eastern, central and western. Eastern Mongolia is composed of flat or undulating plains and central and western Mongolia is comprised of a number of mountain ranges - the Altai-Sayan, Khangai, Khentii and Khuvsgul, interspersed with depressions or basins. The inter-mountain depression between Khangai and Altai mountains contains most of the Mongolia's salt and fresh water lakes. Major rivers occur in the north with the largest river system formed by Selenge, which flows north into Lake Baikal in southern Siberia (Fig. 1) (Gunin 1999).

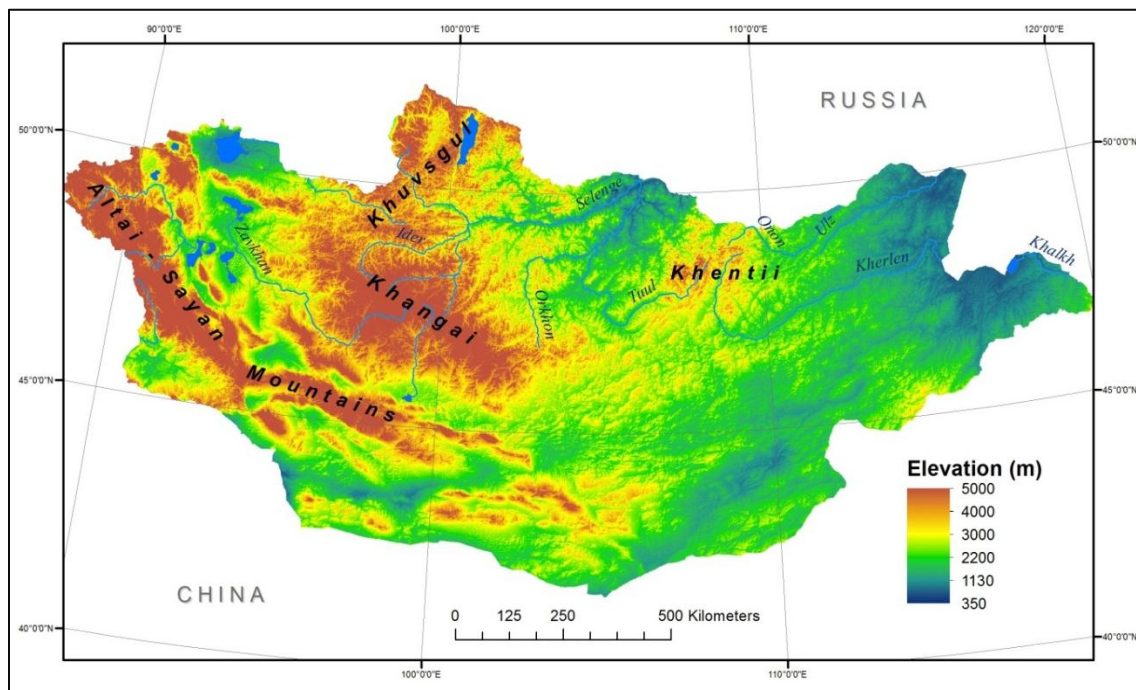


Figure 1: Topographic Map of Mongolia.

Most ecological zones are aligned latitudinally, with altitudinal variation superimposed. In the west, the organization of ecosystems turns almost longitudinal, with desert-steppe belt extending all the way to Uvs province. Several distinct biomes gradually transition from north to south and five distinct bio-geographic zones are observed: high mountains, taiga, forest-steppe and steppe, dry steppe grassland, and the Gobi desert (Fig. 2).

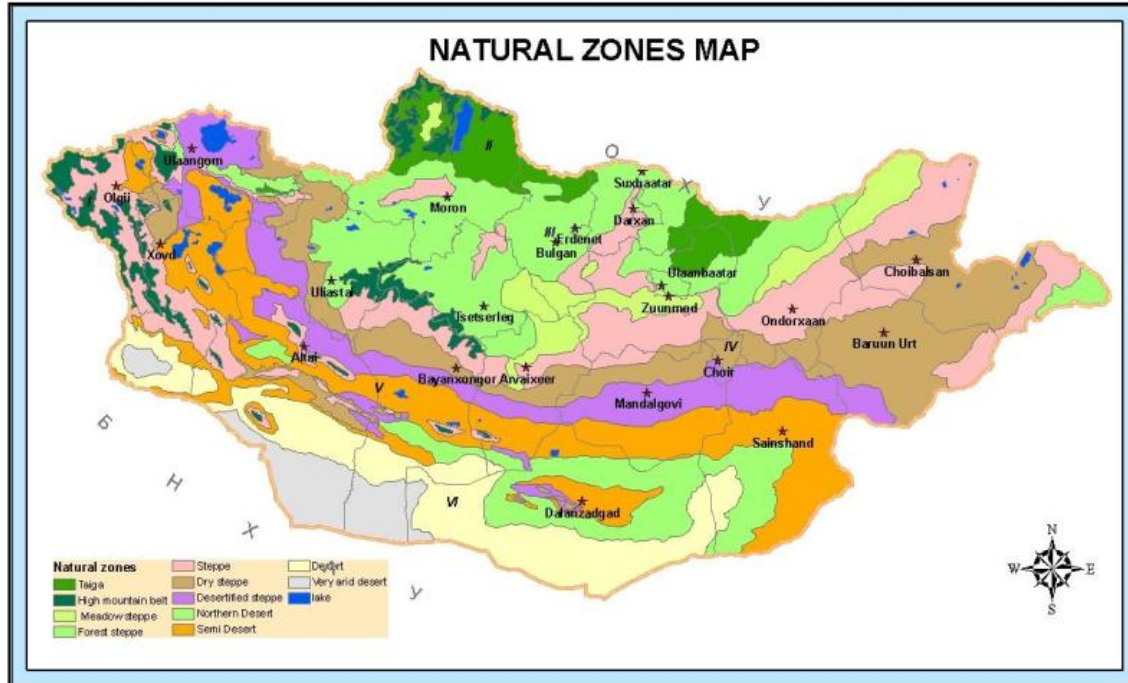


Figure 2: Ecological Zones of Mongolia (NGIC NAMHEM).

Five landscape-ecological zones were delineated (Gunin 1999) based on similar landscape forming processes, water availability, and structure of vegetation and soil: Altai-Sayan, Transbaikial, Daguria-East Mongolia, Central Mongolia, Central Asian, and Khyangan (Fig. 3). Most of Mongolia falls into a transition belt between the forest and desert biomes. Eighty percent of its territory is occupied by temperate grasslands and used for extensive herding in semi-nomadic pastoral fashion. The country is split into five major zones with different livestock production capacities (Suttie 2005): Khangai-Khuvsgul (mixed grazing with yaks replacing cattle at higher altitudes), Selenge-Onon (mostly agricultural production), Altai (main types of livestock and yaks), Central & Eastern steppes (horse, cattle, sheep, goats, and camels), and Gobi (camel, horses, cattle and goats) (Fig. 4).



Figure 3: An approximate aggregation of soums into landscape-ecological zones based on descriptions by Gunin (1999).

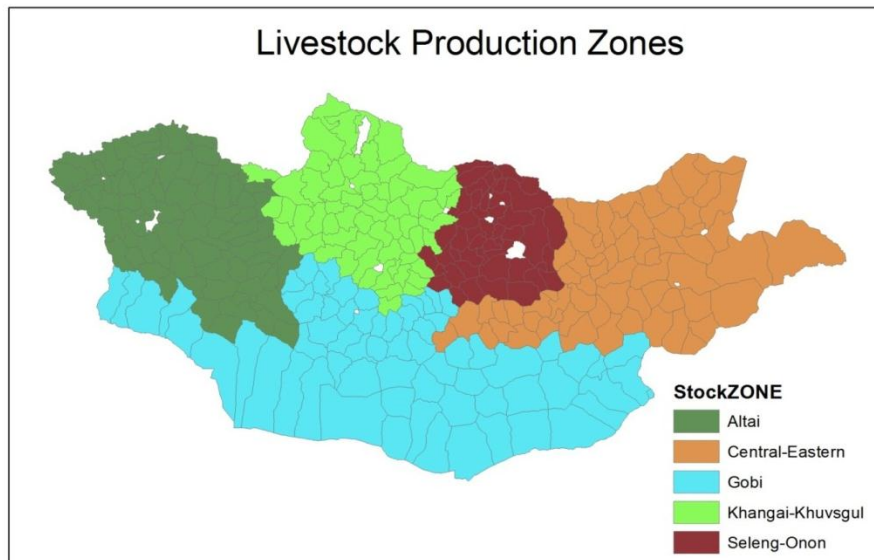


Figure 4: Livestock production zones based on description by Suttie (2005).

Because Mongolia is situated in the central part of Eurasia, it is isolated by its natural topographic features from the rest of the continent. The western and north-western mountain ranges intercept moisture carried by atmospheric flows from the Atlantic, and the Pacific monsoons dissipate from east to west between 110-120° E. As a result, the climate is markedly continental, cold and semi-arid with large daily and seasonal temperature amplitudes, low precipitation and intensive solar radiation. Cold, long winters last about six months, and summers are short and hot. Fall and spring are very short transitional seasons. January is the coldest month of the year, with average air temperatures of -15°C to -35°C depending on the location (Fig. 4). July is the warmest month with average air temperatures ranging between 15°C in the mountains to 25°C in the Gobi desert. Most precipitation falls during the

summer months of June through September, with an annual mean ranging from 300-400 mm in the northern taiga to less than 50 -100 mm in the Gobi desert (Batima 2005).

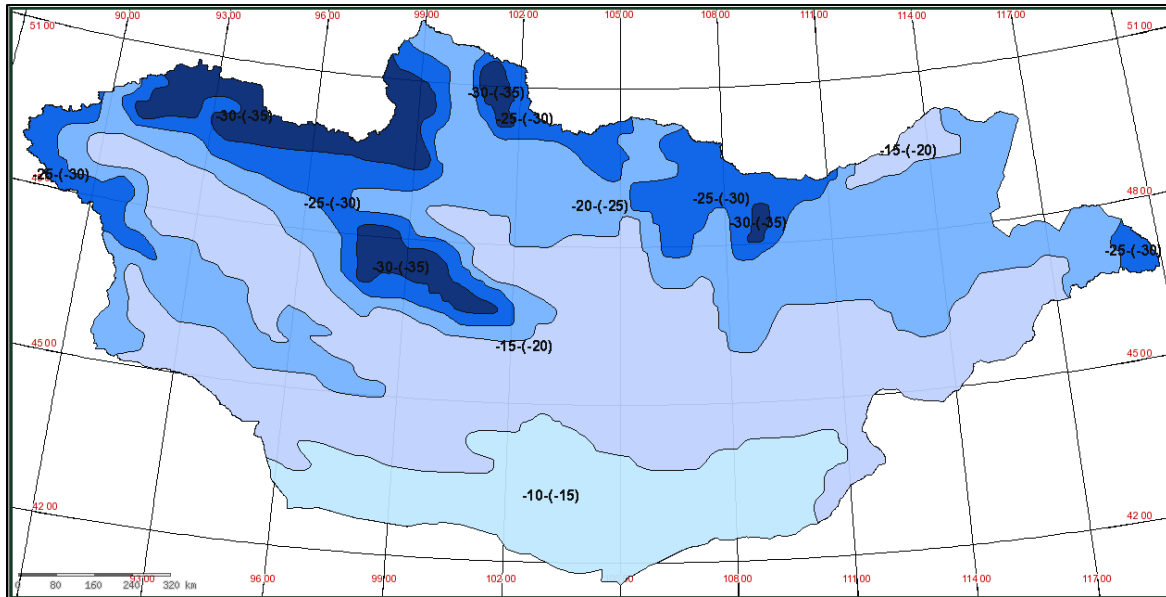


Figure 5: A map of January long-term mean air temperature (Source: National Geo-Information Center (NGIC) Database of National Agency of Meteorology, Hydrology and Environmental Management of Mongolia (NAMHEM)).

Winter weather is dominated by the Siberian anti-cyclone, which brings freezing temperatures and low precipitation. On average, snow amounts to less than 20% of total annual precipitation, but the time of its onset and melt-out, as well as snow depth and density, play crucial roles in livestock herding. The timing of formation of snow cover varies geographically and mountains experience the longest duration of stable snow (120-150 days), followed by eastern steppes (70-120) and the Gobi desert (30-60). The average snow depth can range from 0.5 to 25 cm with the maximum accumulation of snow falling on February and March (Batima 2005).

Mongolia is subject to various extreme weather events and natural hazards including fires, dust storms, droughts and dzud, with the last two most prominently controlling physical survival of livestock. Snow cover starts building up in November and persists through March (Morinaga, Tian et al. 2003). According to Morinaga et al. (2003), interannual anomalies in winter snow that lead to dzud formation are controlled by large-scale atmospheric circulation patterns, North Atlantic Oscillation (NAO) and Scandinavian pattern (SCA, previously known as EU1). SCA in its positive phase intensifies the Siberian high north of Mongolia in December and upon its temporary weakening, the accumulated cold-air mass flows southward bringing spells of severe winter weather, such as that which occurred as a record-breaking blizzard and cold wave in January 2001 (Bueh and Nakamura 2007). Geographically, the largest snow-cover anomalies concentrate in the west where low temperatures contribute to a fast increase in snow depth during the first two months of the winter. Morinaga (2003) cautions that negative correlation between temperature and snow depth varies and depends on a range of temperature, i.e. low temperatures are not necessarily accompanied by deep snow whereas high temperatures may be

accompanied by shallow snow depths. This non-linear relationship between the two most important climatic drivers explains differentiation of dzud into distinct types.

Data Used

I investigated livestock mortality over Mongolia using the administrative division of soums (equivalent to a county) as a spatial unit of analysis. Response and predictor variables were compiled from a variety of sources (Table 1). Soum-level maps of all variables were created to visualize their spatial patterns (See Appendices 1-7).

Table 1: Source datasets.

Dataset Name	Source	Dates	Resolution	References
Annual Livestock Mortality	NSO of Mongolia	1991 – 2008	Soum	(Mongolia 2008)
Global Inventory Modeling and Mapping Studies – biweekly time series of AVHRR NDVI	GLCF	1981 - 2006	8 km	(Tucker 2004)
Vegetation Continuous Fields MOD44B	Global Land Cover Facility	2001	500 m	(Hansen 2003)
Global Monthly EASE-Grid Snow Water Equivalent	NSIDC	1978 - 2007	25 km	(Armstrong 2007)
Terrestrial Air Temperature: 1900-2008 gridded Monthly Time Series	Center for Climatic Research, University of Delaware.	1900-2008	51 km	(Matsuura 2009)
ASTER DEM	METI and NASA	-	30 m	(METI/NASA 2010)

Livestock Statistics

Statistics of livestock population and mortality for all soums were obtained from the National Statistical Office, Ulaanbaatar, Mongolia. Livestock records span the period of 1991 through 2008 and the statistics are compiled annually in December. The dataset contains the following variables: population

counts for 5 types of domestic stock including camel, horse, cattle, sheep and goat; total population count; mortality counts for each type of stock, and total mortality count. It should be noted that the name for a livestock mortality count variable is translated from Mongolian as “mortality due to unnatural causes” which includes mortality from dzud and other natural hazards such as floods, droughts and hail. Mongolian law requires every herder household to be registered in a soum of his residence so that he has access to various public services provided by the administration of the soum as well as performs his tax duties. If a herder moves to a different soum, he is responsible to update his residential status and the associated demographics. Therefore, we can assume that the mobility of herders and their livestock is accurately reflected in this dataset (Saizen, Maekawa et al. 2010).

NDVI

A seasonal normalized difference vegetation index (NDVI) variable was derived from the Global Inventory Modeling and Mapping Studies dataset (GIMMS) to reflect a state of vegetation photosynthetic capacity and serves as a proxy for drought conditions (Tucker 2004). It is calculated from AVHRR spectral reflectance measurements of near-infrared (NIR) and visible red (VIS) channels:

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)}$$

The GIMMS NDVI product covers the 25-year period from 1981 to 2006 and this study focused on NDVI from 1992-2003. GIMMS dataset has an advantage of providing an uninterrupted series of remote sensing data obtained from the NOAA AVHRR satellite platform for a period that coincides with the statistical dataset. In addition, its processing methodology is consistent and uses an improved algorithms making it superior to other AVHRR-derived NDVI products (M. Brown and E. Vermote, personal communication, April 2010). The spatial resolution of the NDVI product is 0.073° by 0.073° or 8 x 8 km in Mongolia. Each tile was composited over 15-day periods throughout a year in order to construct cloud-free coverage of the Earth at multiple times for each year. Each NDVI pixel value represents the maximum NDVI recorded at that location over the compositing period, selected based on the maximum value composite (MVC) method (Tucker 2004).

SWE

A snow-related variable was derived from the dataset developed by the National Snow and Ice Data Center (NSIDC). The Global Monthly EASE-Grid Snow Water Equivalent (SWE) climatology data set was used directly to derive a SWE variable which serves as a proxy for snow depth in our analysis. This product is derived from Scanning Multichannel Microwave Radiometer (SMMR) and enhanced with snow cover frequencies derived from the Northern hemisphere EASE-Grid Weekly Snow cover and Sea Ice Extent (v. 2). The dataset is organized as 25 km Equal-Area Scalable Earth Grids and covers the time period of interest (Armstrong 2007).

Temperature

Temperature is an important environmental factor in dzud formation and therefore, was included in the analysis. The variable was derived from the Terrestrial Air Temperature: 1900-2008 gridded Monthly

Time Series, produced by Kenji Matsuura and Cort J. Willmott at the Center for Climatic Research, Dept. of Geography, University of Delaware. The dataset used station data from several sources world-wide to interpolate monthly averages of air temperature to a 0.5° by 0.5° latitude/longitude grid, which is equivalent to 51 x 51 km (Matsuura 2009).

Digital Elevation Model

The elevation variable was derived from the ASTER Global Digital Elevation Model at a spatial resolution of 30 meters produced by the Ministry of Economy, Trade and Industry of Japan (METI) and the National Aeronautics and Space Administration (METI/NASA 2010).

GIS Data

GIS layers of soum boundaries and provincial centers were developed and provided by the Information and Computer Center at the National Agency for Meteorology, Hydrology and Environment Monitoring of Mongolia.

Methods

Structure of the Dataset and Derivation of Variables

Previous research indicates that dzud disasters are characterized by snow or ice cover, stormy weather, and lack of pasture (Morinaga and Shinoda 2005). Each type of dzud has key characteristics that define its hazardous impact on livestock: for white dzud it is the depth and persistence of snow cover; for black dzud it is the absence of snow cover and low temperatures that freeze surface water; cold dzud is characterized by extremely low temperatures and possibly high winds; and the formation of iron dzud requires a combination of snow cover and fluctuating temperatures that produce an ice sheet or frozen soil. In addition, vegetation productivity from a previous summer season determines the amount of fodder available to livestock in winter season. Therefore, the direct environmental factors that create dzud conditions are winter temperature, precipitation, and wind, while summer vegetation productivity influences the intensity of dzud. In addition to the climatic and vegetation productivity factors mentioned above, I included an elevation variable, which may explain geographic incidence of dzud or locational predisposition to a particular combination of meteorological conditions.

The temporal aggregation of environmental independent variables was designed around the availability of livestock statistics which consisted of annual counts of livestock population for 308 counties in Mongolia. Livestock statistics are compiled in December of each year, and the recorded mortality of livestock represents a number of animals that perished within a calendar year, which is assumed to reflect conditions from two growing seasons of vegetation and two winter seasons. However, because the peak mortality happens in the early spring, it is reasonable to assume that the preceding summer season and the present year's winter season most directly affect the observed mortality. Based on this assumption, all climate-related predictors were calculated seasonally for each county:

SINDVI_{year} – seasonally integrated normalized difference vegetation index (unitless) calculated over the growing season from the middle of April until the middle of October of the calendar prior to the year of measured mortality. SINDVI is a vegetation index derived from remote sensing measurements which indicates “greenness” of the land cover (Tucker 2004). In this study it is used as a proxy for the amount of new-growth vegetation available to grazers. Because vegetation growth happens during the short summer season, the vegetation variable was calculated as a seasonally integrated NDVI using a methodology outlined by Stow (Stow 2003). This method defines SINDVI as the sum of NDVI values for each pixel and all time intervals of multiple value composites (MVCs) where the NDVI exceeds a critical value of 0.1. Resulting SINDVI composites were also corrected for woody vegetation in the northern and mountainous regions of Mongolia by using the MODIS Vegetation Continuous Fields (Hansen 2003) and removing the percentage of SINDVI due to woody vegetation cover. This was done to focus on NDVI associated with pasture conditions, which are more likely to affect grazing. The mean of the corrected SINDVI was calculated for each county. The amount of vegetation available for grazing most directly influences animals’ body weight and thus their ability to survive harsh winter conditions. Therefore, we logically expect that high SINDVI is associated with low mortality.

SASWE_{year} – seasonally averaged snow-water equivalent (measured in mm) was calculated over the winter season from the first detection of snow cover in November through March of each year, ending in the calendar year in which mortality was measured. An average of the final SASWE was calculated for each county. This variable can have both positive and negative relationships with livestock mortality depending on the type of dzud and geographic location.

SATMP_{year} – seasonally averaged monthly temperatures in °C calculated over the winter season from November through March of each year. SATMP was calculated similarly to SASWE. A grid of a mean seasonal temperature was converted to a raster and a mean was calculated for each county. The expectations of performance and explanatory power of this variable in our study may have limitations because of the coarse spatial and temporal resolution of monthly time-series of the Terrestrial Air Temperature dataset (Matsuura 2009).

The expected relationship of SATMP with mortality is the most complicated of all variables. It can act alone or in conjunction with SASWE to create dzud conditions. Four types of interaction of SATMP and SASWE can theoretically elicit high mortality of livestock: very low SATMP in the absence of SASWE characteristic of cold dzud, low SATMP with high SASWE which precipitate white dzud, fluctuating SATMP with SASWE which cause formation of iron dzud, and SATMP below 0°C and no snow create black dzud. Localized incidence of inversions in mountain valleys in the western and central parts of Mongolia is very possible, which adds finer scale variability in behavior of the temperature variable.

ELEV – average elevation in every county, measured in meters. The overall expected relationship of ELEV with stock mortality is positive because mountainous regions have lower temperatures and higher precipitation and thus meteorologically are more prone to dzud conditions.

Ideally, the variables should capture deviation of environmental conditions from normal, not only because an underlying assumption of the study is that anomalous weather precipitates the disasters but

also because averaged variables ignore variability of observations and thus lose information that may explain higher mortality in any given year. The temporal and spatial aggregation of the above mentioned predictors resulted in significant smoothing of variability within each variable, but seasonal averages of NDVI, SWE and temperature were the best available options and focused the analysis on geographic and inter-annual variability.

The analysis would be incomplete if we only attempted to explain abnormal livestock mortality with hazardous environmental conditions as it is well established that disasters arise when natural hazards meet human vulnerability (Singh 2006). The data on disaster preparedness or other socio-economic indicators of herders' vulnerability to natural disasters were not available at the level of soums. However, from the statistical dataset it was possible to derive variables describing total density of livestock and the proportion of each type of livestock in a county herd, which are the only factors in this study that can be controlled by humans. Every livestock has differentiated resilience to dzud and drought based on its morphological characteristics and various geographic ranges of prevalence dictated by ecological zones that support its grazing patterns (Tuvaansuren 1986). Whether or not herders actively manage the size and composition of their herds in response to environmental or economic stimuli, these two variables implicitly and partially reflect on vulnerability of the human system to dzud. Therefore, the following livestock variables were derived and included into this study:

LMR_{year} – livestock mortality rate expressed as percentage. This is used as the response variable and is calculated as livestock losses of the present year divided by the livestock population at the end of the previous year for each county. Because livestock statistics are compiled in December, it is reasonable to assume that livestock population at the beginning of the following year is the same as recorded in December of the previous year. The rate was converted into percent to compare livestock mortality to the background rate.

$LMRLG_{year}$ - natural log of livestock mortality rate. Because LMR had a highly skewed distribution, the percentage rate was natural-log transformed for regression analysis.

PR_LMR_{year} – previous-year livestock mortality rate expressed as percentage. This variable is included into the analysis to examine the effect of previous dzud on livestock losses in the next year. We expect that locations that have experienced increased mortality a year prior to dzud will sustain higher LMR in the present because of the weakened physical condition of livestock from previous dzud.

LD_{year} – livestock density, in animals/km². LD was calculated as the total livestock population of the previous year divided by the area of a county. I posit that high LD reduces the amount of vegetation available to each individual animal and thus positively interacts with LMR.

$CMLP_{year}$ – percent camel of the total herd.

$CTLP_{year}$ – percent cattle of the total herd. It should be noted that yaks are not differentiated from cattle and count as one in the statistical dataset.

GTP_{year} – percent goat of the total herd.

HRSP_{year} – percent horses of the total herd.

SHPP_{year} – percent sheep of the total herd.

CMLP, CTLP, GTP, HRSP, SHPP variables describe herd composition and were calculated for each county (soum) as percent of each species of the total livestock population. Species resilience to dzud depends on several factors. Livestock composition partially reflects differences in regional distribution of species governed by their selective adaptation to different ecological and climatic conditions. Morphological features such as fur coat and proportion of fat in body weight also contribute to stock survival. Finally, snow depth and density play a key role in animal's ability to access pasture. Badarch (1992) states that small ruminants in steppes and Gobi desert experience difficulty grazing on pasture covered with 8 cm of snow at density of 0.22 kg/cm³ and stop foraging when the snow depth exceeds 13 cm. For big animals, such as horse and cattle, the limiting range of snow depth constitutes 18 - 40 cm above which they cannot graze. Therefore, the relationship of herd composition variables with LMR in this study depends on type of species, geographic location, and SASWE.

Time Series

The statistics of livestock mortality at the soum level were available from 1991 through 2008. We selected a subset of years for analysis based on the following criteria. Livestock mortality was plotted against time (i.e. for each year 1991-2008) to distinguish disaster events of a regional and national scale from localized outbreaks of dzud, which happen every year (Fig. 5). Mongolian herders annually sustain minor losses of animals due to predation, disease, and other causes, and the local scientists estimate this background rate of stock mortality at 7.9% (Begzsuren, et al. 2004). The mortality above 8-10% signifies the onset of dzud and signals national governmental and non-governmental institutions to initiate disaster relief operations (Boldbaatar Shadgar, personal communication, August 2009). For this study, I used 7.9% mortality as the threshold above which we deemed dzud event to have occurred.

The time-series plot shows that dzuds that affected a large part of Mongolia occurred in 1993, 2000, 2001, 2002, and 2003. These events differ in that the dzud of 1993 was not preceded or followed by another dzud year, but years 2000 – 2003 represent a string of consecutive dzuds that allowed us to examine the effect of previous events and adaptations to them on subsequent mortality. In addition to dzud years, two non-dzud years, 1996 and 2004, were selected for the analysis to compare the behavior of the predictor variables at the background mortality level.

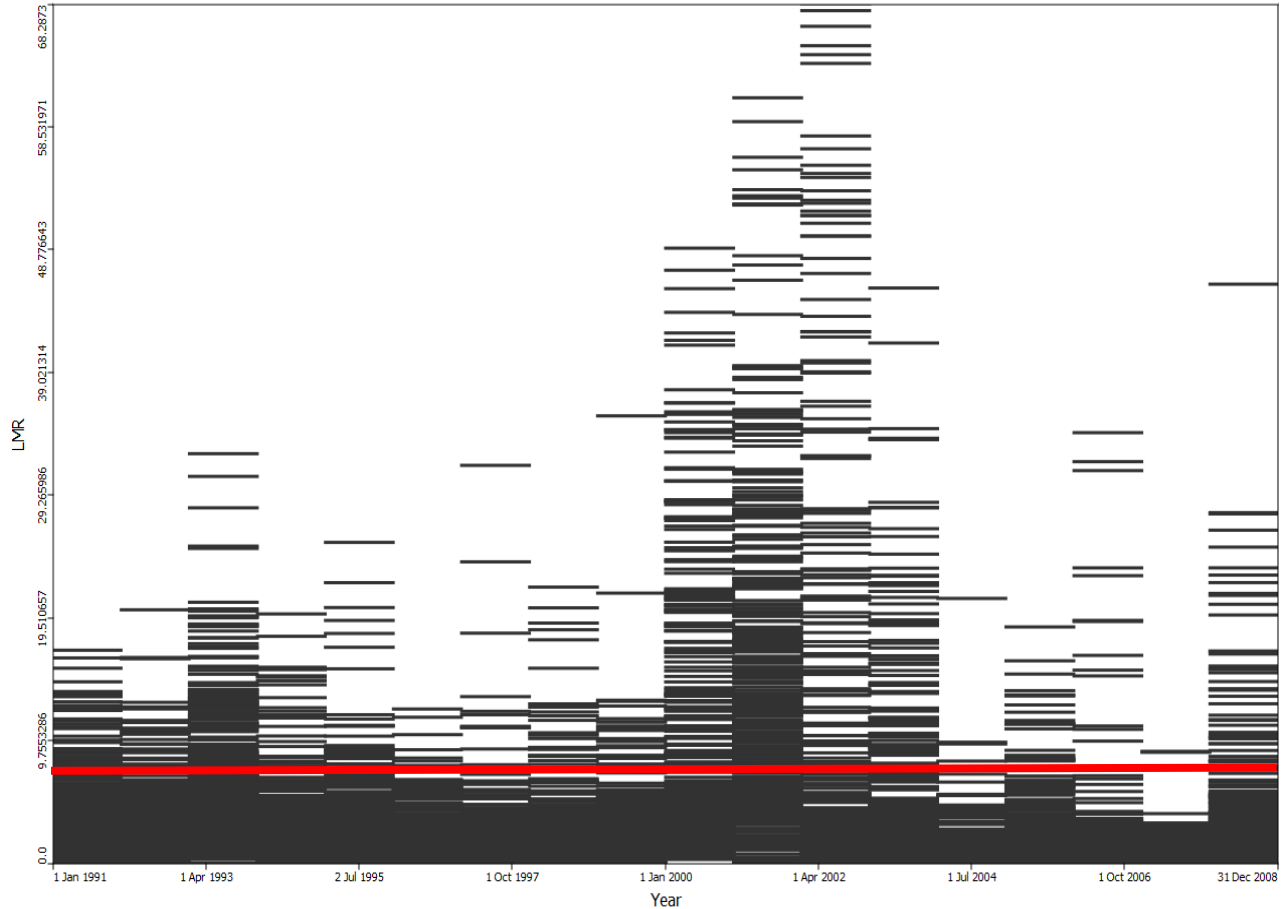


Figure 6: The time-series plot of livestock mortality rate. Each line represents an annual LMR value for a county and the red line delineates the 7.9% threshold (STIS 2010).

Regression Analysis

The research question focuses on understanding the relationships between environmental precursors to dzud (factors) and livestock mortality (response), and regression analysis was deemed a suitable method for modeling such relationships. Because of the spatially dependent nature of the variables and the possibility that relationships may vary in space, both aspatial and spatial regression methods were used. Both global and local regression models were tested and the analysis was done using ArcGIS Spatial Statistics extension (ESRI 2009), GeoDa (Anselin 2006), and JMP (JMP 1989-2011).

Global Models – OLS and SAR

I first used Ordinary Least Square Regression (OLS) to evaluate the relationships between the factors and the response. OLS fits a model using a single linear equation that best describes the dependent variable as a function of the predictors:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon \quad (1)$$

where y is the response variable and x are the predictors, β are regression coefficients that denote positive or negative relationships between the response and a predictor as well as the strength of those relationships, and ε is the random error term (residuals) that stands for variability in the dependent variable not explained by the model. The magnitude of residuals indicates the explanatory power of a model (Mitchell 1999). As a linear regression method, OLS assumes normally distributed and independent errors. If these assumptions are violated, the results of the model are invalid. OLS is a global model meaning that each coefficient in the equation represents a single averaged value that best fits all observations in the dataset. Global models derived from the OLS are only valid if there is little spatial variation in the relationships, i.e., the model is stationary (Fotheringham, Brunsdon et al. 2002).

For the OLS analysis, I undertook an extensive process of calibrating the best model for each year based on indicators of performance and explanatory power of different combinations of the predictors as measured by R^2 and adjusted R^2 , coefficients, probability statistics and the Akaike Information Criterion (AIC). In addition, Joint F-Statistic and Joint Wald Statistic were used to diagnose the effectiveness of explanatory variables in conjunction with Koenker (BP) test, which determines the consistency of relationships between the factors and the response in space. The Jarque-Bera statistic and Moran's I test diagnosed violations of normality and independence of residuals and the presence of spatial autocorrelation, respectively. The significance of the last two tests indicates whether or not the OLS model is misspecified and its results cannot be trusted. Results of the Lagrange Multiplier (LM) test were used to suggest an appropriate type of a spatial econometric model.

Spatial Autoregressive Models (SAR) are mixed regression models that accommodate spatial autocorrelation and heterogeneity observed within the dataset and use maximum likelihood (ML) estimation method. These models relax the assumption of independence of residuals that must hold true for OLS regression and conceptualize a dependent variable as a process operating in space. Under this assumption, autocorrelated residuals indicate that the process at a location is influenced by its neighbors or its errors have an inherent spatial structure (Anselin 1998). These two types of spatial dependency are represented as spatial lag or spatial error models, both of which depend on specifying spatial relationships between observations in the form of a spatial weights matrix (W).

The *spatial lag model* incorporates a spatial lag operator that consists of a weighted average of the values at neighboring locations. The model can be expressed by the equation:

$$y = \rho Wy + X\beta + \varepsilon \quad (2)$$

where y is a N by 1 vector of observations on the dependent variable, Wy is the corresponding spatially lagged dependent variable using weights matrix W , X is a N by K matrix of observations on the explanatory (exogenous) variables, ε is a N by 1 vector of error terms, ρ is the spatial autoregressive parameter, and β is a K by 1 vector of regression coefficients. The presence of the Wy term becomes an exogenous variable and introduces nonzero correlations between response values.

By contrast, a *spatial error model* incorporates the spatial weights matrix into the error term:

$$y = X\beta + (\lambda W\varepsilon + \xi) \quad (3)$$

where the error term in parenthesis consists of λ , the spatial autoregressive coefficient for the error lag $W\varepsilon$, and ξ , a homoscedastic error term. Spatial dependency of error can be interpreted as unresolved spatial correlation in measurement errors or in variables that are poor predictors of the process. This model deals with poor specification and inefficiency of a regression model rather than a real underlying spatial process.

SAR models are considered mixed local models: while taking into account spatial dependence and structure of a process, they produce global statistics that reflect a constant behavior of each predictor across the study area. Spatial regression models are sensitive to specification of the weights matrix and assume stationarity and simultaneity of spatial processes at work (Anselin 1998). The performance of SAR models is evaluated against the OLS diagnostic tests mentioned above and additionally, by the Likelihood Ratio test (LR), whose statistics should order as follows: $Wald > LR > LM$. If the test results are incompatible with the expected order, misspecifications in the SAR models invalidate the asymptotic properties of ML estimates and test statistics (Anselin 2006).

Local Model – GWR

Geographically Weighted Regression (GWR) is a regression model that assumes linear relationship between the response and factors but accommodates variation of model parameters in space (Fotheringham, Brunsdon et al. 2002). If in OLS every data point contributes equally to the estimation of a parameter value, GWR calculates a set of unique parameters for each regression point based on a distance-delimited neighborhood of influence around each point. The main premise of this approach lies in recognition that observations located closer to the regression point x are more similar to it than observations further off. Furthermore, the weight of an observation towards parameter estimation depends on its proximity to x and is a function of distance decay. While GWR is rather insensitive to the type of weighting function used, it is very sensitive to the selection of bandwidth, which delineates a spatial kernel. By estimating parameters locally, GWR relaxes the assumption of stationarity in the OLS and provides a way to measure and investigate spatially varying relationships. In addition, GWR produces several useful statistics to diagnose the significance and robustness of regression results (Fotheringham, Brunsdon et al. 2002).

A foundation of GWR is a weighted least square function that is very similar to a global regression model except that each parameter is assigned to a specific location in space:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (4)$$

where (u_i, v_i) denotes the coordinates of the i th point in space and $\beta_k(u_i, v_i)$ is a realization of the continuous function of a regression coefficient β_k at point i . Given below in matrix notation, the spatial weights matrix is incorporated into derivation of β_k estimate:

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) y \quad (5)$$

where $\hat{\beta}$ represents an estimate of β , and $W(u_i, v_i)$ is an n by n matrix whose off-diagonal elements are zero and whose diagonal elements denote the geographical weighting of each of the n observed data for regression point i (Fotheringham, Brunsdon et al. 2002).

If the best OLS model displays spatial behavior and spatially varying relationships, the GWR method can be used to accommodate those spatial relationships. In addition to measures of classic model performance, GWR has its own diagnostic tools to check the validity of its statistical results: condition number and coefficient standard error, both of which evaluate local multicollinearity. Moran's I test is also performed on the GWR residuals to determine if the model was able to resolve problems with autocorrelation.

Classification and Regression Tree Analysis (CART)

CART is a regression modeling technique that was introduced with the advent of increased computational power critical for the field of data mining (Breiman et al. 1984). Recursive partitioning provides an alternative statistical technique to explore and model relationships in complex multivariate datasets whose structure violates assumptions of classical regression methods. Usually, recursive partitioning is used to explore relationships in the absence of a good *a priori* regression model. In this study, I used CART because I suspected that the relationships between variables were non-linear and exhibited regional differentiation and high-order interactions that cannot be captured by linear models. For example, a regression tree can identify and easily represent interactions between SASWE and SATMP attributable to different types of dzud, but a linear regression model would require additional manipulation of variables to fit such hierarchical relationships into a functional model. Because the continuous response variable has a threshold of 7.9% that separates dzud from the background mortality, the behavior of LMR above and below the cut off value may be different and poorly estimated with the same linear function (Michaelsen, Schimel et al. 1994). Recursive partitioning was also employed by Tachiiri et al. (2008) to represent non-linear relationships between variables and accommodate non-normality of errors in their analysis of provincial rates of dzud mortality. The advantages of CART and its previous successful application to a similar research topic made it an appealing solution for this analysis.

Regression trees are built in a step-wise manner by examining all possible interactions between the response and the predictors with a goal to maximize the homogeneity within subsets of the response variable. All interactions between the response and every explanatory variable receive a rank and the split is made on the single highest ranking predictor, dividing the response variable into two mutually exclusive groups. Thus, partitioning identifies groupings of factor values (X) that predict best the response (Y) and creates a decision tree where each leaf represents a category in X that identifies a category in Y. Partitioning of a continuous response variable happens by fitting the mean to each leaf by examining the sums of squares due to mean differences. Recursive partitioning was performed with JMP software using the "maximize-significance" criterion, a method unique to the JMP partitioning platform

(SAS 2009). The maximize-significance method calculates significance values for each split candidate and uses them, rather than the raw values of sum of squares to make the best split. This significance is represented by *LogWorth* value:

$$\text{LogWorth} = -\log_{10}(p - \text{value}) \quad (6)$$

Using the maximize-significance criterion produces a partitioning tree with fewer levels and more conservative test statistics. Because this criterion identifies groups with small within-sample variance, it is a more attractive option to use on a spatial dataset as it better preserves spatial clustering in the partitioning process (SAS 2009).

Splitting continues recursively until a leaf cannot be split any further, which results in a tree with too many branches and that needs to be pruned to the optimal size. The desired fit of the final tree is achieved through a cross-validation procedure that tests the predictive accuracy of the model based on the estimates of error. Cross-validation can be implemented either by resampling or K-fold cross-validation. For resampling, the dataset is divided into training and validation subsets, where the training subset is used to build a tree while the validation subset calculates the prediction error. The tree with the smallest prediction error is chosen as the best predictive model. Resampling delivers reliable results when the dataset has enough observations to build good representative training and validation subsets. The dataset of this study consisted of 312 observations, which proved insufficient to build robust subsets; therefore, the K-fold cross-validation was used for pruning (De'ath and Fabricius 2000).

K-fold validation divides the dataset into K-number mutually exclusive subsets, each of which is dropped in turn while the rest of the subsets are used to grow a tree. The resulting tree is used to predict the response of the omitted subsets and to calculate the estimated error for each subset. The sum of errors for all the subsets is calculated for each tree size and represents the estimate of the fit. The error is graphically plotted and the tree with the smallest estimated error rate is chosen as the most efficient tree size (De'ath and Fabricius 2000).

Instead of the error rate, JMP plots R^2 value for each tree size, which is the inverse of the sum of squared error rate because $R^2 = 1 - SS_{err}/SS_{tot}$. In this analysis, the objective became to choose the most efficient tree with the highest R^2 value. The fit measure of a tree increases monotonically with each split reaching its highest value with the maximum number of splits. Therefore, the pruning procedure consists of growing the maximum size of the tree using a K –fold cross validation technique and pruning it through interactive exploration to the size where the rate of improvement of R^2 becomes negligible. The cross-validation was run 50 times and the most frequently occurring optimal tree size was taken as the best cut of the tree (De'ath and Fabricius 2000). Once an optimal tree size is determined, it is taken as a reference but the final tree may be grown larger to explore associative behavior of variables at the finer splits. The *LogWorth* value provides additional guidance in pruning and the splits with high *LogWorth* indicate very significant interactions of variables that merit to be retained in the final tree. Finally, tree branches that modeled mortality rate below the threshold were pruned for the purposes of efficiency.

In this analysis, the cross-validation K= 10 and the leaf size contained a minimum of six observations. The size of the leaf was set rather small because six counties constitute a large enough area to cover half of a province and aggregating to a larger area would defy the advantages of a finer spatial scale of the analysis. The decision trees themselves were visualized to examine the relationships between the factors and mortality, and the predictions from the decision trees were visualized in ArcMap to investigate spatial patterns of identified relationships.

Results

I explored four different regression methods, each of which had varied rates of success in fitting the relationships between mortality and the environmental and livestock factors. Exploration of these four methods led to the conclusion that patterns of dzud mortality had non-linear and varying relationships with some factors that need to be better understood before building an effective predictive model. Recursive partitioning can successfully identify regions with clearly defined relationships and revealed locations where dzud mortality could be adequately explained with the available factor. The description of the results of the explorations is organized by years and focuses predominantly on regression tree modeling (supporting documentation of figures and tables are included in the appendices).

Spatial Patterns in 1993

In the time series of available data, 1993 was the first year of intensive livestock mortality (LMR; see List of Abbreviations). LMR93 ranged from 0.1-35.5% with a mean of 6.74% (Table 2). Of 308 counties, 94 experienced livestock mortality above 7.9%, most of which were located in southernmost tip of Altai mountains, Khangai and Khuvsgul mountain ranges, and parts of Transbaikal region. The year 1993 was distinguished by the heaviest snow precipitation (SASWE93) and lowest vegetation productivity (SINDVI92) of all years of the time series: a mean SASWE93 of 36.56 mm reaching the maximum value of 123.46 mm in Khangai mountains and Transbaikal region with the SASWE93 sum equal to 11259.86 mm. An average value for SINDVI93 stood at 3.08 with an overall sum equal to 948.43. In 1993 the composition of the national herd recorded the highest percent sheep (SHPP92) and camel (CMLP92) and the lowest percent goat (GTP92) in all years (Fig. A1 and Table 2).

Table 2: 1993 Descriptive statistics.

Variable	N	Min	Max	Median	Mean	St dev	Sum	Skew
LMR93	308	0.07	35.56	5.08	6.74	5.87	2074.56	1.58
LMRLG93	308	-2.65	3.57	1.63	1.50	0.98	-	-0.54
SASWE93	308	0	123.46	25.35	36.56	33.78	11259.86	0.71
SATMP93	308	-24.88	-5.35	-15.10	-15.08	3.98	-	-0.25
SINDVI92	308	0.00	7.34	3.14	3.08	1.78	948.43	0.06
ELEV	308	670.88	2868.14	1482.01	1559.67	473.19	-	0.51
LD92	308	1.29	77.89	20.25	21.87	12.78	-	0.77
PRLMR92	308	0.05	18.12	2.74	3.73	2.95	1134.15	1.94

HRSP92	308	2.07	20.74	8.37	8.76	3.29	2698.92	0.57
CTLP92	308	0.54	57.93	10.32	12.07	8.25	3718.39	1.65
GTP92	308	0.72	69.19	16.65	20.21	13.64	6224.24	1.17
SHPP92	308	15.52	81.11	58.70	57.26	11.54	17634.65	1.12
CMLP92	308	0	27.68	0.65	1.70	3.37	523.79	3.94

In the first step of the analysis I attempted to model LMRLG93 with OLS regression. The best OLS model, based on adjusted R^2 , AIC, coefficients, and p-value, included temperature (SATMP93) and SASWE93. However, a low R^2 value (0.22) indicated that the model was very inefficient and the efficiency diagnostics tested significantly for non-normality of errors and spatial autocorrelation of residuals (Tables A1). Diagnostics for spatial dependence did not indicate a preference for either spatial lag or spatial error model and GWR was used in an attempt to accommodate the spatial structure of the data. GWR modeling of LMRLG93 was more efficient than OLS, but did not resolve spatial autocorrelation of the residuals, which indicated that both types of regression models were misspecified and missing key explanatory variables (Table A2).

Accordingly, the recursive partitioning was used to describe and explore patterns and processes affecting livestock mortality. The cross-validation process was used to determine that the optimal tree had 13 splits and explanatory power of $R^2 = 0.469$. This tree size was used as a reference, and in the process of interactive exploration the full tree was pruned to 14 splits and reached R^2 of 0.520 (Fig. 7). The cross-validation for a 14-split tree size yielded lower $R^2 = 0.4448$ (Fig. A2).

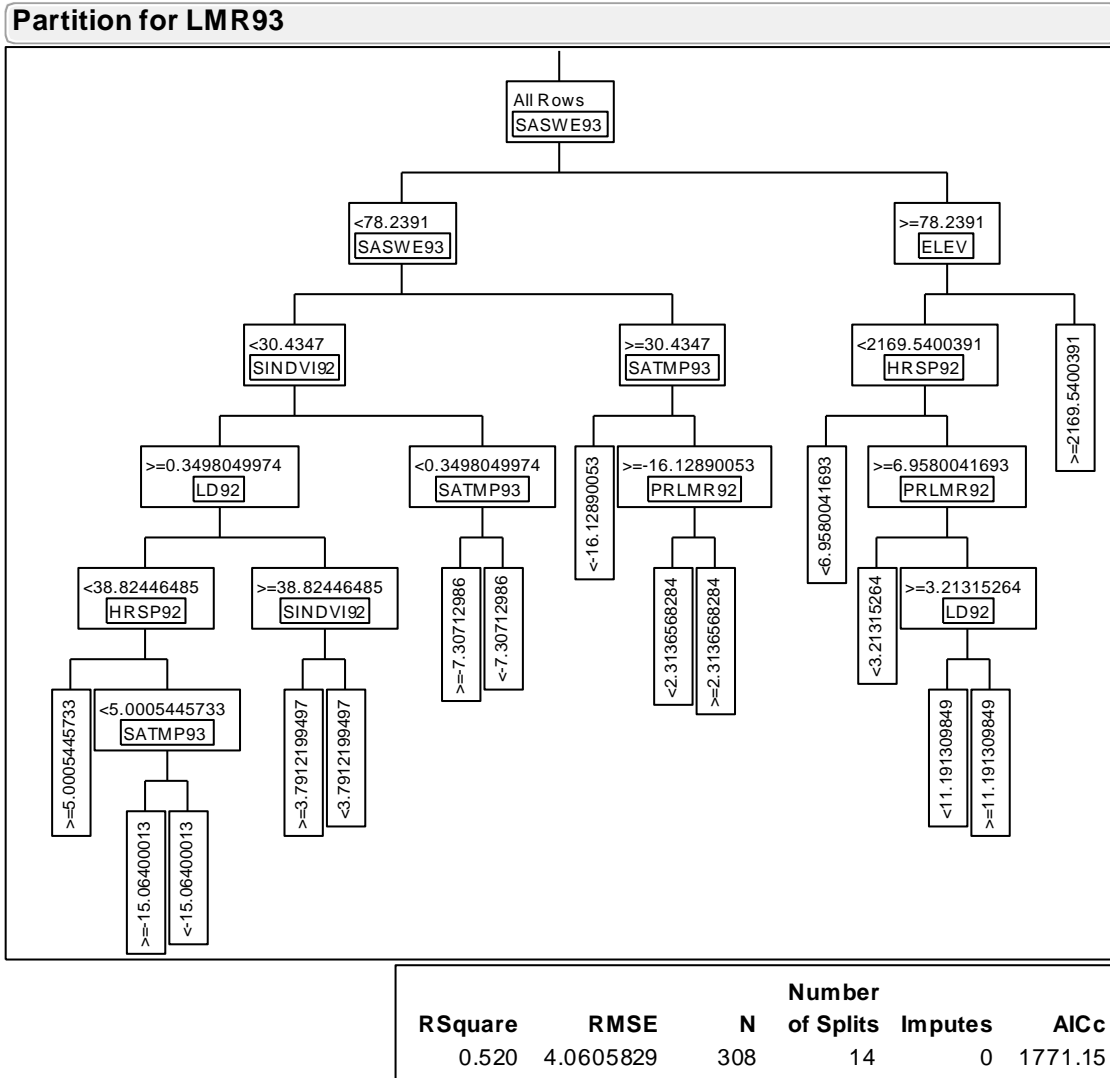


Figure 7: 1993 Regression tree.

The first split of the tree root was based on SASWE93 and effectively separated Khangai, Khuvsgul, and Khentii mountains and parts of Transbaikal region from the rest of the country. A branch with higher mortality and SASWE93>78.2 mm was further divided by elevation into ELEV < and > 2170 meters where the highest LMR93 ($\mu = 20.6\%$) was associated with SASWE93>78.2 and ELEV>2170. Observations with ELEV<2170 m (LMR93, $\mu=10.89$) were further divided by percent horse into HRPS92 < and > 6.96%. A leaf with HRSP92>6.96% was split by previous-year livestock mortality on PRLM92 < and > 3.21%, where the leaf with the higher PRLM92 was further split by livestock density on LD92 < and > 11.19.

Counties where SASWE93<78.2 were further split on SASWE93 < and > 30.4 mm into branches modeling low and medium mortality levels. The branch where SASWE93>30.4 had medium mortality ($\mu=7.5\%$) and showed strong, positive association with SATMP93 and PRLMR92. The highest mortality (LMR93 $\mu=11.78\%$) in this branch was associated with SASWE93>30.43, SASTMP93> -16.13, and PRLMR92>2.31.

Observations from this branch are adjacent to the area of the high mortality branch and occupy the Transbaikal region and a cluster of dzud impacted counties in Central Mongolia.

The left branch of the tree contained observations where SASWE93<30.4. It was further divided into SINDVI92 < and > 0.35, which separated counties in the desert from the semi-desert ecoregion. In counties located in the Gobi desert where mean LMR93 = 9.75%, dzud was associated with SINDVI92 <0.35, and SATMP93 < -7.30. The leaf where SINDVI92> = 0.35 was further split on LD92>= 38.82 and on SINDVI92< 3.79, which isolated a cluster of dzud- affected counties located in Central Mongolia (Fig. 7, Fig. A3)

Finally, the left-most branch where SINDVI92> = 0.35, LD<38.82, HRSP92< 5.0 and SATMP93< -15.06 separated counties with LMR93=9.73% located in Bayankhongor province at the innermost end of Altai Sayan mountain range. These counties were adjacent to the clusters of dzud affected counties in Khangai mountains (Fig. A3).

Spatial Patterns in 1996

The year 1996 represents one of the most favorable years in the time series, whose LMR stayed low at an average of 2.22% and exceeded the background threshold only in eight counties. LMR96 was not affected by the preceding dzud (unlike LMR04) and was distinguished by low SATMP96 ($\mu = -15.30$), highest CTLP95 ($\mu = 13.56$) and HRSP95 ($\mu = 10.14$), and lowest SASWE96 ($\mu = 10.73$ and $\Sigma = 3370.15$) among all years (Table 3, Fig. B1).

Table 3: 1996 Descriptive statistics.

Variable	N	Min	Max	Median	Mean	St dev	Sum	Skew
LMR96	314	0.10	14.57	1.69	2.22	1.98	696.20	2.28
LMRLG96	314	-2.35	2.68	0.53	0.45	0.88	-	-0.34
SASWE96	314	0	79.07	2.81	10.73	14.80	3370.15	1.80
SATMP96	314	-24.96	-6.34	-15.09	-15.30	3.83	-	-0.25
SINDVI95	314	0.03	7.31	3.27	3.18	1.85	999.08	0.04
ELEV	314	670.88	2868.14	1482.01	1559.67	473.19	-	0.51
LD95	314	1.17	92.80	22.01	24.36	15.43	-	0.92
PRLMR95	314	0.09	23.88	1.88	3.01	3.52	945.32	2.94
HRSP95	314	1.94	31.36	9.70	10.14	4.33	3183.01	0.80
CTLP95	314	0.62	57.06	12.23	13.56	8.82	4256.81	1.32
GTP95	314	3.25	74.09	23.48	26.87	14.22	8436.91	0.91
SHPP95	314	16.29	73.50	49.02	48.18	10.08	15130.03	-0.49
CMLP95	314	0	19.99	0.64	1.25	2.20	393.24	4.28

The best OLS model included a number of factors: SINDVI95, ELEV, CMLP95, CTLP95, and HRSP95. The explanatory power of the model was very low ($R^2 = 0.18$) and the residuals exhibited spatial autocorrelation. Diagnostics for special dependence did not indicate a preference for a spatial

econometric model; therefore, GWR method was attempted as an alternative spatial model but failed to resolve autocorrelation in the residuals. These results pointed to misspecification of the regression models and missing key variables (Tables B1 and B2).

Accordingly, recursive partitioning was used to investigate relationship between LMR96 and the predictors. Modeling livestock mortality in 1996 was equivalent to investigating the power of predictors to explain the background mortality rate and explore the relationship between the factors and the response variable in the absence of dzud. The cross-validation procedure suggested the optimal tree size of eight splits and through the process of interactive exploration, the final tree size achieved 12 splits and $R^2 = 0.59$ (Fig. 8 and B2).

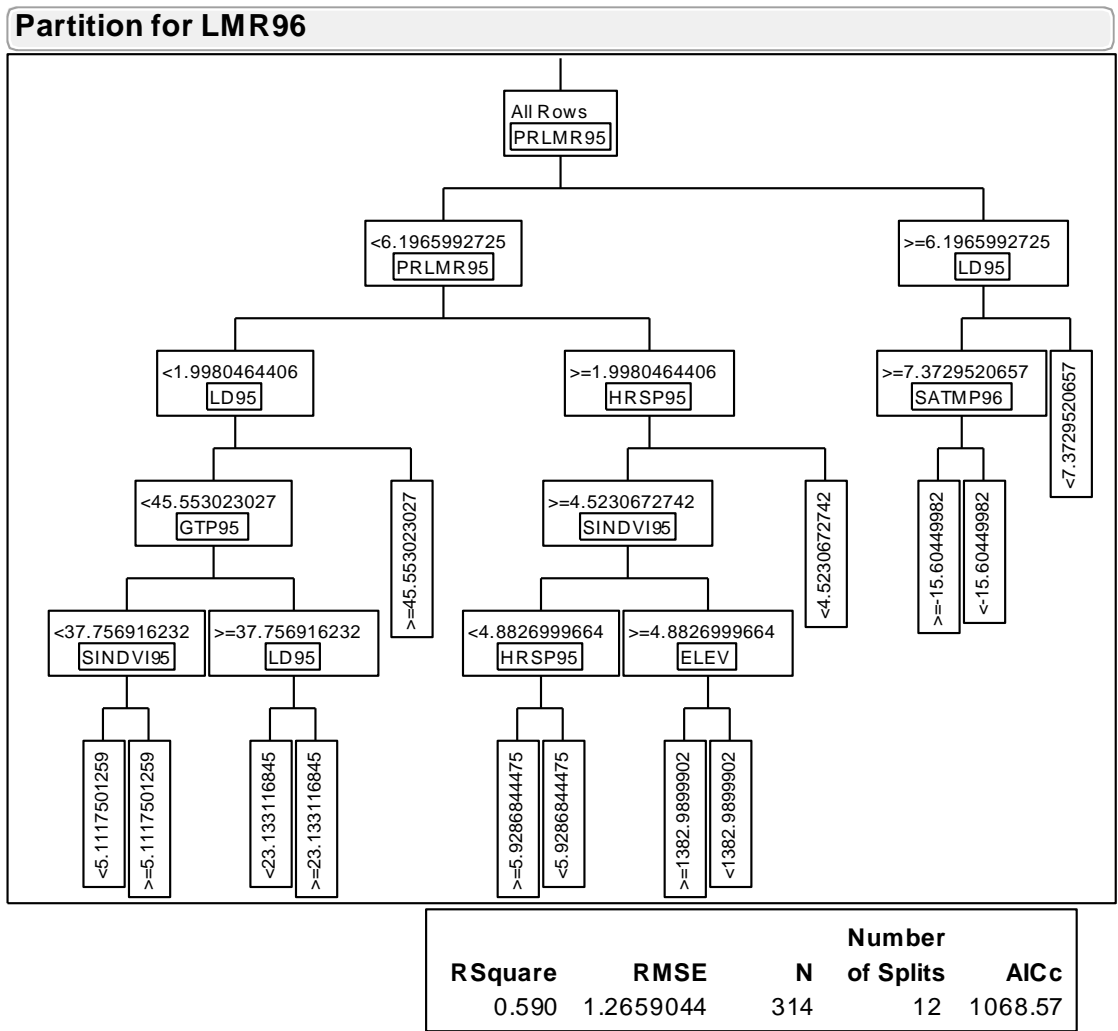


Figure 8: 1996 Regression tree.

The first split was based on PRLMR95 where PRLMR95 > 6.20% was associated with the higher mortality. The right branch was further divided on LD95 < and > 7.37, where higher LMR96 ($\mu=8.04$) was associated with LD95 < 7.37. The leaf with LD95 > 7.37 was further split into two terminal nodes of SATMP96 < and > -15.5, where SATMP96 < -15.60 was associated with LMR96 = 5.76.

The middle branch of the tree was divided on PRLMR95 < and > 2.00 where PRLMR95 > 2.00 was associated with higher LMR96 ($\mu = 2.42$). This leaf was further split on HRSP < and > 4.52 where higher LMR96 ($\mu=4.94$) was associated with lower HRSP95. HRSP95> 4.52 leaf was further divided on SINDVI95 < and> 4.88. The leaf of SINDVI95> 4.88 was further split on ELEV < and > 1383, and the leaf of SINDVI95< 4.88 was split on HRSP95 < and> 5.93.

The left branch of the tree with the lowest mortality (LMR96 = 1.46) originated from leaf of PRLMR95 <2.00, which was further split on LD95 and GTP95. The leaf of GTP95> 37.76 was split on LD95 and the leaf of GTP<37.76 was further split on SINDVI95.

Spatial Patterns in 2000

The year 2000 marked the beginning of a multi-annual dzud episode that finished in 2003. The LMR00 ranged from 0.37% to 44.92%, with a mean of 9.17% (Table 4). The 113 counties affected by dzud were spatially distributed along the northwest – southeast diagonal across the country (Fig. C1). The year was distinguished by the lowest PRLMR99 and CMLP99 ($\mu = 2.49$ and $\mu = 1.02$, respectively), second to lowest SASWE00 ($\mu = 17.14$) and highest LD99 ($\mu = 28.93$) in the time series. HRSP00 and CTLP00 represented a very high share of the national herd, and more than half of the SINDVI00 observations recorded lower than average values ($\mu = 3.16$, median = 3.12) indicating that drought conditions affected large area of the country (Fig. C1).

Table 4: 2000 Descriptive statistics.

Variable	N	Min	Max	Median	Mean	St dev	Sum	Skew
LMR00	312	0.37	44.92	4.55	9.17	10.31	2861.30	1.59
LMRLG00	312	-1.00	3.80	1.52	1.59	1.16	-	0.04
SASWE00	312	0	120.35	8.28	17.14	21.05	5347.75	1.86
SATMP00	312	-25.58	-5.47	-15.40	-15.45	4.06	-	-0.25
SINDVI99	312	0.04	7.59	3.12	3.16	1.89	987.33	0.10
ELEV	312	670.88	2868.14	1482.01	1559.67	473.19	-	0.51
LD99	312	1.08	101.63	26.83	28.93	18.10	-	0.90
PRLMR99	312	0.05	37.64	1.55	2.49	3.23	777.55	5.40
HRSP99	312	2.20	22.44	9.73	9.70	3.74	3026.41	0.28
CTLP99	312	0.37	56.23	11.35	12.76	8.74	3982.25	1.40
GTP99	312	6.10	76.81	27.68	31.09	13.53	9701.28	0.96
SHPP99	312	14.81	64.28	46.52	45.42	9.39	14170.34	-0.60
CMLP99	312	0	15.83	0.50	1.02	1.77	319.72	4.23

The first step of the analysis attempted to model LMRLG00 with a means of OLS regression. The best OLS model included SINDVI99, SASWE00, LD99, HRSP99, and GTP99. However, a low R^2 value ($R^2 = 0.36$) indicated that the model was inefficient; the model tested significant for non-normality of errors and spatial autocorrelation of residuals. Diagnostics for spatial dependence indicated a preference for a

spatial lag model, which was tested on the same set of factors (Table C1). Spatial lag model had higher efficiency than OLS (AIC=707) and resolved spatial autocorrelation in the residuals. However, the diagnostics of spatial lag model indicated misspecification and missing variables, which made its results unreliable (Table C2).

The cross-validation procedure suggested 12 splits to be the optimal tree size, while in the process of interactive exploration the final tree contained 15 splits and achieved $R^2 = 0.673$ (Fig. 9 and Fig. C2).

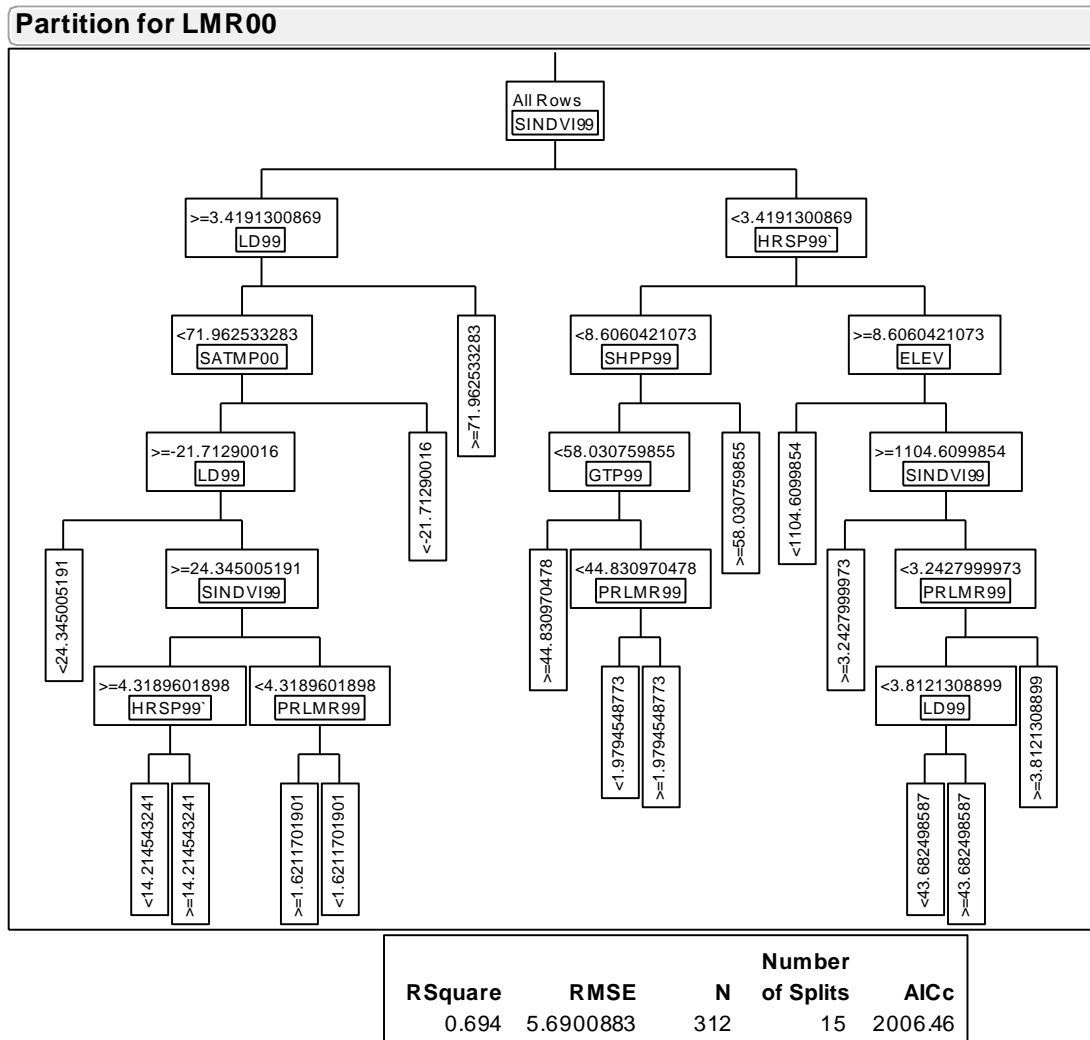


Figure 9: 2000 Regression tree.

The very first split was based on SINDVI99 < and > 3.42, where SINDVI99<3.42 was associated with higher mean LMR00 = 12.88. The split effectively separated the north-central and north-eastern parts of Mongolia that were not affected by drought and dzud. The right branch of the tree that contained observations with high LMR00 was further split on HRSP99 < and > 8.61, where higher HRSP99 is associated with higher LMR00 = 20.37. This split separated western, south-western and parts of the Gobi desert that had lower HRSP99 values and lower LMR00 = 8.32 from the area of high impact organized along the northwest-southeast axis (Fig. C3). The HRSP99>8.61 was split on ELEV < and >

1105, where higher ELEV is associated with higher LMR00=24.53. The leaf with ELEV>1105 continued dividing based on SINDVI99 < and > 3.24, where lower SINDVI was associated with higher LRM00 =26.53. The leaf with SINDVI99<3.24 was split on PRLMR99 < and > 3.81, with PRLMR99 >3.81 associated with higher mean LMR00 = 37.61. The leaf with lower PRLMR99 <3.81 was split based on LD99 < and > 43.68 into terminal nodes with LMR00 equal 21.28 and 31.51.

The middle branch of the tree that stemmed from the leaf of SINDVI99<3.42 and HRSP99<8.61 contained counties with dzud mortality located predominantly in the northwest of Mongolia. Both splits were based on livestock composition variables, SHPP99 and GTP99, where the last split isolated semi-desert ecoregion from the Gobi desert (Fig. C3). The leaf of GTP99<44.83 was further divided based on PRLMR99, where higher LMR00 = 15.19 was associated with PRLMR99 >1.98.

The left branch of the tree contained mostly counties not impacted by dzud. The first split of SINDVI99>3.42 leaf isolated a small cluster of counties in the central Mongolia with LD99 >71.96 and mean LMR00 = 16.42. The leaf of LD99 <71.96 was further split on SATMP00, where SATMP00 < -21.71 was associated with higher LMR00 = 10.54 and located in Khangai and Khuvsgul mountains. The counties belonging to the leaf of SATMP00> -21.71 were not affected by dzud and located in the north-central and north-eastern Mongolia (Fig. C3). This leaf was further divided into LD99 < and > 24.34, with the leaf of LD99 > 24.35 having higher LMR00 = 4.91. This leaf in turn was split based on SINDVI99 < and > 4.32, where the leaf with lower SINDVI99 had higher LMR00 = 7.74 and was further split based on PRLMR99 < and > 1.62 into terminal nodes with PRLMR99 < 1.62 having mean LMR00 = 11.77. The leaf of SIDNVI99> 4.32 was divided on HRSP99 < and > 14.21 into two terminal nodes with higher HRSP99 associated with higher mean LMR00 = 6.97.

Spatial Patterns in 2001

The highest dzud incidence over the country occurred in 2001: 200 out of 312 counties experienced livestock mortality higher than 7.9% and dzud engulfed the entire country (Fig. D1). In 2001, LMR01 ranged from 0.07% to 61.48% with a mean of 15.0% and temperatures were the coldest of all years (SASTMP01 μ = -16.77, median = -17.38) (Table 5).

Table 5: 2001 Descriptive statistics.

Variable	N	Min	Max	Median	Mean	St dev	Sum	Skew
LMR01	312	0.07	61.48	11.81	14.97	12.31	4671.82	1.41
LMRLG01	312	-2.73	4.12	2.47	2.30	1.07	-	-1.39
SASWE01	312	0	104.94	20.61	27.33	26.60	8526.28	0.76
SATMP01	312	-26.02	-5.17	-17.38	-16.77	4.42	-	0.36
SINDVI00	312	0.06	7.27	3.20	3.13	1.73	976.72	0.12
ELEV	312	670.88	2868.14	1482.01	1559.67	473.19	-	0.51
LD00	312	1.13	83.12	23.81	25.88	15.78	-	0.95
PRLMR00	312	0.37	44.92	4.55	9.17	10.31	2861.30	1.59
HRSP00	312	1.88	21.37	8.95	9.10	3.83	2839.69	0.30

CTLP00	312	0.26	54.39	9.35	11.25	8.86	3510.88	1.42
GTP00	312	7.91	79.27	29.12	32.17	13.14	10036.96	1.03
SHPP00	312	12.81	69.63	47.62	46.41	9.98	14480.91	-0.58
CMLP00	312	0	19.05	0.48	1.06	1.99	331.55	4.85

The best OLS model included SASWE01, ELEV, LD00, PRLMR00, and HRSP00. However, a low R^2 value ($R^2 = 0.26$) indicated that the model was inefficient. It also tested significant for non-normality of errors, heteroscedasticity, non-stationarity and spatial autocorrelation of residuals. Diagnostics for spatial dependence indicated a preference for a spatial error model, which was tested on the same set of factors. (Table D1). The spatial error model had higher efficiency than OLS (AIC=702) and resolved spatial autocorrelation of the residuals. However, the diagnostics of spatial lag model indicated misspecification and missing variables, which made its results unreliable (Table D2).

The results of the cross-validation procedure suggested the optimal tree size for recursive partitioning was 12 splits, and through the interactive exploration process, the final tree was pruned to 16 splits and reached $R^2 = 0.677$ (Fig. 10 and Fig. D2).

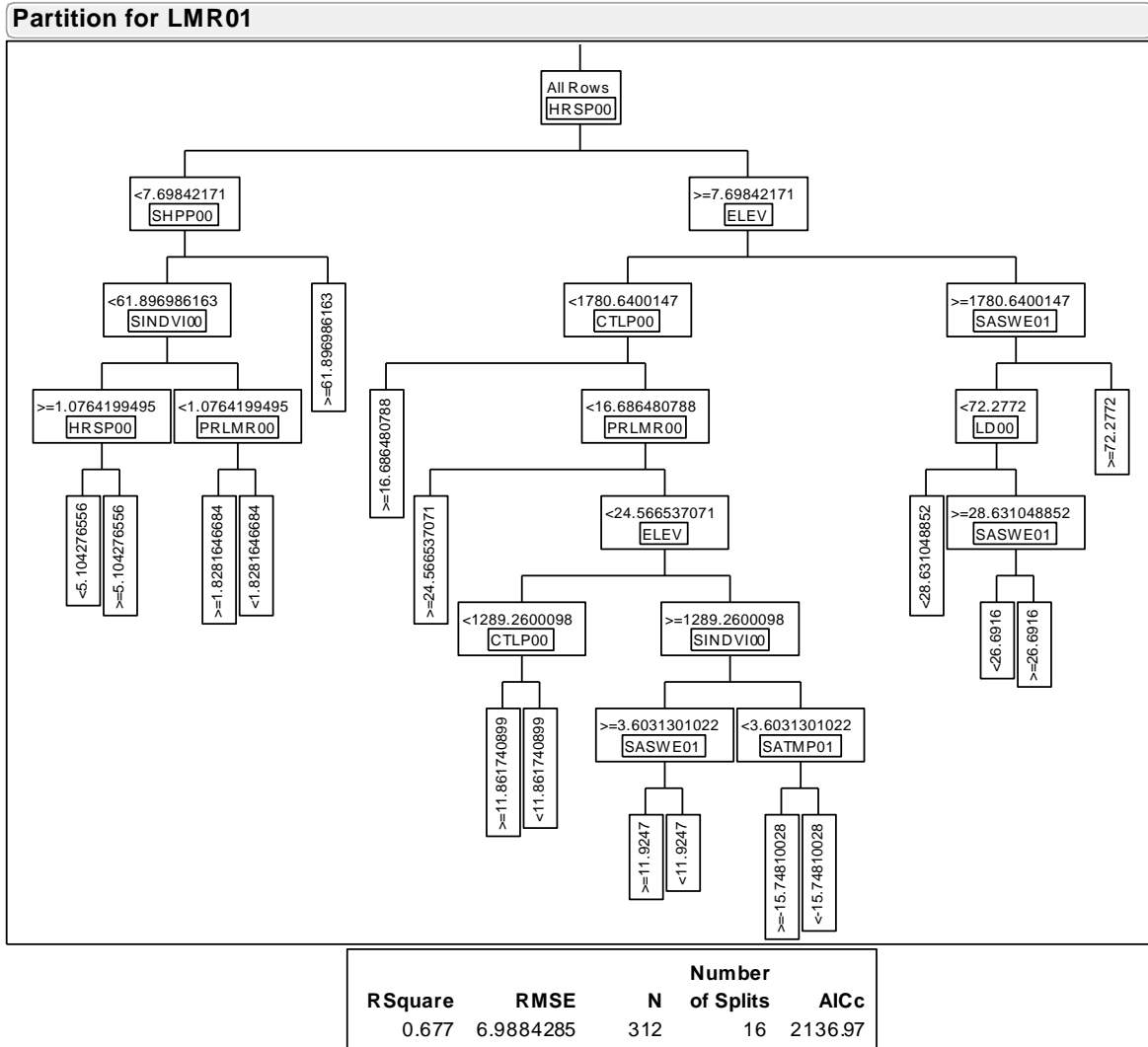


Figure 10: 2001 Regression tree.

The first split was done based on HRSP00 < and > 7.70, where HRSP00>7.70 was associated with higher LMR01 = 17.74. The leaf of HRSP00>7.70 was further split on ELEV < and > 1781, which separated the region of highest impact, Khangai and Khuvsgul mountains and its vicinities, from the rest of the country (Fig. D3). High LMR01 in the right branch was associated with ELEV>1781, SASWE01>72.28 and LD00>28.63.

The middle branch of the tree stemmed from the leaf of ELEV<1781, which was split based on CTLP00 < and > 16.67 where higher LMR01 = 17.02 was associated with CTLP00<16.69. This leaf was further split on PRLMR00 < and > 24.57 where higher LMR01 = 18.82 was associated with PRLMR00 <24.57. The leaf of PRLMR00<24.57 was further split based on ELEV < and > 1289 where ELEV>1289 was associated with higher LMR01 = 23.41. The leaf geographically occupies Khentii range and its vicinity. The leaf of ELEV<1289 covered the eastern part of Mongolia and was further split based on CTLP >11.86 (Fig. D3). The leaf of ELEV>1289 was further split on SINDV100 where higher LMR01 = 31.43 was associated with

SINDVI00<3.6. The leaf of SINDVI00<3.60 was split on SATMP01 < and > -15.75 and the leaf of SINDVI00>3.60 was divided on SASWE01 < and > 11.92.

The left branch of the tree models LMR01 in the western and the Gobi regions of Mongolia. The branch stemmed from the leaf of HRSP00<7.70, which was split on SHPP00 < and > 61.90 where SSHPP00>61.90 was associated with mean LMR01 = 22.33. The leaf of SHPP00<61.90 was further split on SINDVI00 < and > 1.08 and PRLMR00 < and > 1.83 where lower LMR = 12.95 was associated with higher PRLMR00. Observations contained in the leaf of PRLMR00 >1.82 is located in the Gobi desert while observations with PRLMR00 <1.82 were adjacent to Khangai mountains (Fig. D3). The leaf with SINDVI00 >1.08 was split into terminal nodes based on HRSP00 < and > 5.10 where higher LMR01 = 9.85 was associated with HRSP00 > 5.10.

Spatial Patterns in 2002

In 2002, dzud occurred in 94 counties located mostly in the western and southern parts of Mongolia (Fig E1). While 2002 dzud did not reach the impact of the disaster in 2001, the maximum LMR02 recorded was 76.40% with an average of 10.3%. 2002 observed low SASWE ($\mu = 22.07$, $\Sigma = 6886.69$), second to highest SINDVI ($\mu = 3.23$, $\Sigma = 1008.01$) and was the warmest year in the time series (SATMP $\mu = -14.23$). Overall, this year had mild winter conditions and good vegetation cover in the preceding summer (Table 6).

Table 6: 2002 Descriptive statistics.

Variable	N	Min	Max	Median	Mean	St dev	Sum	Skew
LMR02	312	0.02	76.40	2.67	10.31	15.57	3216.55	1.98
LMRLG02	312	-3.70	4.34	0.98	1.25	1.55	-	0.08
SASWE02	312	0	71.16	19.60	22.07	17.89	6886.69	0.62
SATMP02	312	-23.88	-4.42	-14.10	-14.23	4.22	-	-0.10
SINDVI01	312	0.00	7.51	3.38	3.23	1.99	1008.01	0.03
ELEV	312	670.88	2868.14	1482.01	1559.67	473.19	-	0.51
LD01	312	1.18	74.88	19.95	22.60	14.21	-	0.93
PRLMR01	312	0.07	61.48	11.81	14.97	12.31	4671.82	1.41
HRSP01	312	0.77	20.99	8.58	8.74	3.95	2726.40	0.30
CTLP01	312	0.10	51.63	6.29	8.92	8.24	2783.52	1.84
GTP01	312	10.47	80.89	32.69	35.52	13.19	11082.45	1.00
SHPP01	312	11.09	65.86	47.17	45.68	10.27	14252.75	-0.71
CMLP01	312	0	23.90	0.48	1.14	2.25	354.88	5.31

The best OLS model included SINDVI01, SATMP02, SASWE02, ELEV, LD01, PRLMR01, and SHPP01. However, a moderately low R^2 value ($R^2 = 0.47$) indicated that the model had higher predictive power than models of previous years but it still tested significant for non-normality of errors, heteroscedasticity, non-stationarity and spatial autocorrelation of residuals. Diagnostics for spatial

dependence indicated a preference for a spatial lag model, which was tested on the same set of factors (Table E1). The spatial lag model had higher efficiency than OLS (AIC=812) and resolved spatial autocorrelation in the residuals. However, the diagnostics of the spatial lag model indicated misspecification and missing variables, which made its results unreliable (Table E2).

The cross-validation procedure in the recursive partitioning process suggested the optimal tree size of eight splits and in the process of interactive exploration, the final tree was pruned to 11 splits and reached $R^2 = 0.748$ (Fig. 11 and Fig. E2).

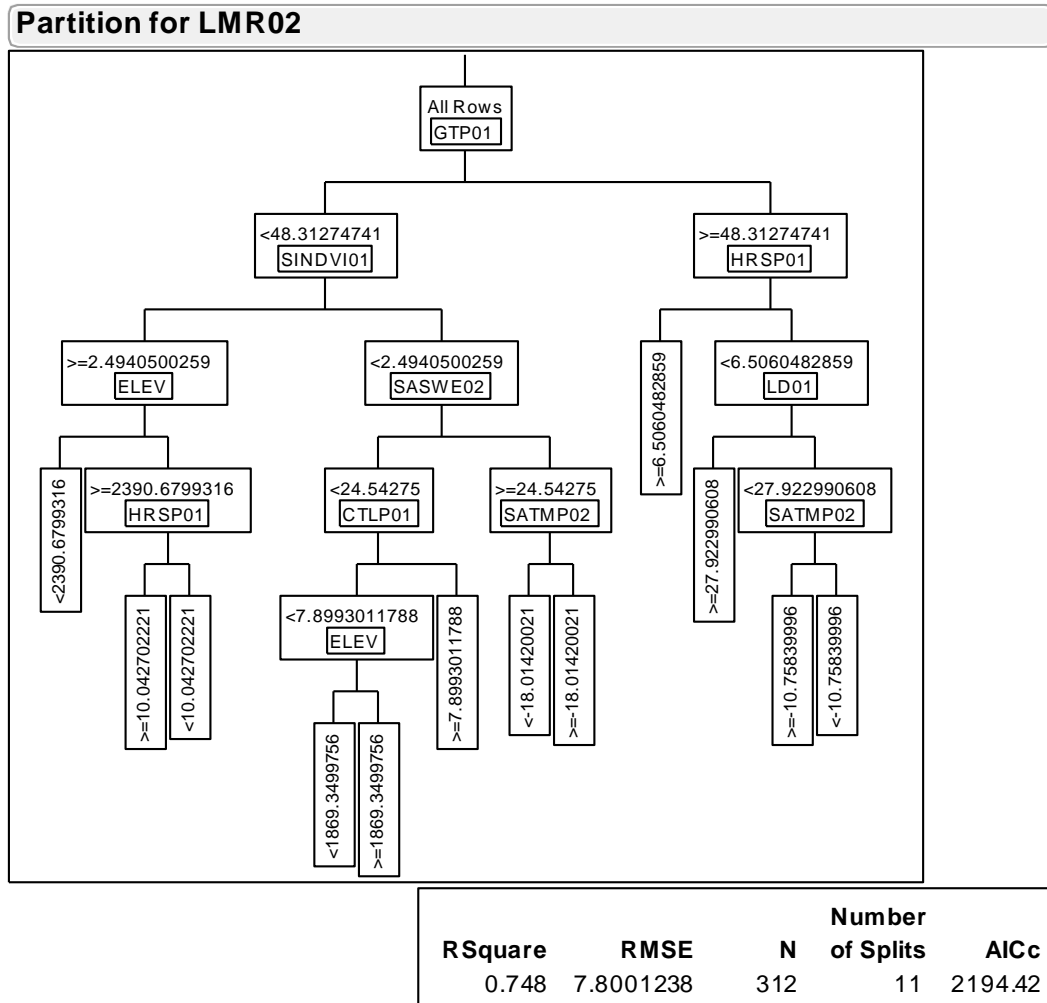


Figure 11: 2002 Regression tree.

The first split of the tree is based on GTP01 < and > 48.31 which separated the zone of the impact covering the Gobi and the western part of the country. The right branch of the tree continued to be split on HRSP01 < and > 6.51 where higher LMR02 = 36.34 was associated with HRSP01 < 6.51. This leaf was further divided into LD01 < and > 27.92, where LD01 < 27.92 was associated with mean LMR02 = 39.13. The leaf of LD01 < 27.92 was split into two terminal nodes on SATMP02 < and > -10.76. Most observations partitioned in this branch were located in the Gobi desert (Fig. E3).

The middle branch of the tree stemmed from the leaf of $GTP01 < 48.31$, which was split on $SINDVI01 < \text{and} > 2.49$. The leaf of $SINDVI01$ was further divided based on $SASWE02 < \text{and} > 24.54$ with higher $LMR02 = 25.71$ associated with $SASWE02 > 24.54$. The leaf of $SASWE02 > 24.54$ was further split into terminal nodes of $SATMP02 < \text{and} > -18.01$, where $SATMP02 > -18.10$ was associated with higher $LMR02 = 35.18$. The leaf of $SASWE02 < 24.54$ was split based of $CTLP01 < \text{and} > 7.90$ where $CTLP01 > 7.90$ was associated with higher $LMR02 = 20.28$. The leaf of $CTLP01 < 7.90$ was divided into terminal nodes based on $ELEV < 1869$, where $ELEV > 1869$ was associated with mean $LMR02 = 11.56$.

The left branch of the tree stemmed from the leaf of $GTP01 < 48.31$ and $SINDVI01 > 2.49$. Geographically, this split separated central and northeastern parts of Mongolia from the zone of impact. The low $LMR02$ in this area was associated with higher $SINDVI01$ and $ELEV < 2391$. A cluster of high mortality ($LMR02 = 18.97$) in this branch was associated with $ELEV > 2391$ and $HRSP01 < 10.04$, which geographically occupied the westernmost end of Altai-Sayan mountain range (Fig. E3).

Spatial Patterns in 2003

The last year that witnessed dzud in this sequence was 2003: 72 of 309 counties experienced high mortality ranging from 0.03 to 41.66% with an average of 5.51%. The clusters of high mortality were located in the north central and southern regions (Fig. F1). This year recorded high $SASWE03$ ($\mu = 32.16$) and the $LD03$ has declined to the level of $LD93$ (Table 7).

Table 7: 2003 Descriptive statistics.

Variable	N	Min	Max	Median	Mean	St dev	Sum	Skew
LMR03	309	0.04	41.66	2.67	5.51	7.23	1703.3	2.18
LMRLG03	309	-3.31	3.73	0.98	0.94	1.32		-0.15
SASWE03	309	0	132.93	18.38	32.16	33.22	9937.90	0.96
SATMP03	309	-25.47	-5.87	-16.43	-16.26	4.19	-	0.06
SINDVI02	309	0.01	7.39	3.12	3.08	1.80	952.22	0.06
ELEV	309	670.88	2868.14	1482.01	1559.67	473.19	-	0.51
LD02	309	1.20	68.25	18.38	21.15	14.10	-	0.94
PRLMR02	309	0.02	76.40	2.67	10.31	15.57	3216.55	1.98
HRSP02	309	0.72	19.94	8.35	8.33	4.01	2573.62	0.31
CTLP02	309	0.10	49.95	6.27	8.31	7.81	2566.70	1.95
GTP02	309	12.82	82.55	35.19	38.80	13.62	11988.33	1.00
SHPP02	309	8.72	65.94	45.21	43.28	10.59	13373.50	-0.77
CMLP02	309	0	21.82	0.46	1.29	2.61	397.85	4.62

The best OLS model included $SINDVI02$, $SATMP03$, $SASWE03$, $ELEV$, $PRLMR02$, $CMLP02$, $CTLP02$, and $HRSP02$. However, a moderately low R^2 value ($R^2 = 0.46$) indicated that the model had poor efficiency. It also tested significant for heteroscedasticity, non-stationarity and spatial autocorrelation of the residuals. Diagnostics for spatial dependence indicated a preference for a spatial lag model, which was

tested on the same set of factors (Table F1). The spatial lag model had higher efficiency than OLS (AIC=767) and resolved spatial autocorrelation of the residuals. However, the diagnostics of spatial lag model indicated misspecification and missing variables, which made its results unreliable (Table F2).

The cross-validation procedure in the recursive partitioning process suggested the optimal size of the tree of 18 splits but after interactive pruning process, the final tree was cut to 15 splits and reached $R^2 = 0.687$ (Fig. 12 and Fig. F2).

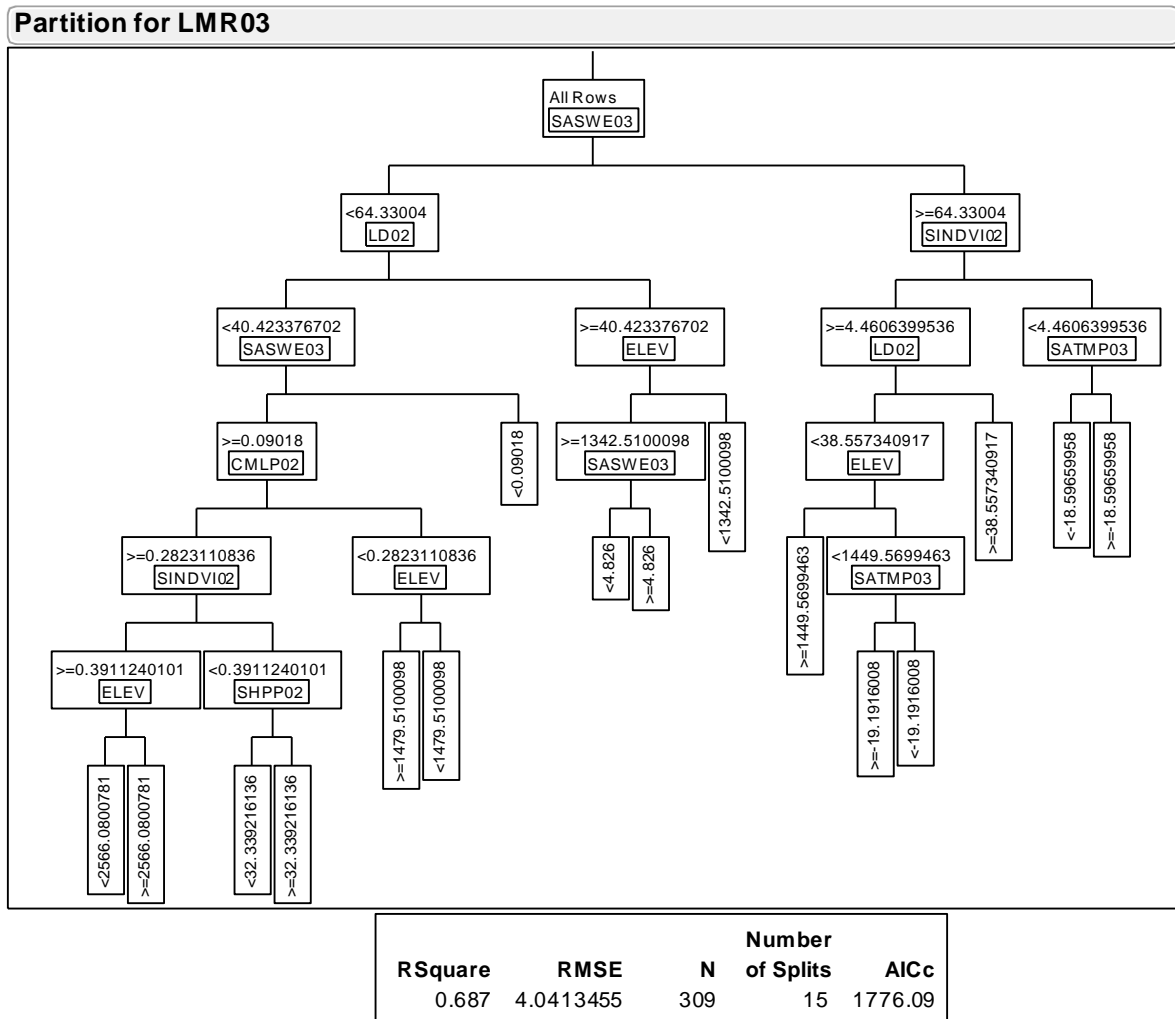


Figure 12: 2003 Regression tree.

The very first split was done on SASWE03 < and > 64.33, where SASWE03 >64.33 was associated with higher LMR03 = 11.62. The right branch of the tree that contained observations of higher mortality proceeded to be split on SINDVI02 < and > 4.46 where higher LMR03 = 19.01 was associated with SINDVI02 < 4.46. The leaf of SINDVI02 < 4.46 was further split on SATMP03 < and > -18.60 into two terminal nodes with higher mean LMR03 = 26.19 associated with SATMP03 > -18.60. The leaf of SINDVI02 > 4.46 was further divided into LD02 < and > 38.56 where higher LMR02 = 17.74 was associated with LD02 > 38.56. The leaf of LD02 < 38.56 continued to be split on ELEV < and > 1450 with ELEV > 1450

associating with low LMR03 = 2.70. The leaf of ELEV<1450 was divided into two terminal nodes of SATMP03 < and > -19.19 with higher LMR03 = 17.69 associated with SATMP03<-19.19.

The middle branch of the tree stemmed from the leaf of SASWE03<64.33 which was split on LD02>40.42 with higher LMR03 = 10.24 associated with LD02> 40.42. This leaf was in turn divided on ELEV < and > 1343 where higher LMR03 = 19.13 was associated with ELEV<1342. The leaf of ELEV > 1343 was further split on SASWE03 < and > 4.83 into terminal nodes where SASWE03 >4.83 was associated with LMR03=10.32. The right and middle branches of the tree geographically separated Transbaikal and Khyangan regions of high impact from the rest of the country (Fig. F3).

The left branch of the tree stemmed from the split of SASWE03<64.33 and LD02<40.42. This leaf was further split on SASWE03 < and > =0.09 where higher LMR03=15.88 was associated with SASWE03<0.09. The observations assigned to this leaf constituted a high impact mortality cluster located in the Gobi desert. The SASWE03>0.09 was further split on CMLP02 < and > 0.28 with CMLP02<0.28 associated with higher LMR03=4.55. This leaf was split into two terminal nodes of ELEV < and > 1480 with ELEV<1480 associating with LMR03 = 10.56. The leaf of CMLP02 > 0.28 was divided on SINDVI02>0.39 where higher LMR03=4.10 was associated with SINDVI02 <0.39. This leaf was split into terminal nodes based on SHPP02 < and > 32.34 where higher SHPP02>32.34 was associated with higher LMR03 = 8.29. The leaf of SINDVI02>0.39 was divided on ELEV < and > 2566 into two terminal nodes where ELEV<2566 was associated with LMR03 = 1.54 and ELEV>2566 was associated with LMR03=5.14.

Spatial Patterns in 2004

The last year of the time series following a four-year dzud spell was 2004. It recorded the lowest LMR04 of all years ($\mu = 1.15$) and very high SASWE04. A chain of dzud events had put a clear imprint on composition of the national herd, with HRSP03 and CTLP03 at their lowest and GTP03 at its highest share in all the years (Table 8 and Fig. G1).

Table 8: 2004 Descriptive statistics.

Variable	N	Min	Max	Median	Mean	St dev	Sum	Skew
LMR04	312	0	22.06	0.71	1.15	1.76	359.31	6.59
LMRLG04	312	-6.91	3.09	-0.32	-0.47	1.23	-	-0.84
SASWE04	312	0	114.72	21.04	30.59	30.21	9544.84	0.97
SATMP04	312	-24.47	-5.34	-15.53	-15.41	3.91	-	0.13
SINDVI03	312	0.05	7.12	3.49	3.22	1.65	1005.02	-0.07
ELEV	312	670.88	2868.14	1482.01	1559.67	473.19	-	0.51
LD03	312	1.15	63.43	19.68	21.91	13.62	-	0.78
PRLMR03	312	0.04	41.66	2.67	5.51	7.23	1703.3	2.18
HRSP03	312	0.78	19.39	7.73	7.99	4.03	2492.68	0.47
CTLP03	312	0.10	51.03	5.52	7.68	7.47	2396.14	2.22
GTP03	312	14.44	85.47	38.31	41.85	13.84	13058.52	0.97
SHPP03	312	7.65	61.69	43.53	41.29	10.58	12883.97	-0.83

CMLP03	312	0	22.91	0.43	1.18	2.50	368.68	4.97
--------	-----	---	-------	------	------	------	--------	------

The best OLS model included PRLMR03, CTLP03, and HRSP03. However, a low R^2 value ($R^2 = 0.24$) indicated that the model was very inefficient. The model tested significant for non-normality of errors and spatial autocorrelation of residuals. Diagnostics for spatial dependence indicated a preference for a spatial lag model, which was tested on the same set of factors (Table G1). Spatial lag model had slightly higher efficiency than OLS (AIC=907) and resolved spatial autocorrelation of the residuals. However, the diagnostics of spatial lag model indicated misspecification and missing variables, which made its results unreliable (Table G2).

The cross-validation procedure of the recursive partitioning suggested the optimal tree size of four splits and through the process of interactive exploration the final tree grew to five splits, reaching $R^2 = 0.226$ (Fig. 12 and Fig. G2).

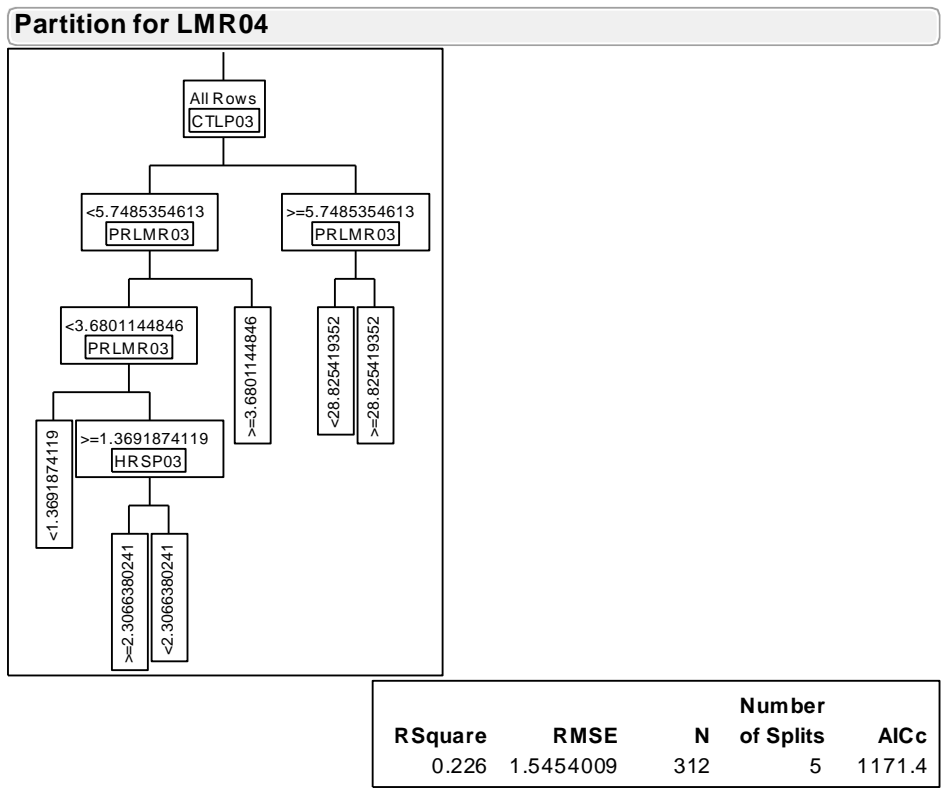


Figure 13: 2004 Regression tree.

The first split was based on CTLP03 < and > 5.75 which separated north-central and north-eastern regions along with all mountain ranges except for the innermost stretches of Altai-Sayan mountain chain. In these parts of the country, the higher LMR04=1.78 was associated with CTLP03>5.75. This leaf was further split on PRLMR03 < and > 28.83 into two terminal nodes where higher LMR04=5.43 was associated with PRLMR03>28.83 (Fig. G3).

The left branch of the tree stemmed from the leaf of CTLP03 <5.75, which was divided on PRLM03 < and > 3.68 where the higher LMR04=1.07 was associated with PRLMR03>3.68. The leaf of PRLMR03<3.68 was further split on PRLMR03 < and > 1.37 where higher LMR04 = 0.63 was positively associated with higher PRMR03. The leaf of PRLMR03>1.37 was split into two terminal nodes of HRSP03 < and > 2.31.

Discussion

The results of the analysis demonstrate that predictors of dzud intensity exhibit heterogeneous relationships in space and evolving dynamics over time. The direction of the associative behavior between the mortality and contributing factors varies according to ecological and physical characteristics of the affected location. This inconsistent association can be a property of a geographic location, true causative association, or an artifact of missing variables and model misspecification. Thus, the main challenge of the analysis is to discern strong predictors of livestock mortality from factors that describe geographic characteristics but carry no explanatory information. The success of the analysis will be also evaluated by the performance of selected methodology to effectively elicit true relationships. The discussion section will first examine the spatial dimensions of the results and then look at temporal dynamics in dzud evolution.

Spatial Dynamics of Dzud Incidence

1993

The most severe dzud impact in 1993 concentrated in mountainous regions with deep snow cover, large numbers of horses in the herd and high previous-year mortality. The region of medium level mortality was located in Transbaikal region, which had lower elevation but similar characteristics as in the mountains. The association of temperature above -16.12 °C with moderate level of mortality in this region points to interactions between snow cover and temperature variables in relationship to dzud mortality: very low temperature and deep snow do not necessarily associate linearly with livestock mortality. Rather, a specific range of temperature together with a significant snow amount created dzud conditions.

Apart from the cluster of high mortality in Ovorkhangai province in Central Mongolia, which was associated with high density of livestock and lower NDVI, most of observations in the leftmost branch of the tree that represents counties with lower dzud mortality were located in the desert and semi-desert ecozones, which are defined by low NDVI, shallow snow cover, low density of livestock, especially lower percentage of horses in a herd. Therefore, the top levels of partitioning of the left branch may not necessarily represent causative factors as much as those splits highlight very distinct climatic and ecological characteristics based on which partitioning dissects the dataset to isolate the regions of the impact in the Gobi and western part of Mongolia. The likely explanatory factors appeared at the bottom of the tree and indicated that dzud was associated with conditions of low temperatures and low snow cover conducive to black dzud (Fig. A3).

1996

Because the climatic conditions were favorable in 1996, partitioning allowed investigating the behavior of variables in relation to background level of mortality. The highest mortality was recorded in Transbaikal region and associated with high previous-year mortality, lower livestock density and low temperature. Counties located in the Gobi region were unaffected by dzud and partitioned based on higher previous mortality, lower percentage of horses and lower NDVI. Partitioning also separates semi-desert and desert regions based on low livestock densities, higher proportion of goats and lower NDVI. The cluster of high livestock density in Central Mongolia appeared again in 1996. The regression tree of 1996 demonstrates that variables of livestock density, vegetation cover, percentage of goats and horses were used to separate ecological regions based on its distinct characteristics (Fig. B3).

2000

The highest mortality in 2000 was associated with drought that spread along the northwest-southeast diagonal across Mongolia. Within the area of impact, the magnitude of losses depended on the proportion of horses in the herd, where larger horse population found in the southeast and smaller population in the northwest. In the southeast cluster, high mortality was associated with properties of higher elevation, high previous-year mortality and high livestock density as well as lower NDVI. The northwestern cluster affected by drought and the Gobi desert were partitioned based on herd composition variables of horses, sheep, and goats. However, their relationships do not logically associate with mortality but rather highlight properties of the desert and semi-desert regions; high mortality in these regions was associated with higher percentage of sheep, lower goat population and higher previous-year mortality. The climatic factor of snow cover was not included into results because of lower significance score but might have been associated with dzud mortality in the western Mongolia. It indicates that the local scale of the analysis is more appropriate for the desert and semi-desert regions and direct comparison of those regions with forest and steppe biomes within a single model has low efficiency.

Khangai-Khuvsgul mountain ranges, Transbaikal region and Dagurian steppes, which are usually characterized by the most severe winter conditions but in 2000 observed lower mortality than the rest of the country. The persistent cluster of high livestock density and low vegetation cover in Central Mongolia appeared again in 2000. This hot-spot of dzud mortality has stood out due to high density of livestock in previous years and has been growing in size. Counties in Khangai and Khuvsgul mountains recorded moderate level mortality associated with very low temperature and high mortality, which underscores this location's vulnerability to dzud due to its physical topography. Finally, in this region the higher mortality was also associated with lower previous-year mortality, which was contrary to the expected relationship and indicated that this variable took place of a missing factor describing patterns of herder migration (Fig. C3).

2001

In the aftermath of the 2000 dzud, the factors and patterns associated with livestock mortality show the lingering effect of the previous-year dzud as well as a contribution of severe winter weather conditions

(Fig. D3). The most important contributing factor was percent horse in herd composition, which has appeared in previous years suggesting that this livestock type has particularly strong and persistent association with dzud. The most severe impact located in Khuvsgul-Khangai mountain ranges characterized by deep snow and the Ovorkhangai hot-spot in Central Mongolia was associated with high density of livestock and deep snow. The split on previous-year mortality, which negatively associated with high livestock mortality was pruned due to low LogWorth, but its contradictory relationship with the response suggests of herders migration into less affected areas.

Medium level mortality was recorded in Transbaikal and Dagurian steppes associated with higher percentage of cattle in a herd characteristic of these regions. A cluster of low mortality associated with high previous-year mortality was found at the hot-spot of dzud 2000, which indicated that herders migrated away from the zone affected by dzud 2000 to the neighboring counties located in Khentii mountains and counties to the east of Khangai range. The observed ripple effect that followed dzud 2000 makes a strong argument that migration of herders has relationship with dzud mortality.

The counties located in the semi-desert and the Gobi were separated from the rest of the country based on the characteristic lower number of horses, higher number of sheep and lower NDVI. In the Gobi the mortality was negatively associated with previous-year mortality, which indicates migration of herders to less affected areas in response to dzud 2000; in the semi-desert, higher NDVI and larger horse population was associated with higher mortality.

2002

In 2002, the areas affected by dzud were limited to the Gobi and western Mongolia; therefore, the partitioning first isolated those ecoregions from the rest of the country (Fig. E3). The partitioning of the right branch demonstrates that top-level splits exploit properties of the ecological regions rather causative relationships to isolate the region of impact. The highest losses were observed at the innermost end of Altai-Sayan range, southern end of Khangai mountains, and parts of the Great Lake Depression and were associated with low temperature.

Middle-level mortality was observed in the Great Lake Depression and the eastern end of the Gobi desert. Both regions have smaller population of goats and low NDVI. The contributing factors in the Depression area included deeper snow cover, low temperatures, higher number of cattle (or yaks) and higher elevation, while the region of low mortality located in the eastern Gobi was segregated based properties of the region including shallow snow, small population of cattle and low elevation. A cluster of high mortality located at the western end of Altai-Sayan mountains was associated with high elevation.

2003

In 2003 high mortality was observed in Transbaikal region and eastern part of the Gobi desert (Fig. F3). In the north, the mortality was associated with deep snow, high livestock density and a range of low temperatures. Usually higher mortality is endemic to mountainous regions, but in 2003, dzud was associated with lower elevation, which indicates that the elevation variable was a surrogate for a

missing variable. The mortality in the Gobi cluster was associated negatively with very low snow precipitation, which indicates the presence of black dzud. The herd composition and NDVI variables that appeared in the partitioning of the Gobi desert were suspected to carry little explanatory information but highlighted properties of this ecoregion.

2004

The 2004 results indicated that low mortality was the effect of the preceding years of dzud. While higher previous-year mortality associated positively with dzud mortality, areas that routinely witness higher dzud mortality were delineated based on percent cattle variable in the absence of extreme climatic conditions (Fig. G3).

Summary of Spatial Analysis

It is evident that some regions in Mongolia were more susceptible to dzud due to their geographic locations. Khangai and Khuvsgul mountain ranges and to a lesser degree Transbaikalian region and Khentii mountains repeatedly experienced white dzud due to their locations on the path of Siberian anti-cyclone, which brings heavy snow precipitation and cold temperatures. In addition, good vegetation conditions, transportation infrastructure and proximity to economic markets make these regions attractive for settlement and livestock rearing as reflected by livestock density numbers. The expanding hot-spot of high mortality covering parts of Ovorkhangai and Bayankhongor provinces is likely shaped by anthropogenic influences due to a favorable economic location and close proximity to three urban centers: Bayankhongor, Arvakheer, and Tsetserleg. Dzud mortality is less intense in the desert and semi-desert regions west of Khangai, and the dynamics between the main drivers of dzud, snow cover and temperature are different. It is most apparent in the desert where very shallow snow cover and low temperatures create black dzud conditions. It is very likely that these ecoregions are also susceptible to iron dzud due to high solar irradiance and a large amplitude of diurnal temperature but the study cannot directly distinguish iron dzud based on the temporal and spatial scales of the analysis.

The results of partitioning suggest that the source of misspecification and low efficiency of regression models lies in regional heterogeneity of dzud dynamics across Mongolia. Livestock profiles and climatic processes in the desert and semi-desert are so distinct from other ecoregions that they create its own unique dzud dynamics. These differences call either for normalization of explanatory variables to smooth regional variation or a separate analysis of those regions. The design of the study failed to accommodate regional variation, and partitioning suggests that a spatial and temporal unit of analysis maybe too large for the desert and semi-desert. Taking into account that livestock distribution is highly localized in response to vegetation conditions and available water resources, a spatial unit of a soum results in smoothed variability within variables due to aggregation. The presence of large national parks and protected areas in the Gobi that are predominantly off limits to livestock grazing also adds inaccuracy to the analysis of mortality by soum. In addition, infrequent and sporadic precipitation events in the desert determine the amount of vegetation and water available for grazers. Annually aggregated variables do not adequately represent temporal fluctuation in availability of food resources for livestock suggesting that finer temporal scale would help better resolve causative associations.

Finally, the analysis indicates that some variable describing a long-distance migration of herders in response to dzud might be a very important predictor to include into a future model. High previous-year mortality usually has a lingering effect on the present-year mortality, because livestock physical condition was undermined from surviving the previous winter. However, in 2001 many locations observed the opposite effect: counties that suffered from dzud of 2000, did not experienced dzud in 2001. Especially distinct are two clusters of low mortality in Dundgovi and Ovorkhangai provinces (Fig. E3). The spatial pattern may reflect the movement of herders escaping from dzud-affected counties in 2000. In the Gobi desert, herder migration to neighboring counties in response to the previous-year dzud also negatively affected livestock mortality in 2001. The spatial distribution of dzud in 2002 suggests that herders who lived along the northwest-southeast axis of severe dzud impact in 2000 and 2001 may have migrated southwest into less affected areas of the Gobi and the western provinces, which may have exacerbated conditions that created the dzud of 2002. It is evident that in the event of a multi-annual dzud, herders mobility as a strategy of risk management plays a prominent role and has a clear spatial footprint.

Temporal Evolution of Dzud Impact

Dzud is often called an evolving disaster to highlight the delayed response of livestock mortality to contributing factors. The analysis shows that the contributing factors evolve on several temporal scales. The finest temporal scale represents intra-seasonal variations in precipitation and temperature that determine the type of dzud and the abrupt mortality increases in response to storm events as compared to gradual wasting of livestock. This temporal scale cannot be resolved because the unit of the analysis is annual livestock counts.

The second temporal scale is inter-annual. The dzud episode of 2000-2003 has demonstrated that previous year dzud helps predict the outcome of the following year dzud. It is reflected in selective modification of herd composition and sub-optimal physical condition of livestock. The annual temporal scale of dzud becomes particularly important when herders experience two or more consecutive dzuds in a row. It is not absolutely known how often such a series of dzud has occurred historically outside of the recent multi-year dzud spell of 2000 – 2003. However, it has been said that this spell was unprecedented in history of Mongolia (Mongolia 2001) so this raises the question of whether this could be a new characteristics of a dzud phenomenon acquired after decentralization of livestock sector. The 2001 model demonstrated that previous-year mortality can have a negative association with livestock mortality if a significant movement of herders happened as a result of adaptation or policy and relief measures taken to mitigate the impact. The ripple effect of spreading dzud is most notable in the Central Mongolian region, which suggests that such effect most likely occurs in the areas of high density of herders and livestock. Such effect is also observed in the desert region where the scarcity of good grazing lands and dzud forces herders to move at greater distances than in steppes and forested areas. Migration of herders to locations of high density of livestock may perpetuate multi-annual dzud events that cause enormous damages to the Mongolian society and certainly deserves a separate study.

Finally, dramatic political and socio-economic changes that took place in the country since 1991 have modified the vulnerability of the Mongolian livestock sector to dzud at large (Bedunah and Schmidt

2004). The time series of the analysis spans a decade between 1993 and 2003. The comparison of dzud events of 1993 and 2000 offers an opportunity to evaluate how changes in political and economic spheres altered vulnerability of the rural society to natural disasters as reflected in livestock mortality.

The change from collective livestock management to private ownership reflects in altered contribution of environmental and anthropogenic factors to stock mortality induced by natural hazards. The model of 2000 was dominated by factors related to vegetation conditions, livestock density and herd composition while dzud of 1993 was almost entirely driven by winter weather conditions (Fig. A3). The model of 1993 has low explanatory power while later dzud episodes were modeled more successfully with the selected variables. Taking into account that livestock privatization happened in 1992 – 1993 while the State Emergency Fund was still in operation, the low explanatory power of factors in 1993 could be due to the model lacking any information on disaster preparedness of herders. By 2000, the State run preparedness program had ceased to exist and the variables of the analysis better represent the driving factors of dzud.

Comparing descriptive statistics of variables for 1993 and 2000, we saw that winter 2000 had milder conditions, low NDVI and a dramatically different distribution of livestock density. Maps of the two partition trees showed that white dzud in 1993 had a very different spatial footprint than drought in 2000. The regions most impacted in 1993 were Khangai – Khuvsgul mountain ranges and the areas of Transbaikal region in the north, which by virtue of its geographic location and topography can develop the most challenging winter conditions for livestock survival. The spatial footprint of dzud in 2000 was organized along the northwest-southeast diagonal axis, of which Central Mongolia witnessed the highest mortality. It was associated with low NDVI, herd composition and high livestock density. Because Central Mongolia has witnessed influx of herders since privatization period, the livestock density may have aggravated the existing environmental conditions resulting in increased vulnerability of herders to dzud. Similarity of NDVI values in 1993 and 2000 suggests that the effect of low NDVI could have been less dramatic had the density of livestock remained the same.

Conclusion

The insights gained through this study reveal several characteristics of dzud phenomenon that improve our understanding and ability to model, predict and mitigate this natural disaster. The processes that govern dzud dynamics are non-stationary and vary in space due to ecological heterogeneity of the Mongolian landscape. The spatial analysis showed that higher losses are observed during white dzud, which is endemic to mountainous and northern regions, and low intensity but high frequency black dzud events occur in the Gobi and semi-desert regions. The driving factors that frequently show strong association with livestock mortality are vegetation cover, snow water equivalent, temperature, livestock density, and previous-year mortality. Inclusion of herd composition variables, except for the percent horse, did not add explanatory power to the model but rather detracted from its efficiency. An additional factor describing herder mobility should be incorporated into future models. Finally, on the decadal time scale, the analysis shows that the vulnerability of the Mongolian herders to dzud has increased and the contribution of different factors to dzud mortality has changed.

The design of the study inherently had several weaknesses related mainly to coarse temporal and spatial resolution of the analysis due to unavailable ground data. Field measurements at weather stations would be necessary to derive variables such as a drought index or indices of anomalous temperature and precipitation. Some meteorological data were available from the U. S. National Climatic Data Center (NCDC) site, but their spatial coverage over Mongolia is sparse and temporal coverage inconsistent. Because reliable weather data were not available at the time of the study, information on grassland productivity and snow amounts relies exclusively on remote sensing datasets, in the form of the normalized difference vegetation index (NDVI) and estimates of snow water equivalents (SWE), respectively. This approach inherits several disadvantages such as loss of information due to coarse spatial and temporal resolutions and future studies should develop variables based on ground observations of weather data augmented by remote sensing products.

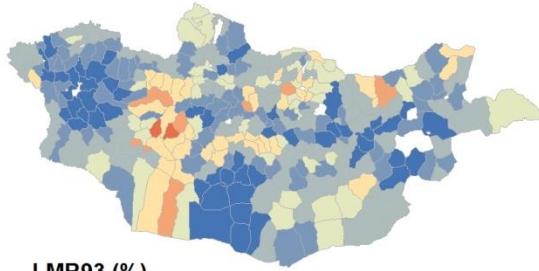
Based on the results of the study, several improvements could be introduced into future modeling studies. It seems reasonable to assume that equilibrium and non-equilibrium ecosystems within Mongolia have different dzud dynamics (Begzsuren, Ellis et al. 2004; Sternberg, Middleton et al. 2009). Models that incorporate both types of ecosystems into a single framework at the same spatial and temporal resolution have low efficiency and prone to misspecification. Normalization of explanatory variables against their long-term running average would make comparable such distinct ecosystem as the Gobi desert and forest-steppe and would improve the efficiency of modeling. The approach with different temporal and/or spatial scales should be also explored further.

The non-linear and interactive relationships between snow depth and temperature could be better accommodated by a snow-temperature index. A simple interaction term of snow water equivalent and temperature in a multiplicative form was tested in GWR 1993 model and significantly improved explanatory power of the model, which indicates that indexation of snow and temperature should be explored in further research. A variable describing migration of herders also should be developed and included into a future predictive dzud model. An attempt to introduce such a variable based on annual increase and decrease of number of herder households in counties was tested on 2000-2003 datasets and replaced the negative associations between previous-year mortality and livestock mortality variables. The human population variable could be also used as a proxy for herder migration.

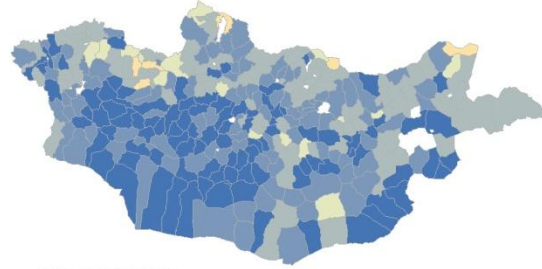
The findings of the study provide valuable insights into a mechanism of dzud development which have far reaching implications for the national disaster management authorities, international development and disaster relief agencies. In order to develop effective mitigation policies, it is essential to understand factors that cause dzud and contribute to vulnerability of rural population. Contribution of herders migration in response to dzud should be better understood so that the advantage of their mobility is capitalized rather than become a maladaptation in a new system of decentralized livestock management.

Appendices

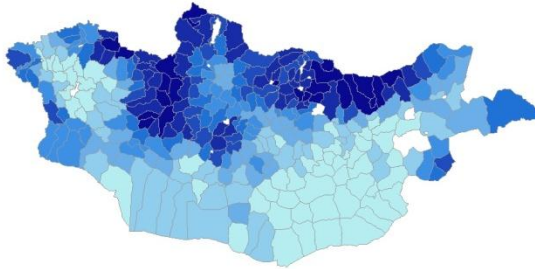
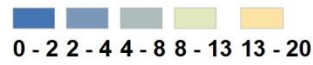
Appendix A



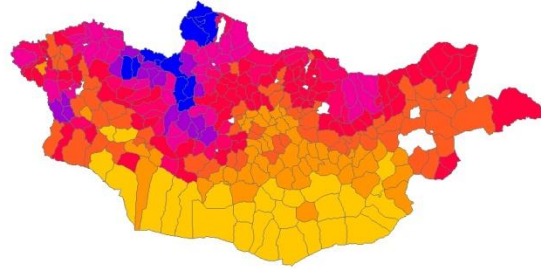
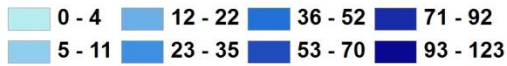
LMR93 (%)



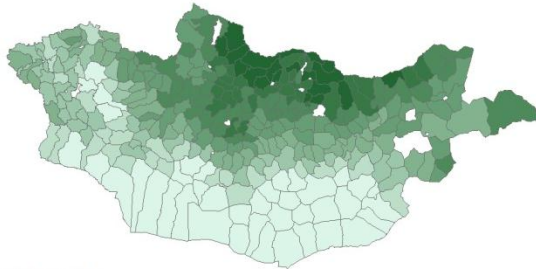
PRLMR92 (%)



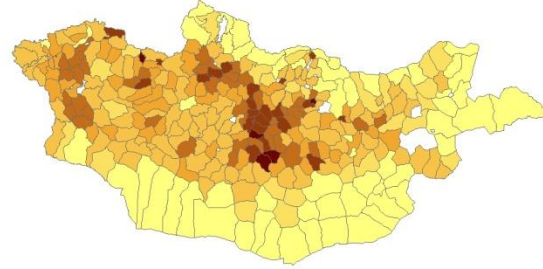
SASWE93 (mm)



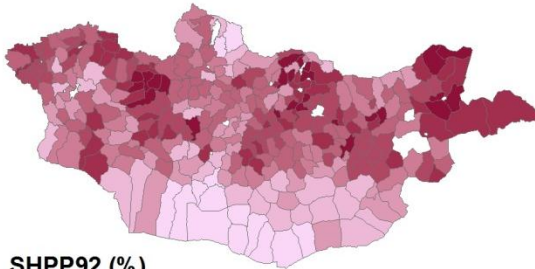
SATMP93 (°C)



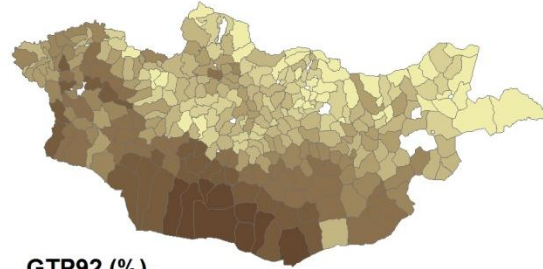
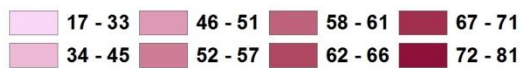
SINDVI92



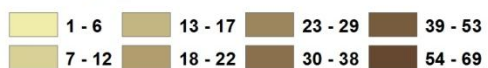
LD92 (animals/km2)



SHPP92 (%)



GTP92 (%)



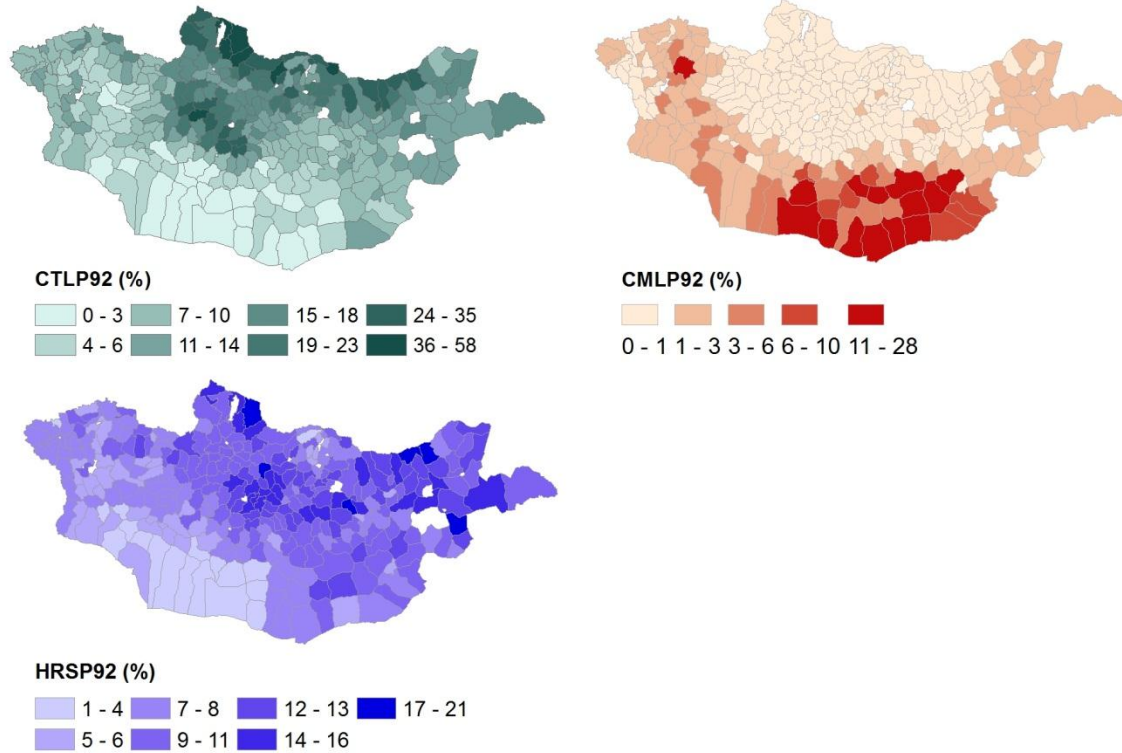


Figure A1: Spatial distribution of variables in 1993.

Table A1: 1993 OLS regression output.

REGRESSION

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **soum_stats93nonull**

Dependent Variable : **LMRLG93**

Mean dependent var : 1.50272

S.D. dependent var : 0.981688

Number of Observations: 308

Number of Variables : 3

Degrees of Freedom : 305

R-squared : 0.221152

Adjusted R-squared : 0.216045

Sum squared residual: 231.18

Sigma-square : 0.757967

S.E. of regression : 0.870613

Sigma-square ML : 0.750584

S.E of regression ML: 0.866363

F-statistic : 43.302

Prob(F-statistic) :2.79603e-017

Log likelihood : -392.85

Akaike info criterion : 791.7

Schwarz criterion : 802.89

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	1.877133	0.2514453	7.465372	0.0000000
SATMP93	0.04168294	0.01196027	3.485116	0.0005641
SASWE93	0.01638065	0.001812101	9.039592	0.0000000

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 12.52473

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	20.12729	0.0000426

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	2	5.258427	0.0721352
Koenker-Bassett test	2	3.971815	0.1372561

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	5	9.937084	0.0770377

DIAGNOSTICS FOR SPATIAL DEPENDENCE

FOR WEIGHT MATRIX : **queen1.GAL** (row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.323892	9.5045257	0.0000000
Lagrange Multiplier (lag)	1	84.5782192	0.0000000
Robust LM (lag)	1	2.4227551	0.1195845
Lagrange Multiplier (error)	1	82.8795486	0.0000000
Robust LM (error)	1	0.7240845	0.3948074
Lagrange Multiplier (SARMA)	2	85.3023037	0.0000000

===== END OF REPORT =====

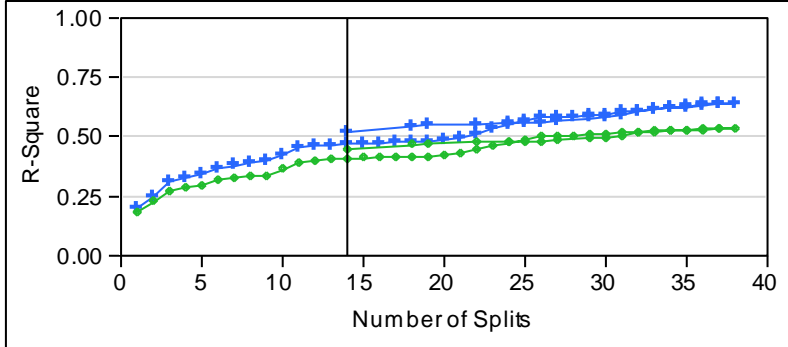
Table A2: 1993 GWR model report.

VARNAME	VARIABLE	DEFINITION
Bandwidth	343910,96881300000	
ResidualSquares	202,58677007000	
EffectiveNumber	18,55687633290	
Sigma	0,83661167701	
AICc	775,45797690200	
R2	0,31748254403	
R2Adjusted	0,27608278847	
Moran's Index	0.24335	
Z Score	7.002551	
p-value	0.00000	
Dependent Field	0,00000000000	LMRLG93
Explanatory Field	1,00000000000	SATMP93
Explanatory Field	2,00000000000	SASWE93

Crossvalidation

k-fold		SSE	RSquare
10	Folded	5868.82022	0.4448
	Overall	5078.4067	0.5196

Split History



K-Fold in Green

Figure A2: 1993 Cross-validation results.

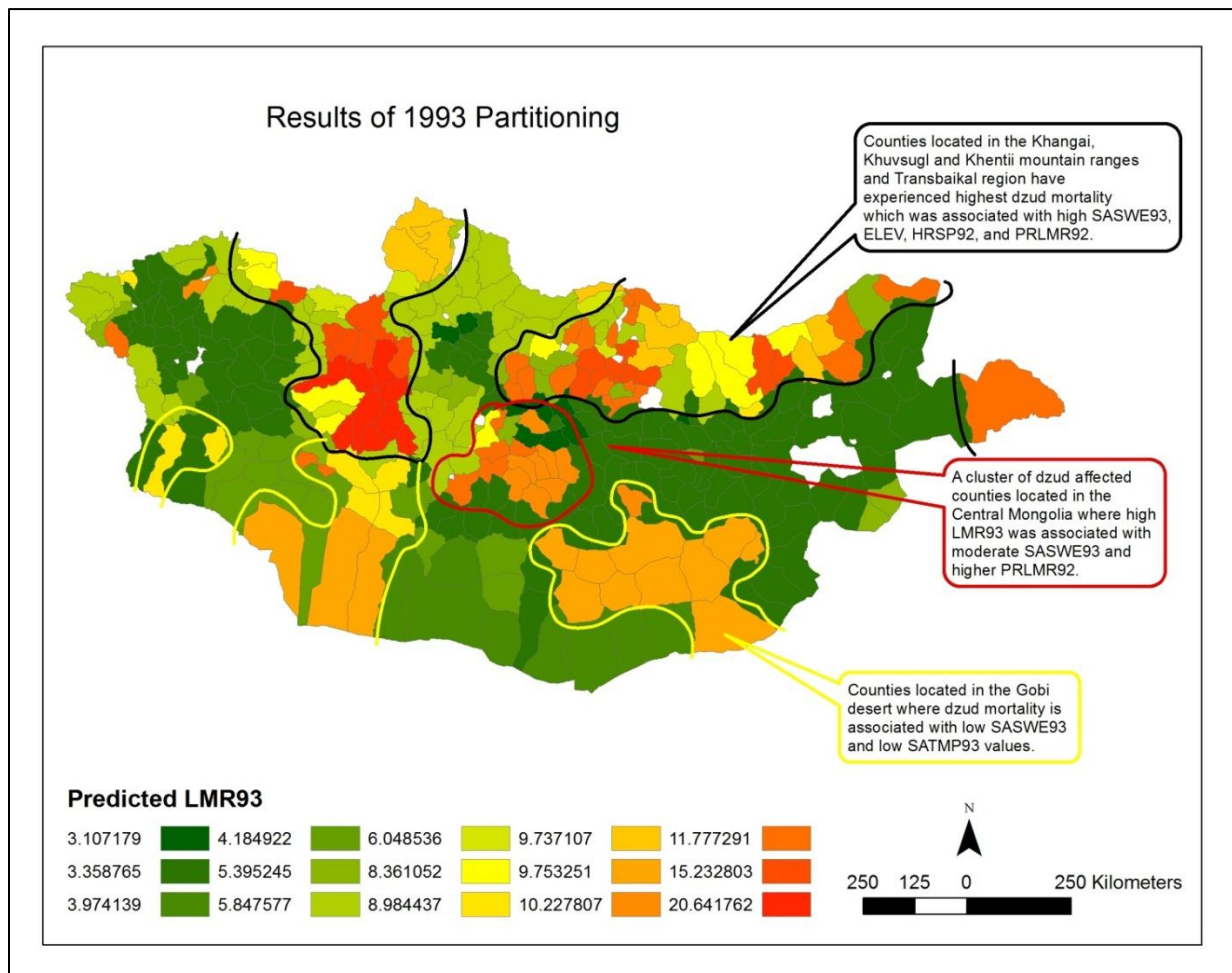
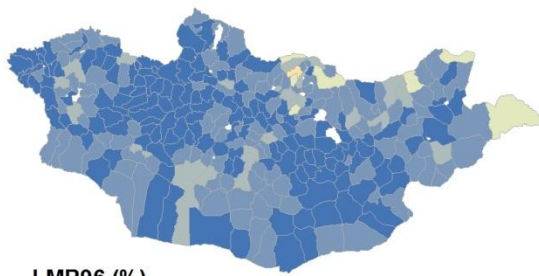
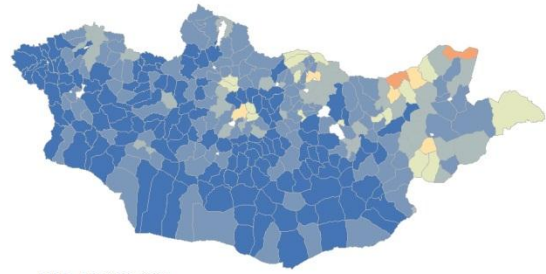
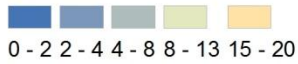


Figure A3: Map of 1993 Regression Tree.

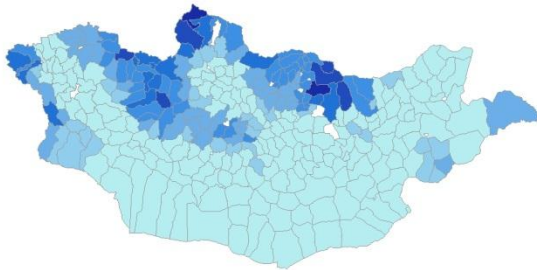
Appendix B



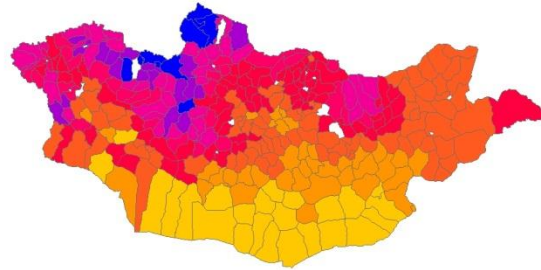
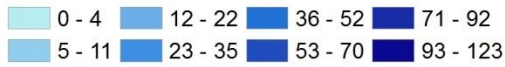
LMR96 (%)



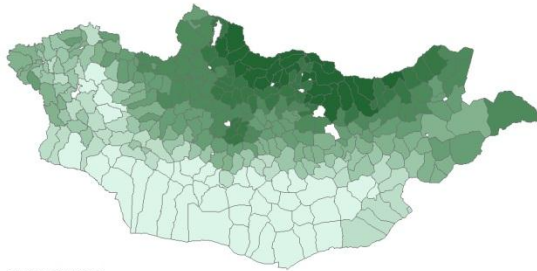
PRLMR96 (%)



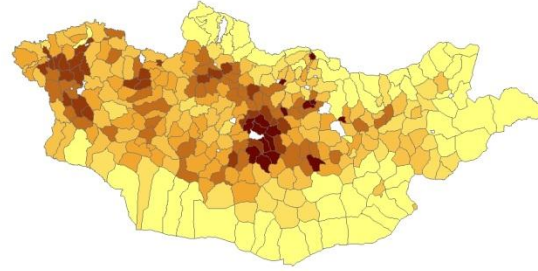
SASWE96 (mm)



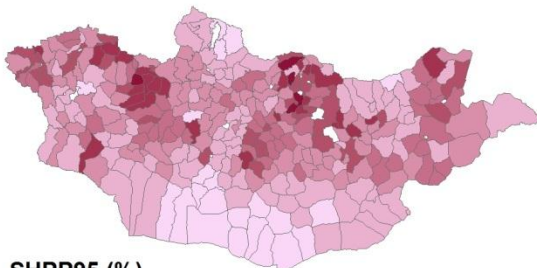
SATMP96 (°C)



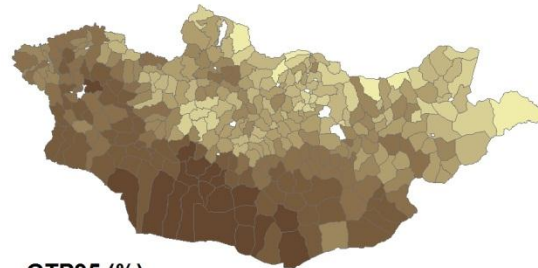
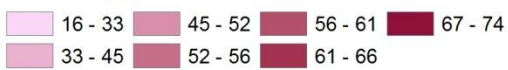
SINDVI95



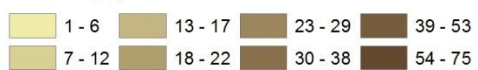
LD95 (animals/km2)



SHPP95 (%)



GTP95 (%)



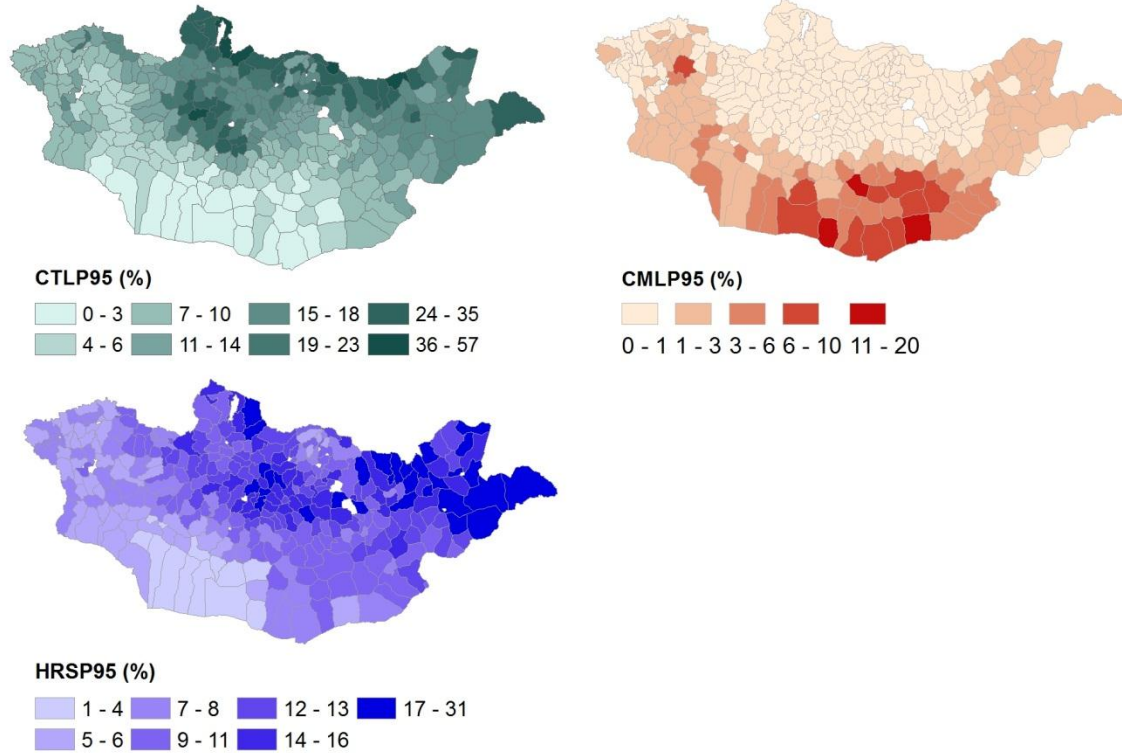


Figure B1: Spatial distribution of variables in 1996.

Table B1: 1996 OLS regression output.

REGRESSION

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : soum_stats96nonull

Dependent Variable : LMRLG96

Mean dependent var : 0.445653

S.D. dependent var : 0.877953

Number of Observations: 314

Number of Variables : 6

Degrees of Freedom : 308

R-squared : 0.181072

Adjusted R-squared : 0.167778

Sum squared residual: 198.207

Sigma-square : 0.643528

S.E. of regression : 0.802202

Sigma-square ML : 0.631232

S.E of regression ML: 0.794501

F-statistic : 13.6203

Prob(F-statistic) :5.10977e-012

Log likelihood : -373.314

Akaike info criterion : 758.627

Schwarz criterion : 781.124

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	1.036109	0.2775415	3.733168	0.0002252
SINDVI95	0.1023565	0.04532558	2.25825	0.0246297

ELEV	-0.0006124307	0.0001050841	-5.828003	0.0000000
CMLP95	0.8793209	0.2532806	3.471726	0.0005911
CTLP95	0.03099095	0.009013702	3.438205	0.0006662
HRSP95	-0.05546745	0.015027	-3.691186	0.0002639

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 16.30604

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	5.784518	0.0554508

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	5	4.125475	0.5314959
Koenker-Bassett test	5	3.856859	0.5702034

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	20	24.25621	0.2313794

DIAGNOSTICS FOR SPATIAL DEPENDENCE

FOR WEIGHT MATRIX : **queen1.GAL** (row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.175393	5.412383	0.0000000
Lagrange Multiplier (lag)	1	25.0698663	0.0000006
Robust LM (lag)	1	0.5987924	0.4390392
Lagrange Multiplier (error)	1	24.8311453	0.0000006
Robust LM (error)	1	0.3600714	0.5484666
Lagrange Multiplier (SARMA)	2	25.4299377	0.0000030

Table B2: 1996 GWR regression report.

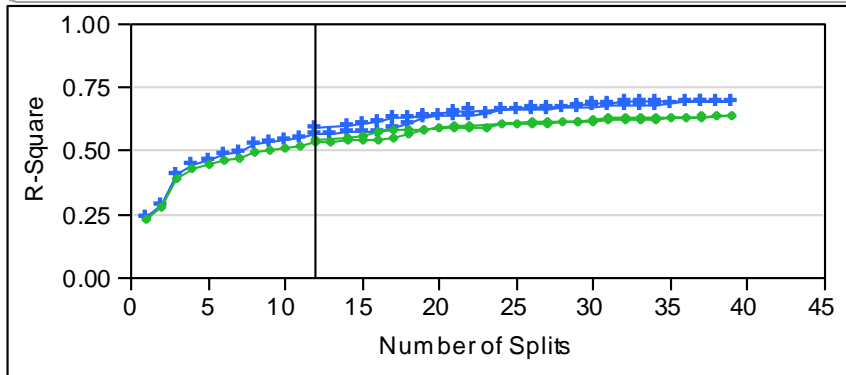
VARNAME	VARIABLE	DEFINITION
Neighbors	182,000000000000	
ResidualSquares	166,79458840100	
EffectiveNumber	23,19530261780	
Sigma	0,75733890829	
AICc	733,38907425500	
R2	0,31085695392	
R2Adjusted	0,25825897806	
Moran's I	0.186464	
Z-score	5.412383	
p-value	0.000000	
Dependent Field	0,000000000000	LMRLG96
Explanatory Field	1,000000000000	SINDVI95
Explanatory Field	2,000000000000	ELEV

Explanatory Field	3,00000000000	CMLP95
Explanatory Field	4,00000000000	CTLP95
Explanatory Field	5,00000000000	HRSP95

Crossvalidation

k-fold		SSE	RSquare
10	Folded	559.728737	0.5443
	Overall	503.189358	0.5903

Split History



K-Fold in Green

Figure B2: 1996 Cross-validation results.

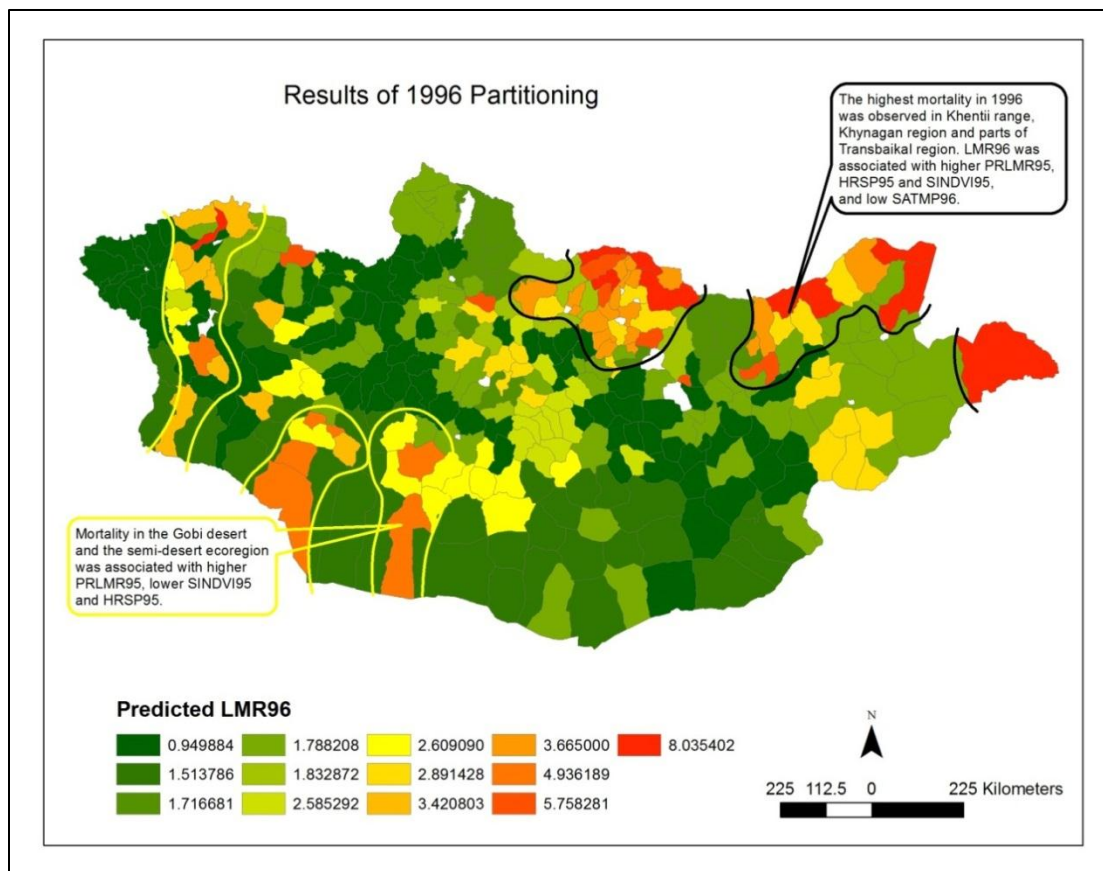
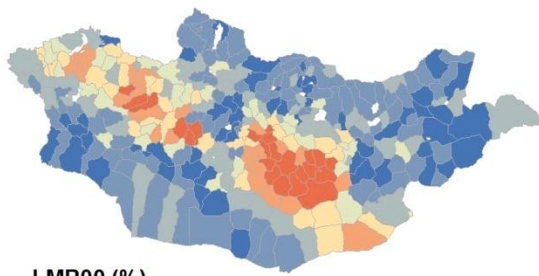
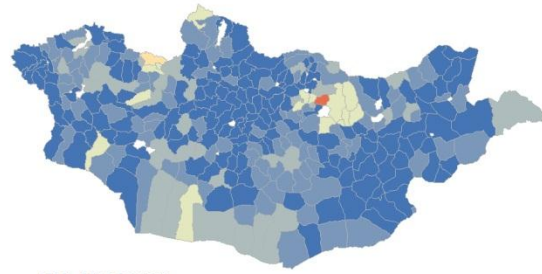
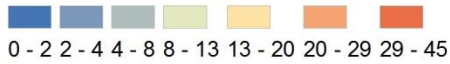


Figure B3: Map of 1996 Regression Tree.

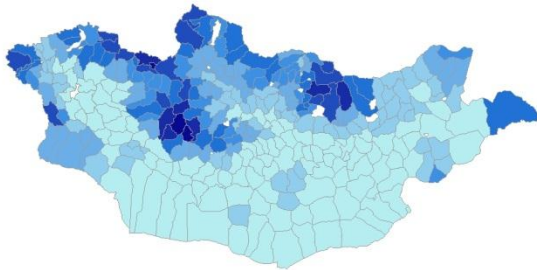
Appendix C



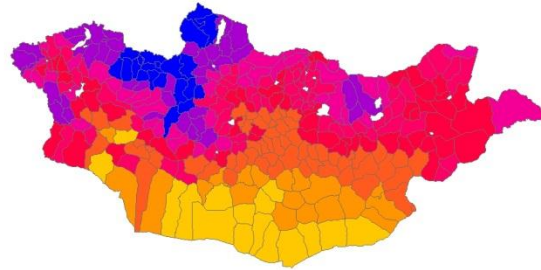
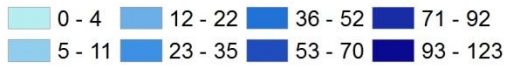
LMR00 (%)



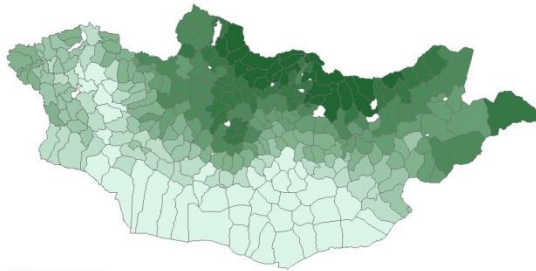
PRLMR99 (%)



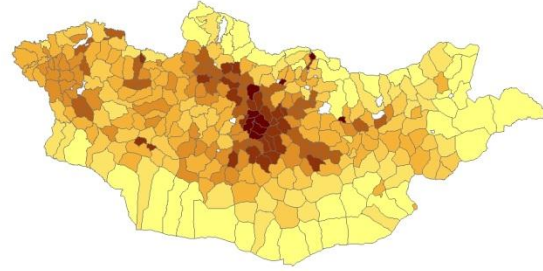
SASWE00 (mm)



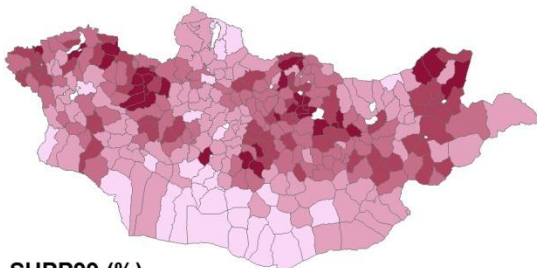
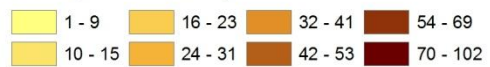
SATMP00 (°C)



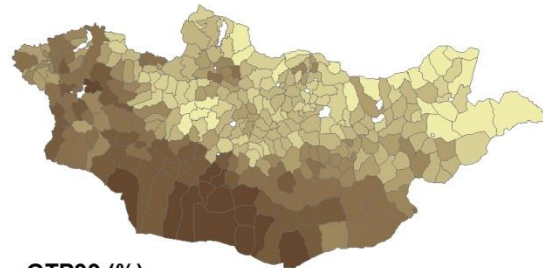
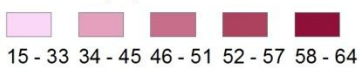
SINDVI99



LD99 (animals/km2)



SHPP99 (%)



GTP99 (%)



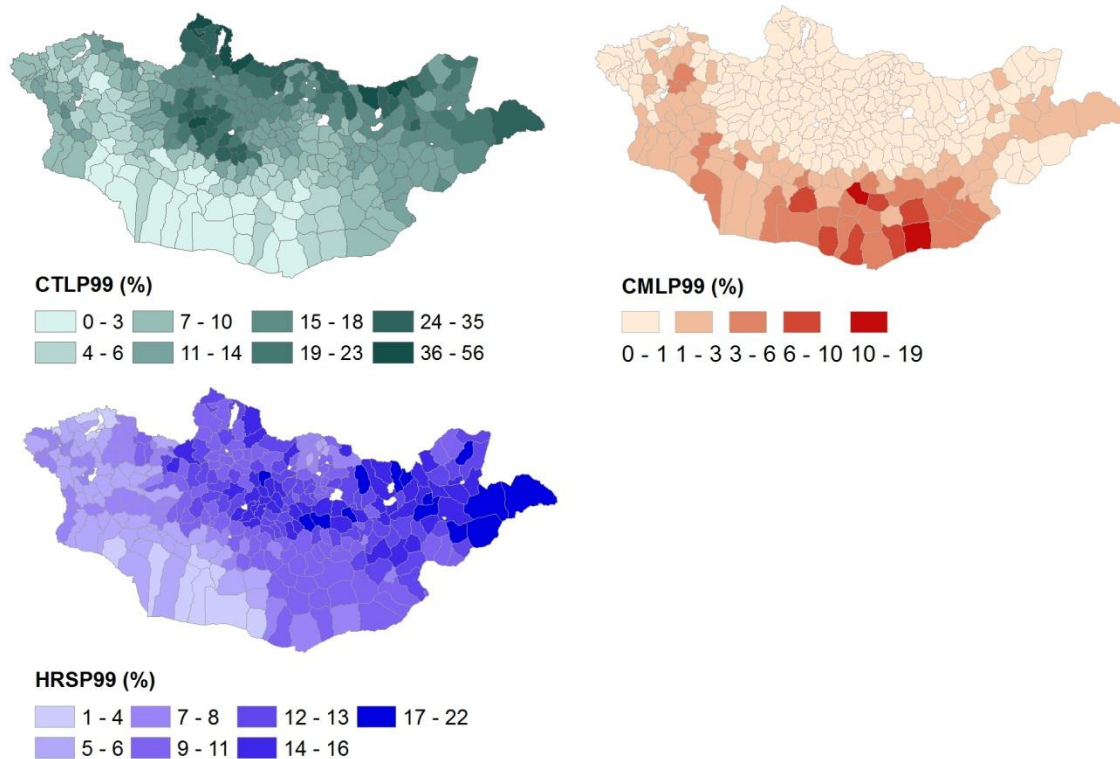


Figure C1: Spatial distribution of 2000 variables.

Table C1: 2000 OLS regression output.

REGRESSION

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **soum_stats00nonull**
 Dependent Variable : **LMRLG00** Number of Observations: 312
 Mean dependent var : 1.59308 Number of Variables : 6
 S.D. dependent var : 1.16166 Degrees of Freedom : 306

R-squared : 0.365411 F-statistic : 35.2404
 Adjusted R-squared : 0.355042 Prob(F-statistic) : 1.9568e-028
 Sum squared residual: 267.179 Log likelihood : -418.516
 Sigma-square : 0.873135 Akaike info criterion : 849.032
 S.E. of regression : 0.934417 Schwarz criterion : 871.49
 Sigma-square ML : 0.856343
 S.E of regression ML: 0.925388

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	2.610826	0.4613509	5.65909	0.0000000
SINDIV99	-0.4952751	0.0446629	-11.08918	0.0000000

SASWE00	0.01650755	0.003085461	5.350109	0.0000002
LD99	0.02408573	0.003026766	7.957581	0.0000000
HRSP99	0.0493197	0.02071758	2.380572	0.0178976
GTP99	-0.02921747	0.007110266	-4.109196	0.0000510

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 22.24812

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	11.48047	0.0032140

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	5	4.007609	0.5483210
Koenker-Bassett test	5	5.073807	0.4069393

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	20	25.23912	0.1924355

DIAGNOSTICS FOR SPATIAL DEPENDENCE

FOR WEIGHT MATRIX : **queen1.GAL** (row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.389282	11.7330272	0.0000000
Lagrange Multiplier (lag)	1	158.0879564	0.0000000
Robust LM (lag)	1	37.0890295	0.0000000
Lagrange Multiplier (error)	1	121.1303034	0.0000000
Robust LM (error)	1	0.1313766	0.7170090
Lagrange Multiplier (SARMA)	2	158.2193329	0.0000000

Table C2: 2000 SAR regression output.

REGRESSION

SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION

Data set : **soum_stats00nonull**
 Spatial Weight : **queen1.GAL**
 Dependent Variable : **LMRLG00** Number of Observations: 312
 Mean dependent var : 1.59308 Number of Variables : 7
 S.D. dependent var : 1.16166 Degrees of Freedom : 305
 Lag coeff. (Rho) : 0.70853

R-squared : 0.647298 Log likelihood : -346.461
 Sq. Correlation : - Akaike info criterion : 706.922
 Sigma-square : 0.475952 Schwarz criterion : 733.123
 S.E of regression : 0.689893

Variable	Coefficient	Std.Error	z-value	Probability
----------	-------------	-----------	---------	-------------

W_LMRLG00	0.7085297	0.04537617	15.61458	0.0000000
CONSTANT	0.9635848	0.357362	2.696383	0.0070098
HRSP99	0.02087948	0.01543566	1.352678	0.1761587
GTP99	-0.01391931	0.005327085	-2.612932	0.0089770
LD99	0.00748316	0.002330431	3.211062	0.0013226
SASWE00	0.006438602	0.002341131	2.75021	0.0059558
SINDVI99	-0.1898349	0.03758602	-5.050678	0.0000004

REGRESSION DIAGNOSTICS

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	5	2.972793	0.7041806

DIAGNOSTICS FOR SPATIAL DEPENDENCE

SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : queen1.GAL

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	144.11	0.0000000

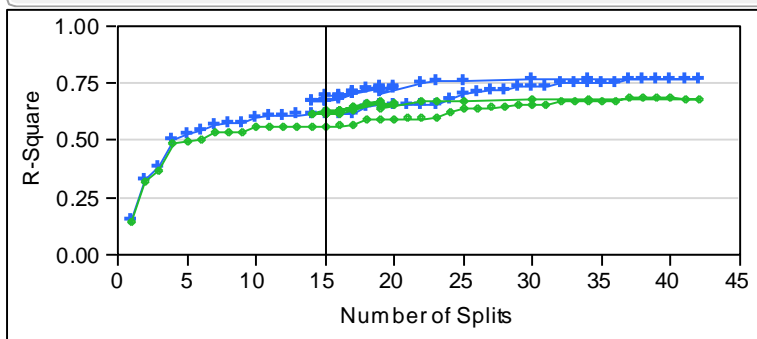
REGRESSION DIAGNOSTICS OF MODEL PERFORMANCE

W > LR > LM ≠ 243.36 > 144.11 > 158.08

Crossvalidation

k-fold		SSE	RSquare
10	Folded	12179.9538	0.6316
	Overall	10101.6566	0.6945

Split History



K-Fold in Green

Figure C2: 2000 Cross-validation results.

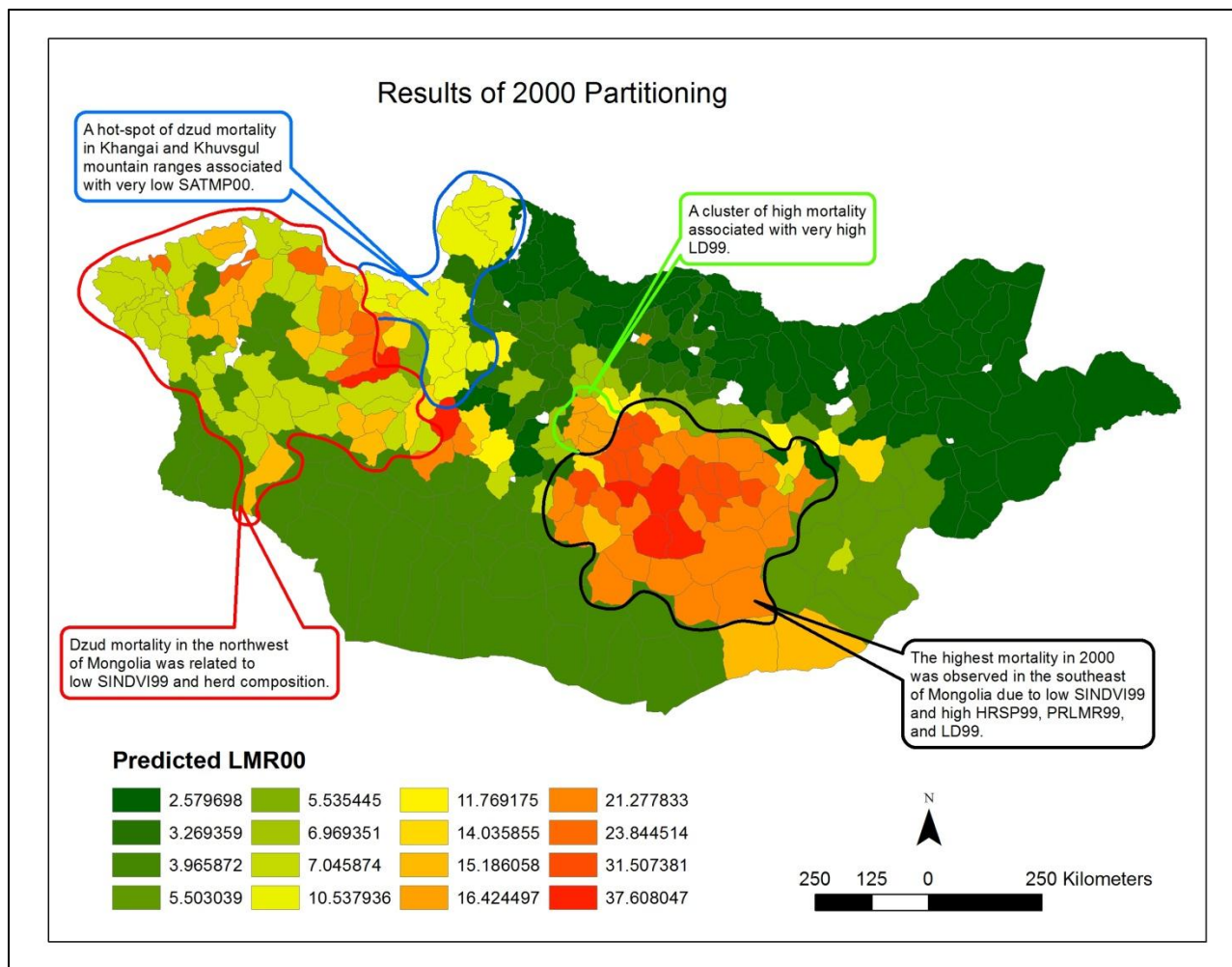
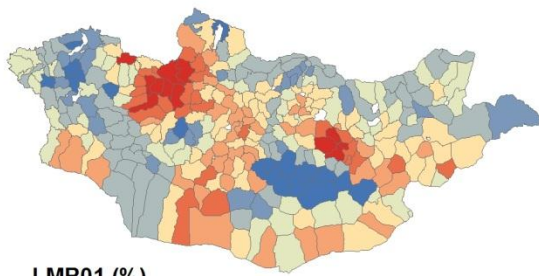
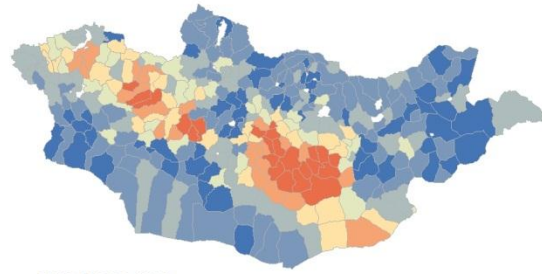


Figure C3: Map of 2000 Regression Tree.

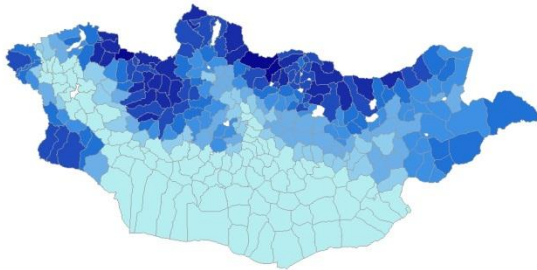
Appendix D



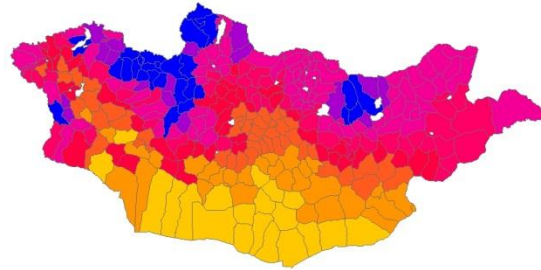
LMR01 (%)



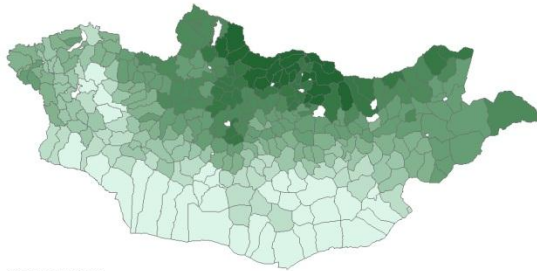
PRLMR00 (%)



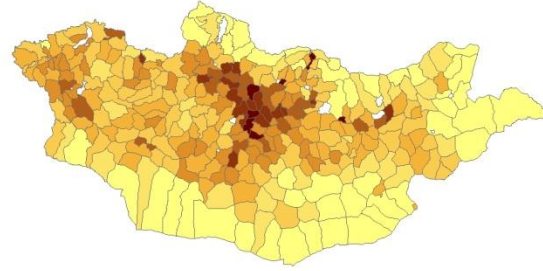
SASWE01 (mm)



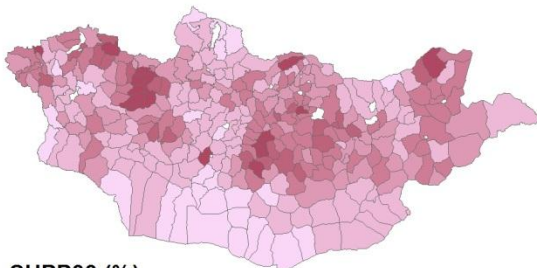
SATMP01 (°C)



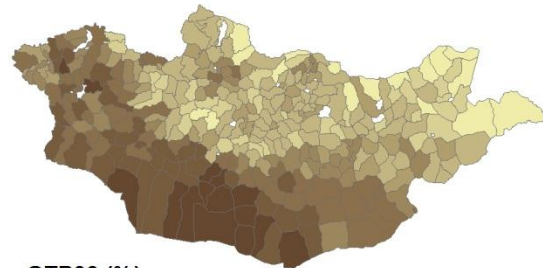
SINDVI00



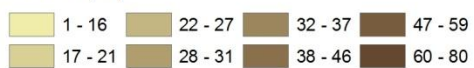
LD00 (animals/km2)



SHPP00 (%)



GTP00 (%)



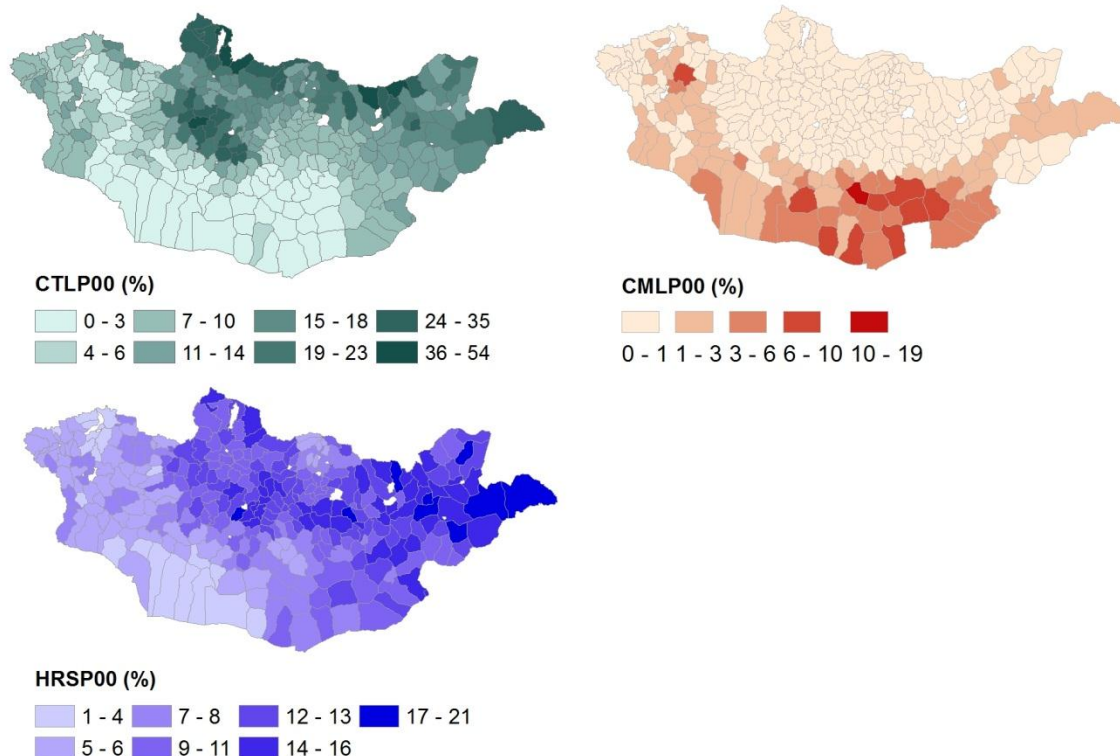


Figure D1: Spatial distribution of variables in 2001.

Table D1: 2001 OLS regression output.

REGRESSION

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **soum_stats01nonull**
 Dependent Variable : **LMRLG01** Number of Observations: 312
 Mean dependent var : 2.30081 Number of Variables : 6
 S.D. dependent var : 1.06507 Degrees of Freedom : 306

R-squared : 0.269098 F-statistic : 22.5321
 Adjusted R-squared : 0.257155 Prob(F-statistic) :3.05819e-019
 Sum squared residual: 258.686 Log likelihood : -413.476
 Sigma-square : 0.84538 Akaike info criterion : 838.953
 S.E. of regression : 0.919445 Schwarz criterion : 861.411
 Sigma-square ML : 0.829122
 S.E of regression ML: 0.910562

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	1.469122	0.2050858	7.163448	0.0000000
SASWE01	0.006592888	0.002022975	3.259007	0.0012439

ELEV	0.000503184	0.0001151315	4.370515	0.0000170
LD00	-0.0258498	0.006397874	-4.040374	0.0000676
PRLMR00	-0.03012813	0.005206715	-5.786399	0.0000000
HRSP00	0.3486239	0.05222519	6.675397	0.0000000

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 11.06256

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	44.50445	0.0000000

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	5	87.91293	0.0000000
Koenker-Bassett test	5	51.5986	0.0000000

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	20	75.23035	0.0000000

DIAGNOSTICS FOR SPATIAL DEPENDENCE

FOR WEIGHT MATRIX : **queen1.GAL** (row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.447757	13.4592541	0.0000000
Lagrange Multiplier (lag)	1	154.8145861	0.0000000
Robust LM (lag)	1	2.2328402	0.1351053
Lagrange Multiplier (error)	1	160.2543865	0.0000000
Robust LM (error)	1	7.6726406	0.0056064
Lagrange Multiplier (SARMA)	2	162.4872268	0.0000000

Table D2: 2001 SAR regression output.

REGRESSION

SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION

Data set : **soum_stats01nonull**

Spatial Weight : **queen1.GAL**

Dependent Variable : **LMRLG01**

Number of Observations: 312

Mean dependent var : 2.300813

Number of Variables : 6

S.D. dependent var : 1.065074

Degree of Freedom : 306

Lag coeff. (Lambda) : 0.755429

R-squared : 0.593334

R-squared (BUSE) :-

Sq. Correlation :-

Log likelihood : -345.177494

Sigma-square : 0.461314

Akaike info criterion : 702.355

S.E of regression : 0.679201

Schwarz criterion : 724.813007

Variable	Coefficient	Std.Error	z-value	Probability
----------	-------------	-----------	---------	-------------

CONSTANT	1.834495	0.363563	5.045879	0.0000005
HRSP00	0.268847	0.0689442	3.899487	0.0000964
LD00	-0.01989176	0.006761697	-2.941829	0.0032629
PRLMR00	-0.02004482	0.00698543	-2.869518	0.0041111
ELEV	0.0001900175	0.0001985174	0.957183	0.3384749
SASWE01	0.008960859	0.003309124	2.707925	0.0067706
LAMBDA	0.7554291	0.04339626	17.4077	0.0000000

**REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY**

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	5	121.0037	0.0000000

DIAGNOSTICS FOR SPATIAL DEPENDENCE

SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : queen1.GAL

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	136.5977	0.0000000

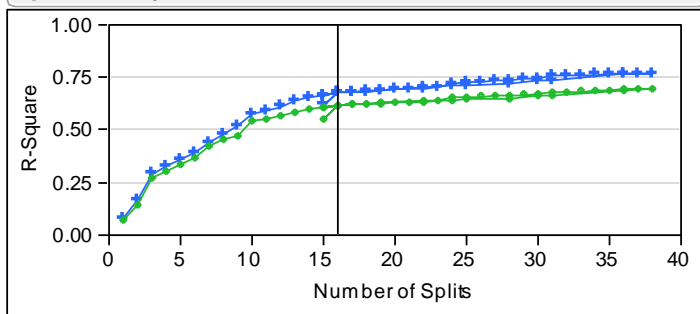
REGRESSION DIAGNOSTICS OF MODEL PERFORMANCE

W > LR > LM ≠ 286 > 136 > 160

Crossvalidation

k-fold		SSE	RSquare
10	Folded	17951.7426	0.6194
	Overall	15237.4976	0.6769

Split History



K-Fold in Green

Figure D2: 2001 Cross-validation results.

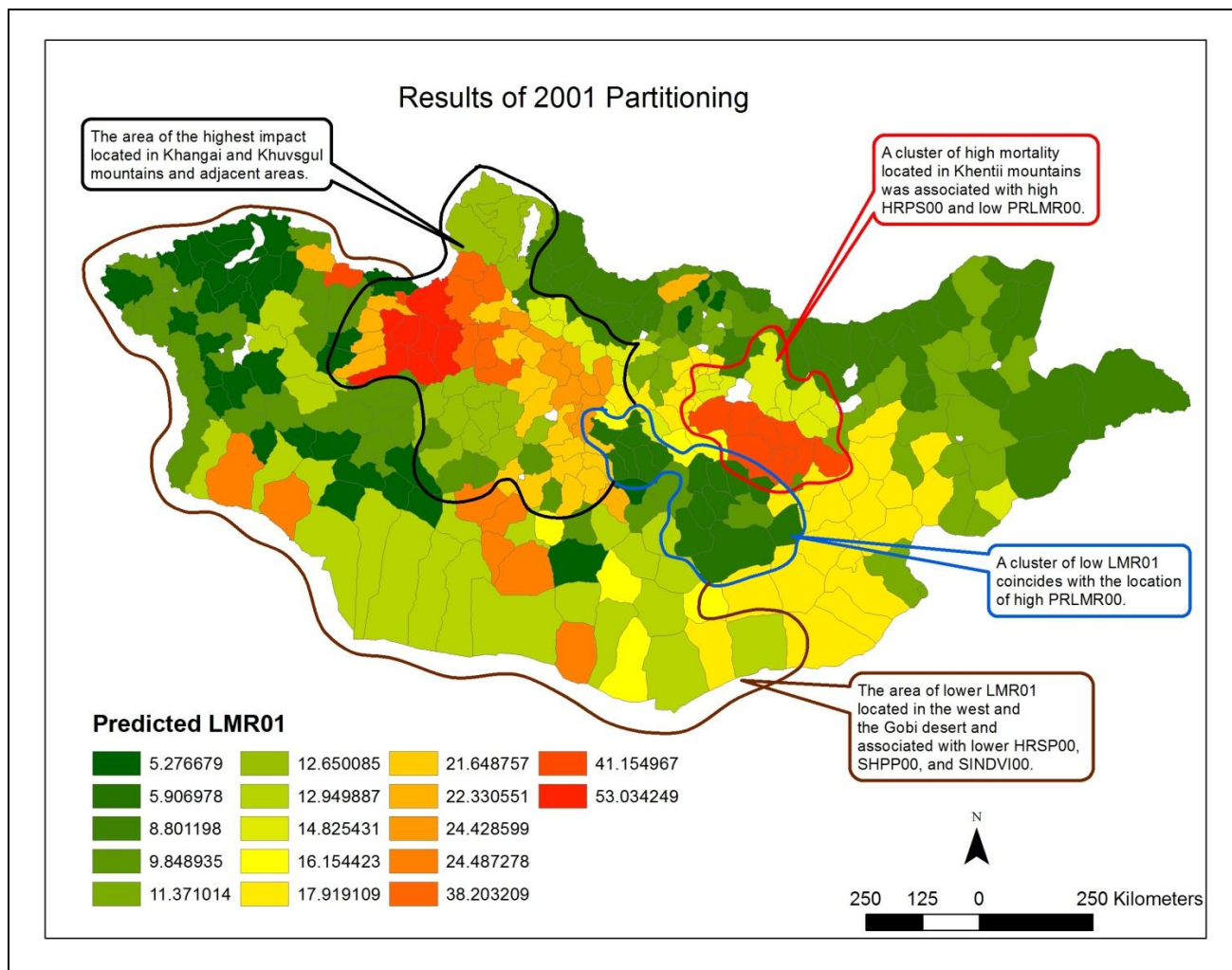
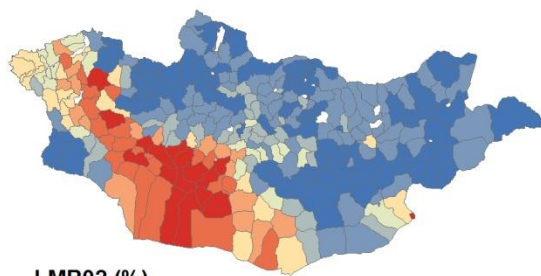
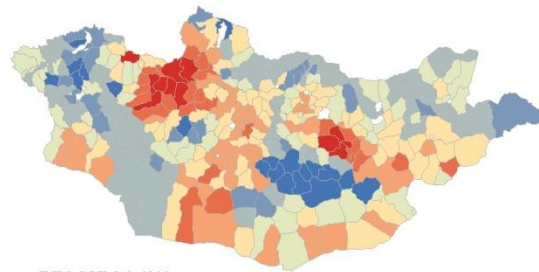


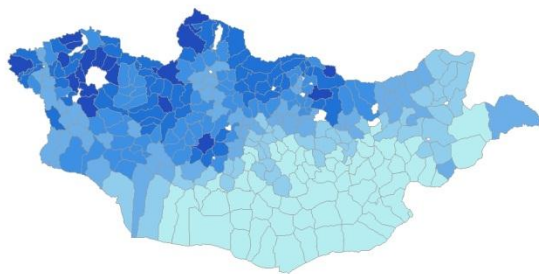
Figure D3: Map of 2001 Regression Tree.



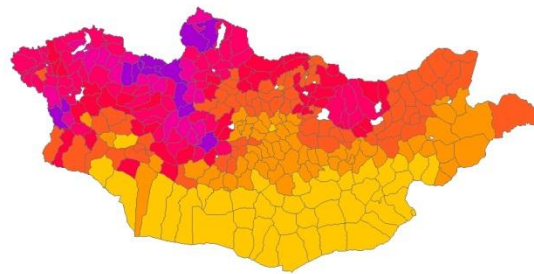
LMR02 (%)



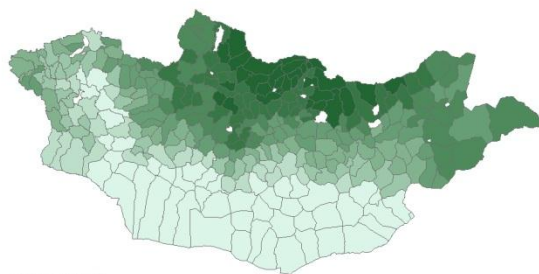
PRLMR01 (%)



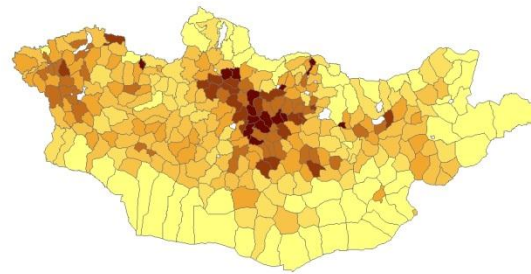
SASWE02 (mm)



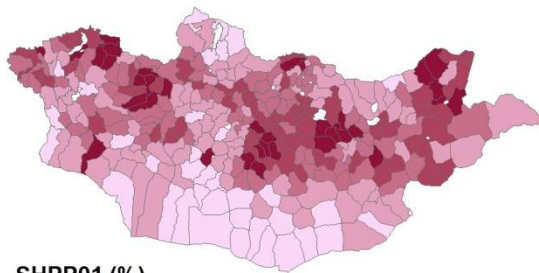
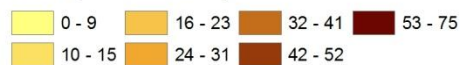
SATMP02 (°C)



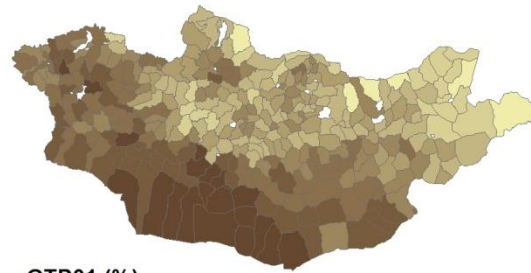
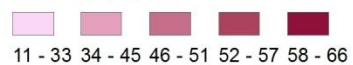
SINDVI01



LD01 (animals/km2)



SHPP01 (%)



GTP01 (%)



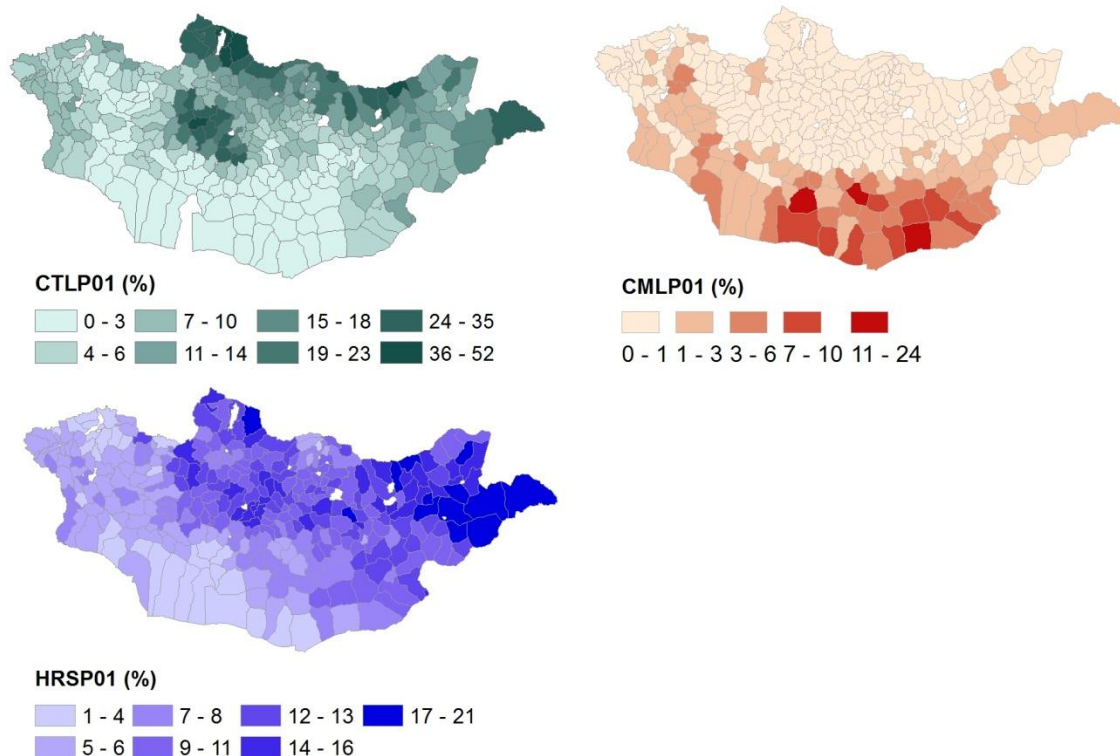


Figure E1: Spatial distribution of variables in 2002.

Table E1: 2002 OLS regression output.

REGRESSION

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **soum_stats02nonnull**
 Dependent Variable : **LMRLG02** Number of Observations: 312
 Mean dependent var : 1.24973 Number of Variables : 8
 S.D. dependent var : 1.54398 Degrees of Freedom : 304

R-squared : 0.473450 F-statistic : 39.0491
 Adjusted R-squared : 0.461326 Prob(F-statistic) :6.31433e-039
 Sum squared residual: 391.634 Log likelihood : -478.171
 Sigma-square : 1.28827 Akaike info criterion : 972.343
 S.E. of regression : 1.13502 Schwarz criterion : 1002.29
 Sigma-square ML : 1.25524
 S.E of regression ML: 1.12037

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	3.473925	0.4555143	7.626381	0.0000000
SINDVI01	-0.2813804	0.04248393	-6.62322	0.0000000
SASWE02	0.0207578	0.005265695	3.942082	0.0001003
ELEV	0.001076137	0.0001757884	6.121773	0.0000000

LD01	0.01344686	0.005056446	2.65935	0.0082440
PRLMR01	-0.02016831	0.005565273	-3.623957	0.0003400
SATMP02	0.07897741	0.02732733	2.890052	0.0041290
SHPP01	-0.03680935	0.007416354	-4.963268	0.0000012

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 28.76178

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	105.9773	0.0000000

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	7	35.86226	0.0000077
Koenker-Bassett test	7	17.61723	0.0138217

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	35	61.33916	0.0038556

DIAGNOSTICS FOR SPATIAL DEPENDENCE

FOR WEIGHT MATRIX : **queen1.GAL** (row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.438804	13.4278084	0.0000000
Lagrange Multiplier (lag)	1	177.2798852	0.0000000
Robust LM (lag)	1	23.3734473	0.0000013
Lagrange Multiplier (error)	1	153.9096684	0.0000000
Robust LM (error)	1	0.0032306	0.9546742
Lagrange Multiplier (SARMA)	2	177.2831157	0.0000000

Table E2: 2002 SAR regression output.

REGRESSION

SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION

Data set : **soum_stats02nonull**
 Spatial Weight : **queen1.GAL**
 Dependent Variable : **LMRLG02** Number of Observations: 312
 Mean dependent var : 1.24973 Number of Variables : 9
 S.D. dependent var : 1.54398 Degrees of Freedom : 303
 Lag coeff. (Rho) : 0.76022

R-squared : 0.730508 Log likelihood : -397.242
 Sq. Correlation : - Akaike info criterion : 812.484
 Sigma-square : 0.64244 Schwarz criterion : 846.171
 S.E of regression : 0.801523

Variable	Coefficient	Std.Error	z-value	Probability
W_LMRLG02	0.7602205	0.04108348	18.50429	0.0000000
CONSTANT	1.017795	0.3383922	3.007738	0.0026321

SINDVI01	-0.09029516	0.0327064	-2.76078	0.0057665
SASWE02	0.004800282	0.003782085	1.269216	0.2043643
ELEV	0.0001831791	0.0001312978	1.395142	0.1629732
LD01	0.006937734	0.003591105	1.931922	0.0533691
PRLMR01	-0.005273411	0.003955252	-1.333268	0.1824440
SATMP02	0.00751601	0.01942984	0.3868282	0.6988835
SHPR01	-0.016284	0.005344193	-3.047046	0.0023112

REGRESSION DIAGNOSTICS

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	7	12.26246	0.0922513

DIAGNOSTICS FOR SPATIAL DEPENDENCE

SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : queen1.GAL

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	161.8581	0.0000000

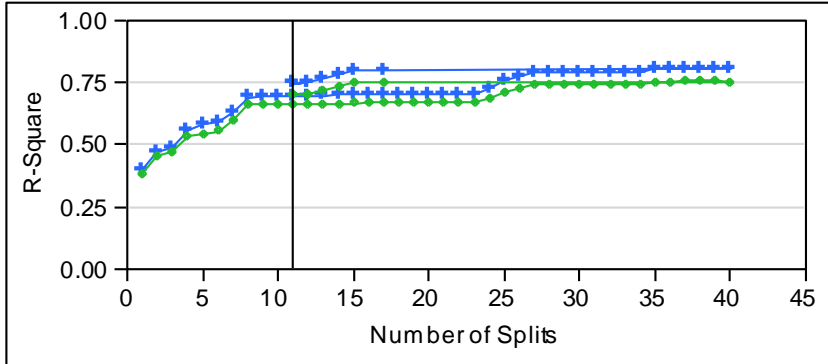
REGRESSION DIAGNOSTICS OF MODEL PERFORMANCE

W > LR > LM ≠ 342 > 162 > 177

Crossvalidation

k-fold		SSE	RSquare
10	Folded	22219.9821	0.7052
	Overall	18982.6825	0.7481

Split History



K-Fold in Green

Figure E2: 2002 Cross-validation results.

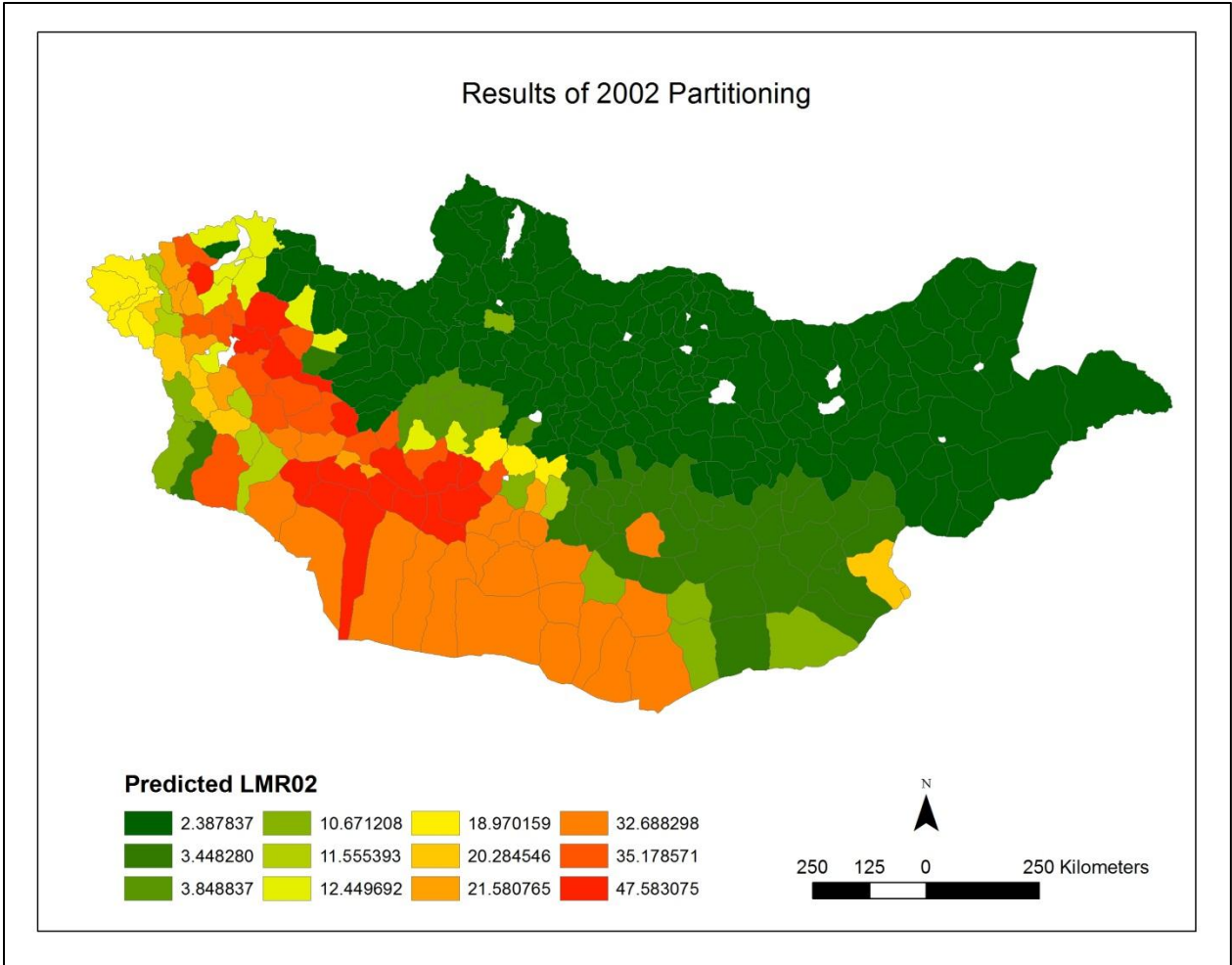
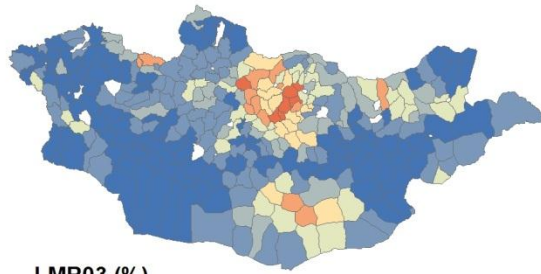
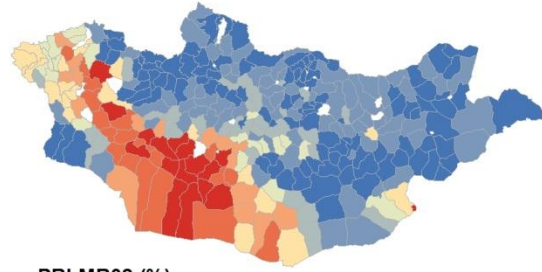


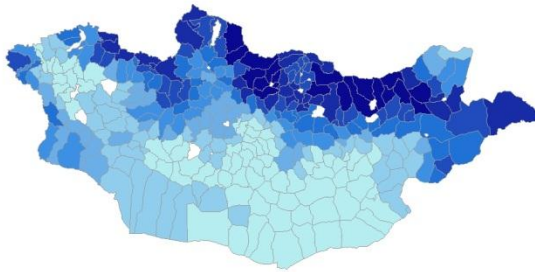
Figure E3: Map of 2002 Regression Tree.



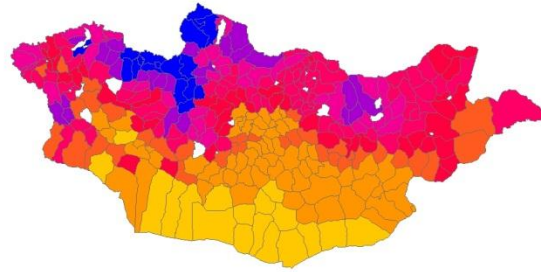
LMR03 (%)



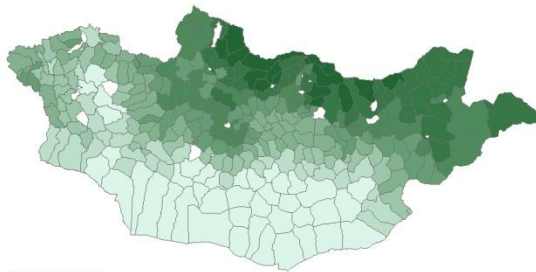
PRLMR02 (%)



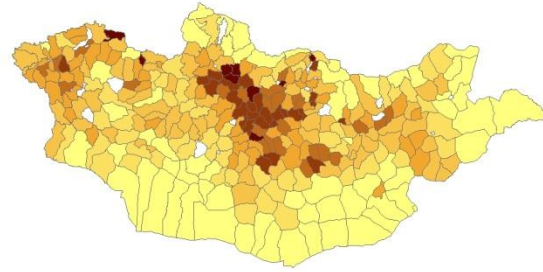
SASWE03 (mm)



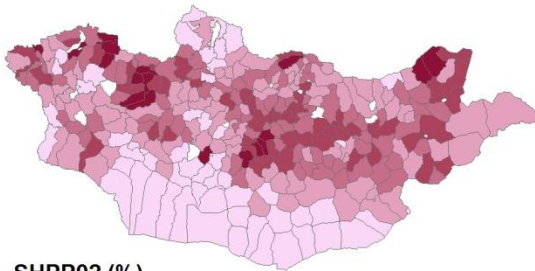
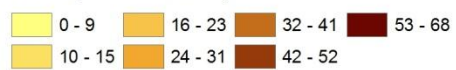
SATMP03 (°C)



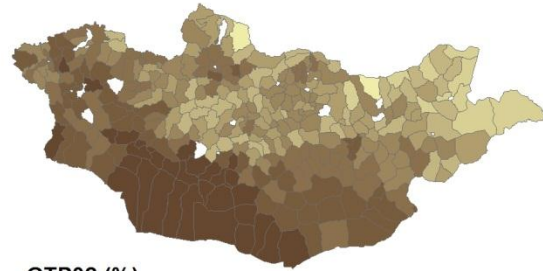
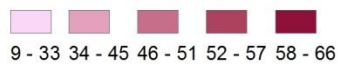
SINDVI02



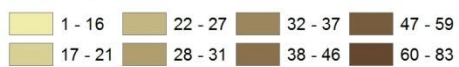
LD02 (animals/km2)



SHPP02 (%)



GTP02 (%)



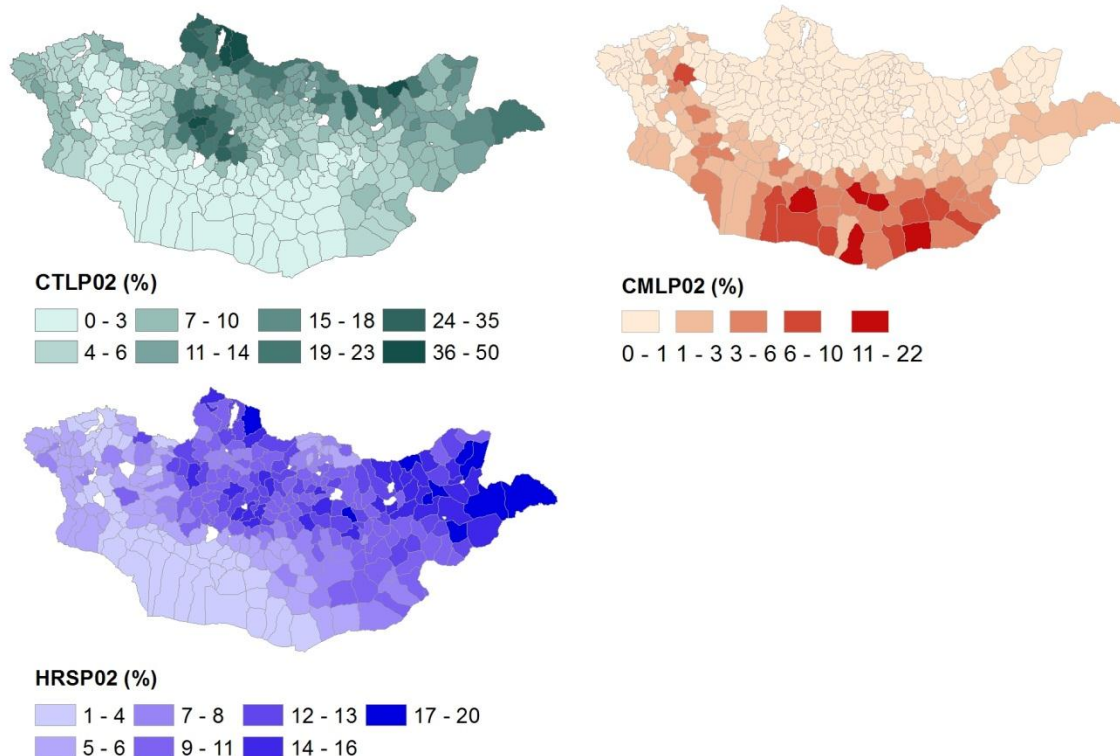


Figure F1: Spatial distribution of variables in 2003.

Table F1: 2003 OLS regression output.

REGRESSION

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **soum_stats03nonull**
 Dependent Variable : **LMRLG03** Number of Observations: 309
 Mean dependent var : 0.935701 Number of Variables : 9
 S.D. dependent var : 1.31962 Degrees of Freedom : 300

R-squared : 0.460923 F-statistic : 32.0634
 Adjusted R-squared : 0.446548 Prob(F-statistic) :3.28085e-036
 Sum squared residual: 290.074 Log likelihood : -428.687
 Sigma-square : 0.966912 Akaike info criterion : 875.373
 S.E. of regression : 0.983317 Schwarz criterion : 908.973
 Sigma-square ML : 0.938749
 S.E of regression ML: 0.968891

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	0.6380564	0.4334955	1.471887	0.1421000
SINDVI02	-0.2325406	0.06379814	-3.644943	0.0003151

SASWE03	0.03198608	0.003155341	10.13712	0.0000000
ELEV	0.0005119659	0.0001466316	3.491513	0.0005525
PRLMR02	-0.01990773	0.004629433	-4.300252	0.0000231
SATMP03	0.0636754	0.0190734	3.338439	0.0009488
CMLP02	0.09796354	0.02877931	3.403956	0.0007545
CTLP02	0.1098727	0.04810909	2.283824	0.0230805
HRSP02	0.2918961	0.05690484	5.129547	0.0000005

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 25.15646

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	5.309515	0.0703159

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	8	21.54847	0.0058247
Koenker-Bassett test	8	19.11405	0.0142615

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	44	70.46251	0.0068576

DIAGNOSTICS FOR SPATIAL DEPENDENCE

FOR WEIGHT MATRIX : **queen1.GAL** (row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.318036	9.8463162	0.0000000
Lagrange Multiplier (lag)	1	128.8123280	0.0000000
Robust LM (lag)	1	55.6020300	0.0000000
Lagrange Multiplier (error)	1	79.4469668	0.0000000
Robust LM (error)	1	6.2366688	0.0125132
Lagrange Multiplier (SARMA)	2	135.0489968	0.0000000

Table F2: 2003 SAR regression output.

REGRESSION

SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION

Data set : **soum_stats03nonull**

Spatial Weight : **queen1.GAL**

Dependent Variable : **LMRLG03**

Number of Observations: 309

Mean dependent var : 0.935701

Number of Variables : 10

S.D. dependent var : 1.31962

Degrees of Freedom : 299

Lag coeff. (Rho) : 0.634295

R-squared : 0.656980

Log likelihood : -373.669

Sq. Correlation : -

Akaike info criterion : 767.339

Sigma-square : 0.597336

Schwarz criterion : 804.672

S.E of regression : 0.772875

Variable	Coefficient	Std.Error	z-value	Probability
----------	-------------	-----------	---------	-------------

W_LMRLG03	0.6342946	0.05093873	12.45211	0.0000000
CONSTANT	0.213158	0.3414079	0.6243498	0.5323978
SINDVIO2	-0.165088	0.05053967	-3.266504	0.0010890
SASWE03	0.01676771	0.002692867	6.226713	0.0000000
ELEV	0.0003413744	0.0001161501	2.93908	0.0032920
PRLMR02	-0.01067302	0.003702008	-2.883035	0.0039388
SATMP03	0.03057958	0.01504391	2.032688	0.0420839
CMLP02	0.03829068	0.02269187	1.687418	0.0915229
CTLP02	0.06630774	0.03786562	1.751133	0.0799229
HRSPO2	0.1182991	0.04592109	2.576138	0.0099911

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	8	9.414233	0.3085650

DIAGNOSTICS FOR SPATIAL DEPENDENCE

SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : queen1.GAL

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	110.0345	0.0000000

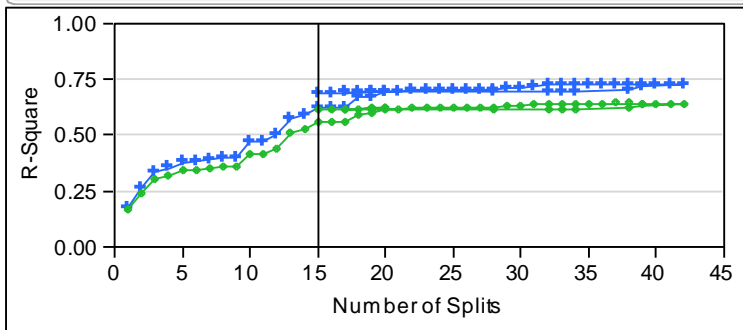
REGRESSION DIAGNOSTICS OF MODEL PERFORMANCE

W > LR > LM ≠ 156 > 110 > 128

Crossvalidation

k-fold		SSE	RSquare
10	Folded	6232.32166	0.6134
	Overall	5046.73438	0.6870

Split History



K-Fold in Green

Figure F2: 2003 Cross-validation results.

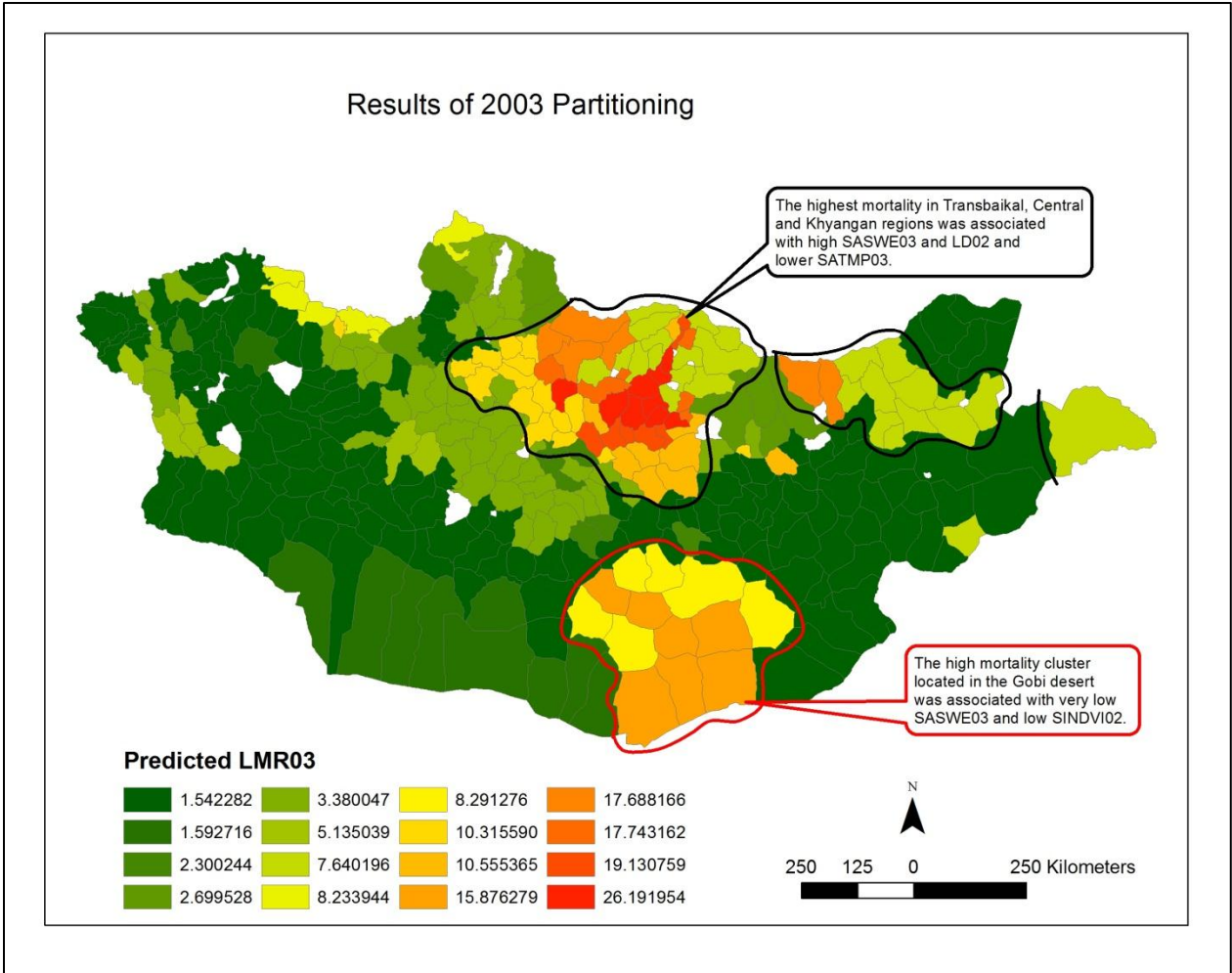
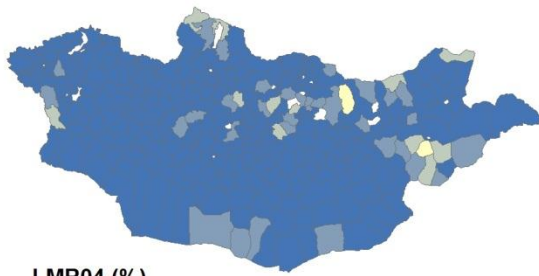
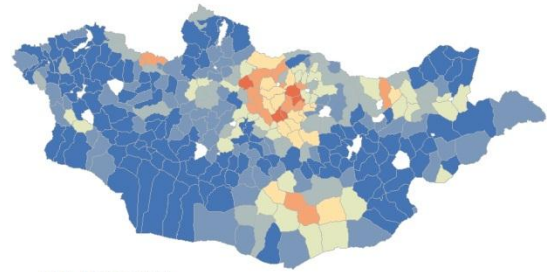


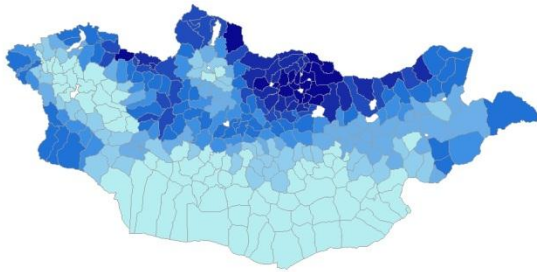
Figure F3: Map of 2003 Regression Tree.



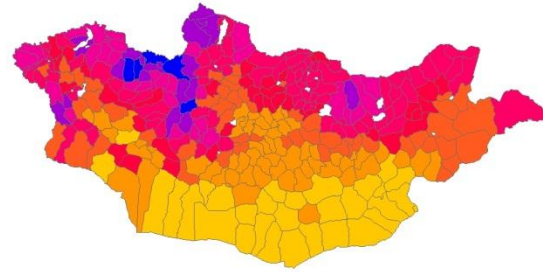
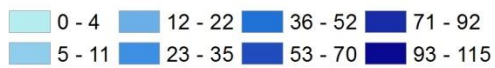
LMR04 (%)



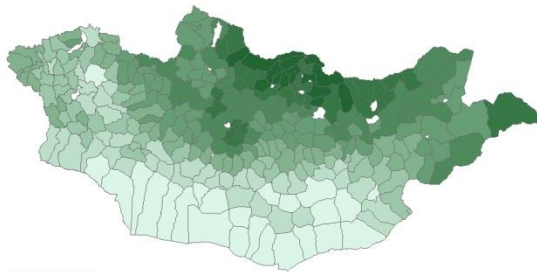
PRLMR03 (%)



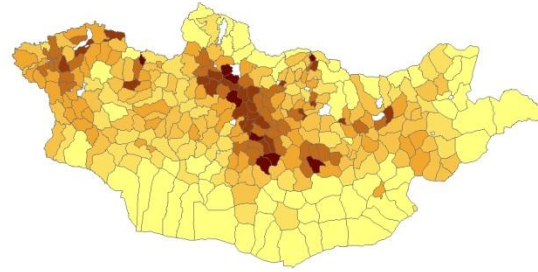
SASWE04 (mm)



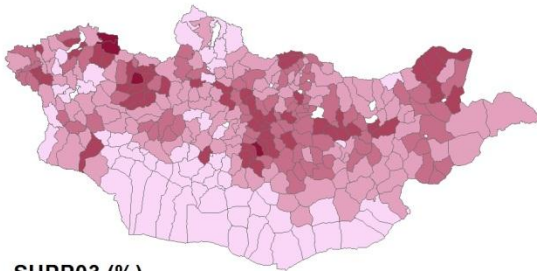
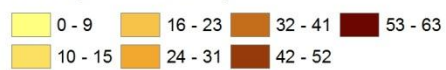
SATMP04 (°C)



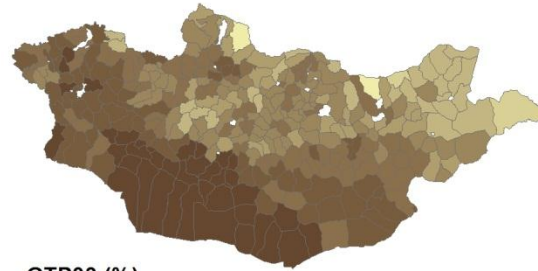
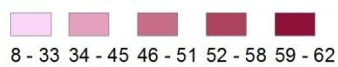
SINDVI03



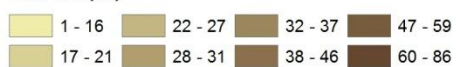
LD03 (animals/km2)



SHPP03 (%)



GTP03 (%)



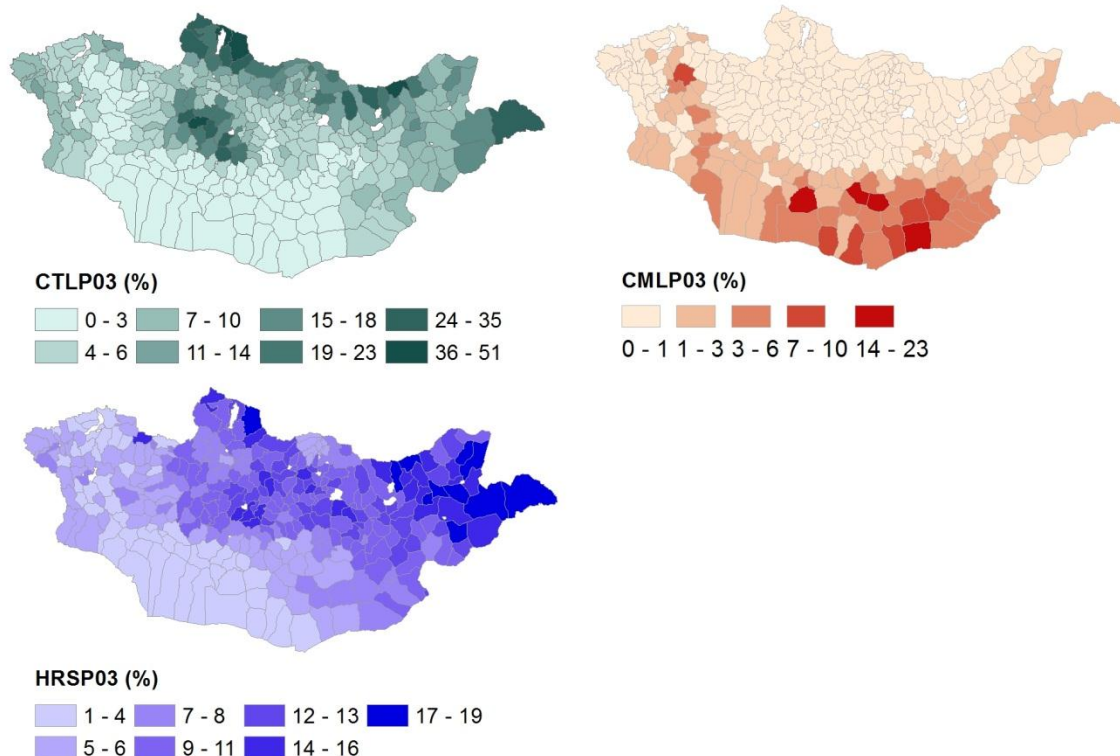


Figure G1: Spatial distribution of variables in 2004.

Table G1: 2004 OLS regression output.

REGRESSION

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **soum_stats04nonull**
 Dependent Variable : **LMRLG04** Number of Observations: 312
 Mean dependent var : -0.459037 Number of Variables : 4
 S.D. dependent var : 1.22007 Degrees of Freedom : 308

R-squared : 0.248959 F-statistic : 34.0325
 Adjusted R-squared : 0.241644 Prob(F-statistic) :5.03162e-019
 Sum squared residual: 348.81 Log likelihood : -460.107
 Sigma-square : 1.1325 Akaike info criterion : 928.214
 S.E. of regression : 1.06419 Schwarz criterion : 943.186
 Sigma-square ML : 1.11798
 S.E of regression ML: 1.05735

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	-1.40245	0.1344956	-10.42748	0.0000000
PRLMR03	0.03839838	0.00883064	4.348313	0.0000187

CTLP03	0.0542125	0.009609314	5.641661	0.0000000
HRSP03	0.03973234	0.01864533	2.130954	0.0338848

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 5.937628
 TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	150.0558	0.0000000

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	3	2.656981	0.4475875
Koenker-Bassett test	3	1.091985	0.7790092

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	9	13.7927	0.1298927

DIAGNOSTICS FOR SPATIAL DEPENDENCE

FOR WEIGHT MATRIX : **queen1.GAL** (row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.160726	4.9257132	0.0000008
Lagrange Multiplier (lag)	1	24.6073351	0.0000007
Robust LM (lag)	1	4.3023214	0.0380604
Lagrange Multiplier (error)	1	20.6489016	0.0000055
Robust LM (error)	1	0.3438879	0.5575936
Lagrange Multiplier (SARMA)	2	24.9512230	0.0000038

===== END OF REPORT =====

Table G2: 2004 SAR regression output.

REGRESSION

SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION

Data set : **soum_stats04nonull**
 Spatial Weight : **queen1.GAL**
 Dependent Variable : **LMRLG04** Number of Observations: 312
 Mean dependent var : -0.459037 Number of Variables : 5
 S.D. dependent var : 1.22007 Degrees of Freedom : 307
 Lag coeff. (Rho) : 0.367353

R-squared : 0.320096 Log likelihood : -448.922
 Sq. Correlation : - Akaike info criterion : 907.844
 Sigma-square : 1.01209 Schwarz criterion : 926.559
 S.E of regression : 1.00603

Variable	Coefficient	Std.Error	z-value	Probability
W_LMRLG04	0.3673527	0.07166466	5.125995	0.0000003

CONSTANT	-0.9391233	0.1558565	-6.025562	0.0000000
CTLP03	0.04039193	0.009477389	4.261925	0.0000203
HRSP03	0.02347182	0.01792203	1.309663	0.1903101
PRLMR03	0.02830944	0.008555936	3.308749	0.0009373

REGRESSION DIAGNOSTICS

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	3	2.999808	0.3916548

DIAGNOSTICS FOR SPATIAL DEPENDENCE

SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : **queen1.GAL**

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	22.37001	0.0000022

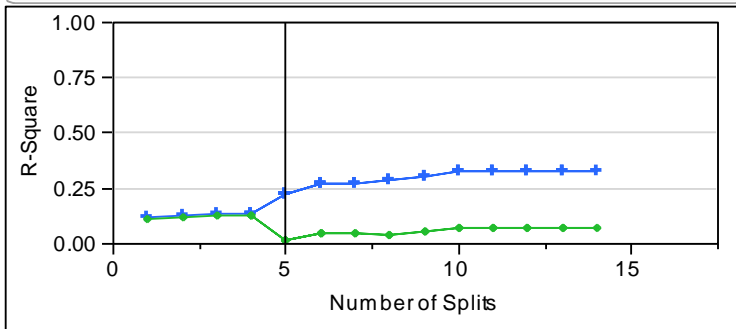
REGRESSION DIAGNOSTICS OF MODEL PERFORMANCE

W > LR > LM ≠ 26 > 22 > 25

Crossvalidation

k-fold		SSE	RSquare
10	Folded	944.825523	0.0182
	Overall	745.138368	0.2257

Split History



K-Fold in Green

Figure G2: 2004 Cross-validation results.

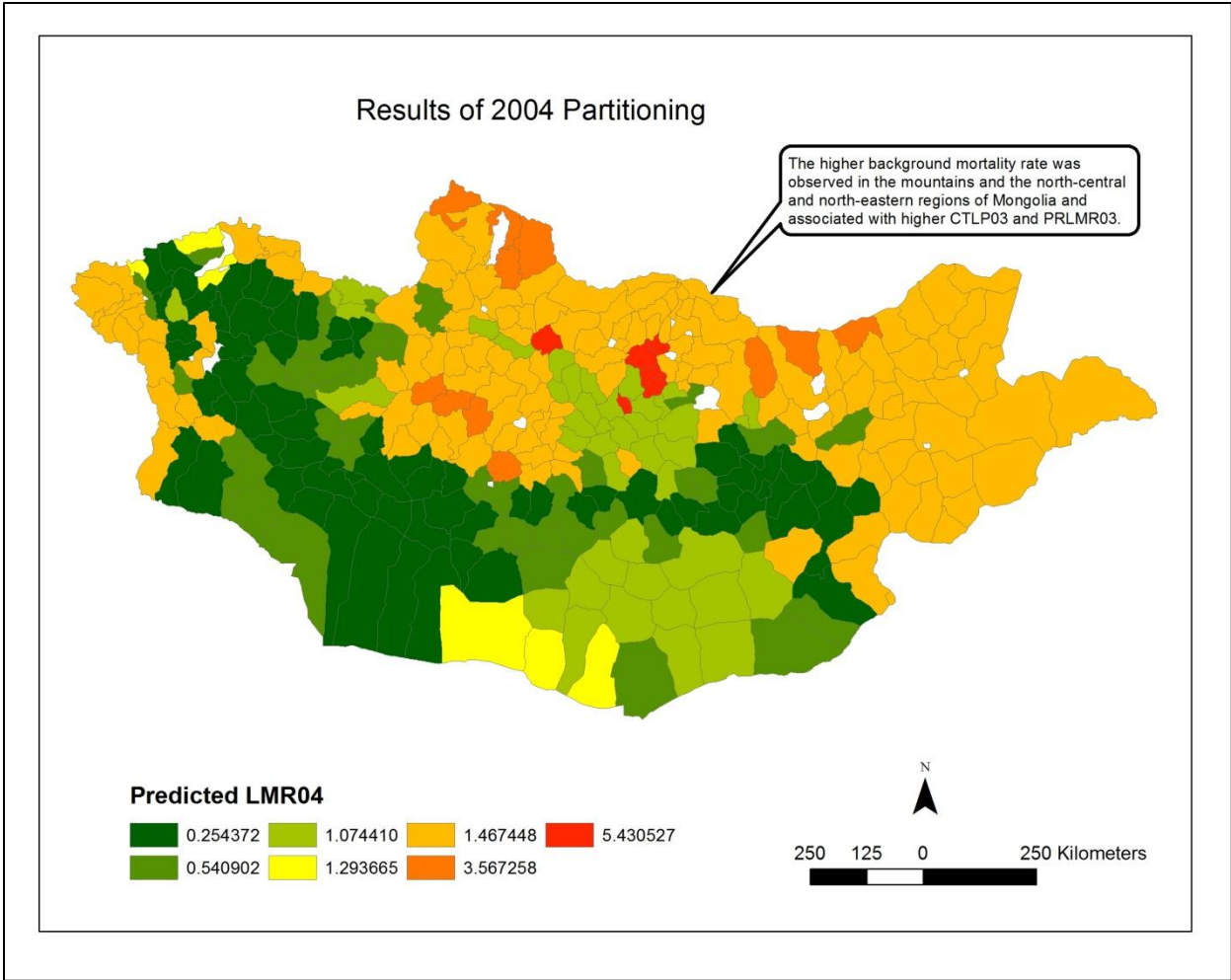


Figure G3: Map of 2004 Regression Tree.

Bibliography

- Anselin, L., Bera, Anil K. (1998). Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. Handbook of applied economic statistics. A. Ullah and D. E. A. Giles. New York, Marcel Dekker: xi, 625 p.
- Anselin, L., Ibnu Syabri and Youngihn Kho (2006). "GeoDa: An Introduction to Spatial Data Analysis." Geographical Analysis **38**(1): 5-22.
- Armstrong, R. L., M. J. Brodzik, L. Knowles, M. Savoie (2007). Global monthly EASE-Grid snow water equivalent climatology. N. S. a. I. D. Center. Boulder, CO.
- Batima, P., Natsagdorj, L., Gombluudev, P., Erdenetsetseg, B. (2005). "Observed Climate Change in Mongolia." AIACC Working Paper No.12.
- Bedunah, D. J. and S. M. Schmidt (2004). "Pastoralism and Protected Area Management in Mongolias Gobi Gurvansaikhan National Park." Development and Change **35**: 167-191.
- Begzsuren, S., J. E. Ellis, et al. (2004). "Livestock responses to droughts and severe winter weather in the Gobi Three Beauty National Park, Mongolia." Journal of Arid Environments **59**(4): 785-796.
- Breiman, L., Freidman, J. H., Olshen, R. A., Stone, C. J. 1984. Classification and Regression Trees. Wadsworth.
- Bueh, C. and H. Nakamura (2007). "Scandinavian pattern and its climatic impact." Quarterly Journal of the Royal Meteorological Society **133**(629): 2117-2131.
- De'ath, G. and K. E. Fabricius (2000). "Classification and Regression Trees: A Powerful Yet Simple Technique for Ecological Data Analysis." Ecology **81**(11): 3178-3192.
- Finch, C. M. (2002). "Mongolia in 2001: Political Consolidation and Continued Economic Reform." Asian Survey **42**(1): 39-45.
- Fotheringham, A. S., C. Brunson, et al. (2002). Geographically weighted regression: the analysis of spatially varying relationships. Chichester, Wiley.
- Gunin, P. D. (1999). Vegetation dynamics of Mongolia. Boston, MA, Kluwer Academic Publishers.
- Hansen, M., R. DeFries, J.R. Townshend, M. Carroll, C. Dimiceli, R. Sohlberg (2003). Vegetation Continuous Fields MOD44B, 2001 Percent Tree Cover. U. o. M. The Global Land Cover Facility. College Park, University of Maryland. **Collection 3**.
- JMP (1989-2011). SAS Institute Inc. . Cary, NC.
- Matsuura, K., C. J. Willmott (2009). Terrestrial Air Temperature: 1900-2008 Gridded Monthly Time Series. D. o. G. Center for Climatic Research, University of Delaware. Newark, DE.
- Mearns, R. (2004). "Sustaining Livelihoods on Mongolias Pastoral Commons: Insights from a Participatory Poverty Assessment." Development and Change **35**: 107-139.
- METI/NASA (2010). ASTER Global Digital Elevation Model.
- Michaelsen, J., D. S. Schimel, et al. (1994). "Regression Tree Analysis of satellite and terrain data to guide vegetation sampling and surveys." Journal of Vegetation Science **5**(5): 673-686.
- Mitchell, A. (1999). The ESRI guide to GIS analysis. Redlands, Calif., ESRI Press.
- Mongolia, National Statistical Office of (2008). Livestock population and mortality 1991-2008. Aggregated database. Ulaanbaatar.
- Mongolia, United Nations and Government of (2001). Mongolia Winter Disaster Dzud: Appeal for International Assistance (February - May, 2001).
- Morinaga, Y., S. F. Tian, et al. (2003). "Winter snow anomaly and atmospheric circulation in Mongolia." International Journal of Climatology **23**(13): 1627-1636.
- Murray, W. (2003). "Informal gold mining and national development: The case of Mongolia." International Development Planning Review **25**(2): 111-128.
- Nixon, F. and B. Walters (2006). "Privatization, Income Distribution, and Poverty: The Mongolian Experience." World Development **34**(9): 1557-1579.

- Saizen, I., A. Maekawa, et al. (2010). "Spatial analysis of time-series changes in livestock distribution by detection of local spatial associations in Mongolia." Applied Geography **30**(4): 639-649.
- SAS (2009). JMP 8 Statistics and Graphics Guide, Second Edition. Cary, NC, SAS Institute Inc.
- Shinoda, M., Morinaga, Y. (2005). "Developing a Combined Drought-Dzud Early Warning System in Mongolia." Geographical Review of Japan **78**(13): 928-950.
- Singh, R. B. (2006). Natural hazards and disaster management: vulnerability and mitigation. Jaipur, Rawat Publications.
- Sternberg, T., N. Middleton, et al. (2009). "Pressurised pastoralism in South Gobi, Mongolia: what is the role of drought?" Transactions of the Institute of British Geographers **34**(3): 364-377.
- Stow, D., Daeschner, S., Hope, A., Douglas, D., Petersen, A., Myneni, R., Zhou, L., Oechel, W. (2003). "Variability of the Seasonally Integrated Normalized Difference Vegetation Index Across the North Slope of Alaska in the 1990s." International Journal of Remote Sensing **24**(5): 1111-1117.
- Suttie, J. M. (2005). Grazing Management in Mongolia. Grasslands of the World. S. G. R. J. M. Suttie, C. Batello. Rome, FAO of the United Nations: 265 - 305.
- Tachiiri, K., M. Shinoda, et al. (2008). "Assessing Mongolian snow disaster risk using livestock and satellite data." Journal of Arid Environments **72**(12): 2251-2263.
- Tucker, C. J., J.E. Pinzon, M.E. Brown (2004). Global Inventory Modeling and Mapping Studies, NA92apr15a.n11-VIg - NA03oct15a.n16-VIg. 2.0.
- Tuvaansuren, G. (1986). "Results of zoo-meteorological observation in Mongolia." Papers in Meteorology and Hydrology **11**: 132-145.