12. Gobi Forage Livestock Early Warning System

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12.1 BACKGROUND

The ability to inventory forage biomass over large landscapes can be an important component in the assessment of drought impacts, natural resource management options, environmental degradation, and changing climate. For Mongolian herders, an understanding of forage biomass availability in the surrounding landscape can assist in determining whether to move, buy or sell animals, and assess the level of risk for decision-making. However, the time and resources required to conduct accurate assessments of forage biomass over large landscapes are prohibitive, and in many areas such as Mongolia, the infrastructure and funding does not exist to conduct a comprehensive national characterization.

Another complicating factor is that decisions regarding livestock movement and stocking/de-stocking may require near real-time information, especially in the face of drought or severe winter weather events (*dzud*[12]). Forage quantity assessment is almost impossible to conduct over large land areas on a near real-time basis because of logistical and time constraints, thus the information needed for livestock related decisions is not always available when it is needed most. The inability to make decisions at critical times could lead to vegetation overuse which, in turn, can lead to environmental degradation.

During the period from 1999 to 2001, as much as 35 percent of Mongolia's livestock were lost to drought and dzud. In the Gobi region of the country, livestock mortality reached 50 percent, with many households losing entire herds (Siurua and Swift, 2002). Due to these extreme losses and their impact on pastoral livelihoods, the United States Agency for International Development (USAID), through the Global Livestock Collaborative Research Support Program (GL-CRSP) initiated the Gobi Forage Livestock Early Warning System in 2004. The Livestock Early Warning System (LEWS) technology, originally developed in East Africa (Stuth *et al.*, 2003a; Stuth *et al.*, 2005), combines near real-time weather, simulation modelling and remote-sensing data to monitor and forecast livestock forage conditions so that pastoralists and other decision-makers have information for timely decision-making in the face of drought and other disasters. For the Gobi Forage LEWS, Texas A&M University and Mercy Corps partnered to implement the forage monitoring

[12] Mongolian term for an extremely snowy winter in which livestock are unable to find fodder through the snow cover, and large numbers of animals die due to starvation and the cold. The term is also used for other meteorological conditions, especially in winter, that make livestock grazing impossible.

technology in eight *aimags* (provinces) that encompass the area where drought impacts were greatest during the 1999 to 2001 period (Figure 12.1). The goal of the Gobi Forage LEWS was to develop a forage monitoring system that would provide near real-time spatial and temporal assessment of current and forecasted forage conditions. This information would be delivered to herders to assist in their risk assessment and also be provided to local, regional and national government agencies to assist in their drought management, disaster preparedness and agricultural policy efforts.

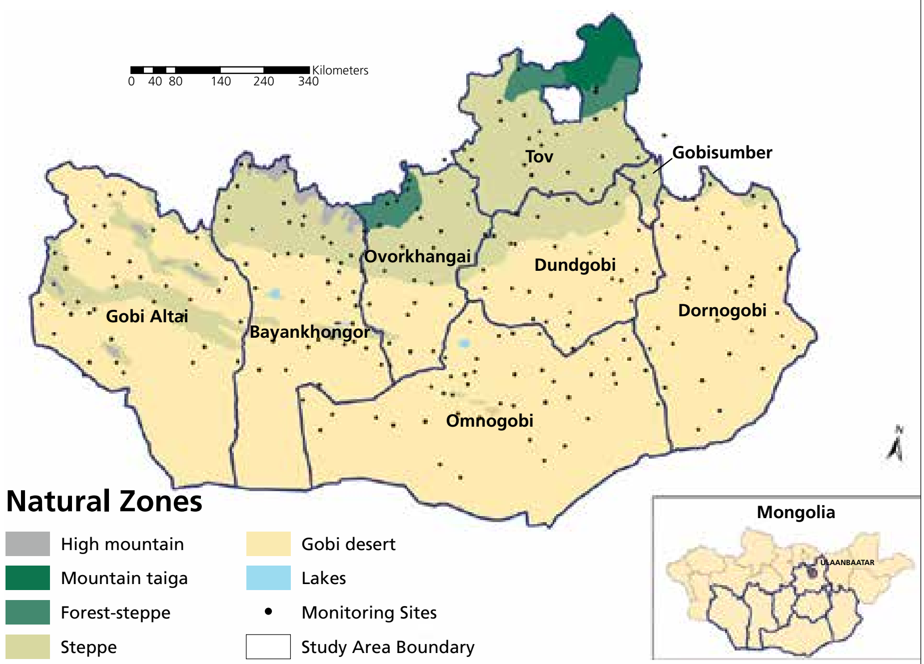
12.2 INPUTS

12.2.1 Project area

Mongolia is a landlocked country with a land area of over 1.5 million square kilometres of which over 90 percent are rangelands. Herders extensively graze their animals during the spring, summer and autumn, then return to protected camps for the winter months (Bedunah and Schmidt, 2004). Sheep and goats are the predominant forms of livestock, followed by cattle, horses, yaks and camels.

Mongolia's climate is continental with extremely cold, dry winters and warm summers. Precipitation generally occurs in the form of rainfall during the summer months (June–August) which coincides with the growing season for most plants. Precipitation is most

FIGURE 12.1
Location of aimag (province) boundaries and natural zones within the Gobi Forage LEWS project area



Note: The five natural zones generally follow the north to south gradient of elevation within the study area. Location of monitoring sites are depicted as the black dots on the map.

abundant in the northern regions of the country, averaging 200 to 350 mm per year, and least abundant in the southern regions which average 100 to 200 mm. A large portion of the country is prone to extreme winter disasters (*dzuds*) which are periods of intensely cold temperatures (< –40 °C) accompanied by snow and/or ice. *Dzuds* usually follow periods of summer drought which can lead to large losses of livestock because animals are in poor condition going in to winter and do not have enough body fat to survive the extreme winter temperatures.

This Gobi Forage LEWS was implemented in the Gobi region of Mongolia (Figure 12.1). The area includes the administrative *aimags* (provinces) of Gobi Altai, Bayankhongor, Ovorkhangai, Omnogobi, Dundgobi, Dornogobi, Gobi Sumber and Tov. Within this region, five natural zones exist that generally follow the north to south elevational gradient and include the High Mountain, Mountain Taiga (Forest), Forest Steppe, Steppe and Gobi Desert zones (Yunatov *et al.*, 1979). The High Mountain zone represents areas above the tree line and consists mainly of tundra vegetation. The Mountain Taiga zone is dominated by forest species, mainly Siberian larch (*Larix sibirica*) and Siberian pine (*Pinus sibirica*). The Forest Steppe zone represents a transition between the Mountain Taiga and Steppe zones and consists of grasslands interspersed with forested areas. Trees such as Siberian larch (*Larix sibirica*) and Siberian pine (*Pinus sibirica*) can be found on north slopes and *Stipa* and *Festuca* grasses on southern slopes. The Steppe zone consists of grasslands dominated by *Stipa*, and *Cliestogenes* grass species and *Artemisia* forbs and has the largest concentration of livestock production within the study area. The Gobi Desert zone is the most arid zone (<200 mm of precipitation) with the dominant plants consisting of *Stipa* and *Allium* species and subshrubs such as *Caragayna* and *Amygdalus* species.

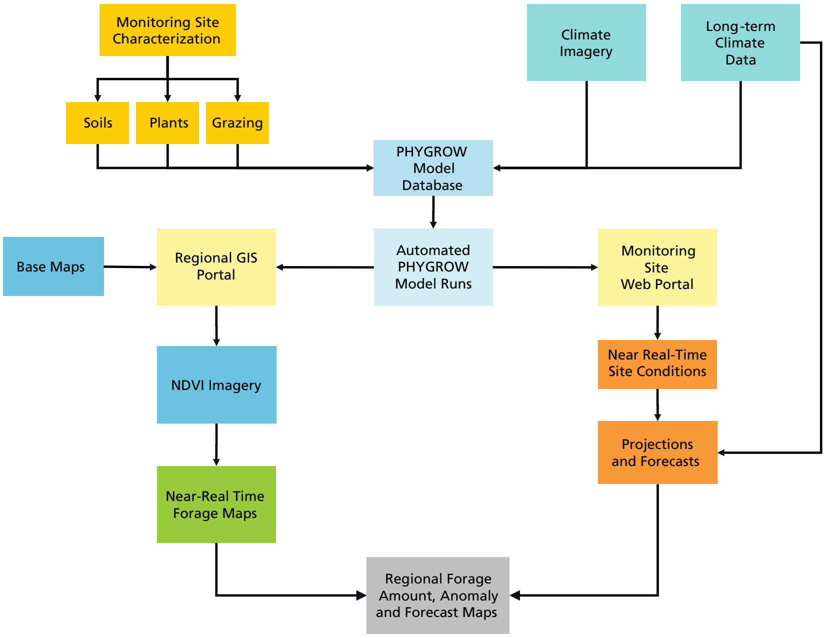
12.2.2 LEWS framework

LEWS combines field data collection from a series of monitoring sites, simulation model outputs, statistical forecasting and GIS to produce regional maps of current and forecast forage conditions (Figure 12.2). The system uses the Phytomass Growth Simulation Model (PHYGROW) (Stuth *et al.*, 2003b) as the primary tool for estimating forage conditions. Field data collected from monitoring sites established across the region are used to parameterize and calibrate the model. Model runs for the monitoring sites are driven by near real-time climate data. The simulation model runs for each monitoring site are executed every 15 days and the outputs are made available via web portal (http://glews.tamu.edu/mongolia). To produce maps of forage conditions, the total forage available to livestock is output for each monitoring site and is co-located with remote-sensing imagery data (Normalized Difference Vegetation Index [NDVI]) for the region and geostastistical interpolation is conducted to create regional maps of available forage. The LEWS system also incorporates a statistical forecasting system which provides a projection of available forage conditions for 60 days into the future.

12.2.3 Climate data sources

Climate data are acquired from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC). The rainfall product used as a driving variable in the forage simulation modelling was the Climate Prediction Center Morphing Product

FIGURE 12.2
Integrated framework for the Livestock Early Warning System modelling system for East Africa and Mongolia



Note: Data on plants, soils and grazers are collected from monitoring sites in the field and the data are stored in the PHYGROW model database. Climate data are acquired from national data sources and also stored in the database. The database provides data to the PHYGROW automated modelling process and the simulations are run nightly. Data are made available to the GIS portal and the Monitoring Site web portal. The GIS portal merges the simulation model outputs for the monitoring sites and with Normalized Difference Vegetation Image data. Co-kriging interpolation is used to create near real-time forage maps which are made available to regional and local stakeholders. Statistical forecasting is also conducted to provide maps and data of probable conditions.

(CMORPH) (Joyce *et al.*, 2004) (referred to hereafter as the "CMORPH product"). This product is produced by NOAA each 24-hour period and represents the accumulated rainfall that occurs between 0:00 and 24:00 Greenwich Mean Time (GMT). The CMORPH product is acquired automatically from the NOAA servers via internet and downloaded to servers at the Center for Natural Resource Information Technology (CNRIT) at Texas A&M University. The rainfall products are delivered as gridded images having a geographic range of 80.0° to 120.0° East longitude and 40.0° to 55.0° North latitude, covering the entire country of Mongolia and portions of northern China and southern Russia. Grid cell spacing of the image was 0.07276° in the longitudinal direction and 0.07277° in the latitudinal direction (approximately 8 km at the equator). During the initial comparisons of CMORPH rainfall estimates with weather station rainfall data from Mongolia, it was discovered that the product was overestimating rainfall in many locations within the study area, especially in the Steppe and Forest Steppe zones. Large overestimations occurred during the summer months (peak rainfall) and may have been related to a known problem with CMORPH and other satellite rainfall products where rainfall is detected by the rainfall algorithms, but none of the rainfall reaches the soil surface because of evaporation (Janowiak *et al.,* 2005).

To overcome this issue, a daily bias correction was calculated and applied to the product using rainfall data collected from approximately 200 weather stations within the Mongolia CMORPH domain. The station data were acquired on a near real-time basis from NOAA as part of the Global Telecommunications System (GTS) data feed. GTS is a world-wide network of climate monitoring stations that provide data to the World Meteorological Organization (WMO) as part of the World Weather Watch system. The bias-adjusted CMORPH data were used for PHYGROW simulation modelling.

Temperature data for the model were acquired from the NOAA Global Data Assimilation System (GDAS) that produces daily maximum and minimum temperature surfaces for the entire globe. Resolution of the data is 1 degree at the equator (approximately 110 km).

12.2.4 Simulation model

The PHYGROW was used for the prediction of forage biomass for monitoring sites within the study region. PHYGROW is a point model that contains four integrated submodels: climate, soil, plant growth and grazing. The model simulates a soil water balance, multi species/functional group plant growth and livestock grazing on a daily time step. PHYGROW is based on the light use efficiency model concept (Montieth, 1972; 1977) that simulates plant growth under optimal conditions (water not limiting). The model then discounts plant growth based on the amount of water stress (calculated from the water balance), temperature stress (based on species temperature tolerances for growth) and livestock grazing demand.

The model contains parameters for soil surface and layer information, plant species and community data, livestock grazing management and stocking rates, and is driven by daily climate data (Stuth *et al.*, 2003b). The soil subcomponent of the model has 13 unique parameters that include soil depth, bulk density, infiltration and water-holding capacity variables. The plant subcomponent allows simulation for individual species or functional groups. Plant community composition parameters include initial standing crop, percent basal cover for grasses, frequency of forbs, and canopy cover of shrubs and trees. For each individual plant species/functional group in the model, there are 27 plant parameters including minimum, optimal and maximum temperatures for growth, radiation use efficiency, leaf area index, leaf and wood turnover, leaf and wood decomposition, and canopy water movement. The grazing subcomponent of the model has 19 variables related to the kind/class of grazing animal including forage intake, stocking rate and grazing preference class for each plant species parameterized in the model. Lastly, the climate subcomponent has six variables which include year, day, maximum and minimum temperature, rainfall and solar radiation.

12.2.5 Monitoring site characterization

Permanent vegetation transects were established across the project area to gather information needed to parameterize the PHYGROW simulation model. Line transect and quadrat methods were used to gather plant community information and forage biomass for productivity estimates. During the initial site visit, line transect data, including basal cover of grasses and canopy cover of shrubs, were collected along with forage biomass production estimates to calibrate the model. Sites were visited periodically in the years following initial establishment to collect forage biomass data for further calibration and validation of the model.

12.2.6 Forage mapping

The geostatistical method of co-kriging was used to map forage biomass for regional maps of available forage. Co-kriging is a geostatistical interpolation method that calculates estimates for unknown points by using the weighted linear average of the available samples of the primary and secondary variables. The secondary variable (covariate) is cross-correlated with the primary variable of interest and is usually sampled more frequently and regularly (Isaaks and Srivastava, 1989), thus allowing estimation of unknown points using both variables. Forage biomass output from the PHYGROW simulation model for each of the monitoring sites was used as the primary variable in co-kriging interpolation. For the secondary variable, the Normalized Difference Vegetation Index (NDVI) data prepared by the National Aeronautics and Space Administration (NASA) Global Inventory Modelling and Mapping Studies program (Tucker *et al.*, 2005) was used. ArcGIS software was used to conduct the co-kriging interpolation and forage maps were produced every 15 days.

12.2.7 Statistical forecasting

To provide a forecast of probable future forage conditions, an auto-regressive integrated moving-average (ARIMA) (Box *et al.*, 1994) forecasting model is used. This method provides a 90-day forecast of forage conditions using time series analysis. The ARIMA approach uses modelled forage for past dates and matching historical NDVI conditions along with current forage estimates to predict future forage biomass (Alhamad *et al.*, 2007). The forage biomass values are based on 10-day moving averages.

12.3 APPROACH

The assessment of livestock forage biomass on a near real-time basis is especially important in Mongolia where drought and winter disasters (*dzud*) that deplete vegetation resources represent a major risk confronting livestock producers. Since the majority of the livestock producers are nomadic or semi-nomadic herders, knowledge of the surrounding forage conditions becomes a critical factor in risk management decision-making about livestock, especially during drought (Kogan *et al.*, 2004). Herders often respond to drought by moving livestock to another location, but the movement is not always coordinated due to the lack of information about vegetation conditions, thus leading to increased animal numbers in areas not affected by drought.

In pastoral regions, livestock is the main component of personal wealth and well-being for livestock herders. Providing early warning information on droughts or other disasters can improve marketing options for livestock prior to market crashes during drought and removing animals from drought stricken areas can reduce the likelihood of environmental impacts. Regional early warning assessments can also provide needed information to policy-makers and relief organizations to develop disaster response or mitigation strategies.

The approach for establishing the Gobi Forage LEWS in Mongolia comprised eight main activities, as follows:

1. Monitoring site selection
2. Monitoring site characterization
3. Simulation model parameterization

4. Near-real time simulation for monitoring sites
5. Integration of model output with remotely-sensed data
6. Regional mapping of forage biomass and anomalies
7. Information dissemination
8. Training on use of Gobi Forage products

Each of these activities and the methods used for implementation are discussed below.

12.4 METHODOLOGY FOR ESTABLISHING THE FORAGE INVENTORY

12.4.1 Monitoring site selection

A series of monitoring sites were established across the study area to gather information needed to parameterize the simulation model and to provide a representative sample of the forage productivity across the region. An 8 km x 8 km grid, representing the resolution of the pixels of the CMORPH rainfall data, was superimposed over the Gobi Forage LEWS project area (Figure 12.1). To ensure that sites would be accessible, the grids were stratified by selecting only those grids that were within 30 km of roads. This was done by overlaying the road network on top of the grid within the ArcGIS software and creating a spatial query to select only those grid cells that had their boundaries within 30 km of the roads. From the stratified grids, a subset of grids was randomly selected within each *aimag*, with the number of grids proportional to the land area of each *aimag* and natural zone (Figure 12.1). Once the grids were selected, these were uploaded to Personal Digital Assistants (PDAs) equipped with Global Positioning Systems and ArcPad mobile GIS software. The PDAs were given to field teams and these were used to navigate to the selected grid cells for monitoring site characterization.

12.4.2 Monitoring site characterization

The field teams used the road network to drive to within range of a selected grid, and then drove overland to the land area inside the boundaries of the grid by navigating with the ArcPad software and PDA/GPS. Once inside the grid, the dominant plant community was identified through field reconnaissance and a location for a permanent vegetation transect was established. Due to the large geographic area of the project, the permanent vegetation transects were installed in phases with the first phase occurring in the Gobi Altai, Bayankhongor and Ovorkhangai *aimags* during 2004 (Figure 12.1). In 2005, transects were established in Omnogobi, Dundgobi, Gobisumber and Dornogobi *aimags*. Transects in the Tov *aimag* were established in 2006. A total of 243 monitoring sites were installed across the region (Figure 12.1) during the monitoring site characterization phase.

To gather the necessary plant community parameters for the PHYGROW model at each monitoring site, a modified point-frame method (Ryan, 2005) was used to collect percent basal cover of grasses, frequency of forbs and shrub canopy cover along each permanent transect. Transect lengths ranged from 100 to 500m according to vegetation cover and plant spacing at the sites. Sites having sparse vegetation and low plant cover had longer transects.

Along each transect, the modified point frame (Photo 12.1) was placed on the soil surface and each point on the frame was examined to determine if it intersected the basal area

Photo 12.1
Modified point frame used to collect grass basal area, forb frequency and shrub canopy cover on Gobi Forage LEWS monitoring sites

of a grass species, plant litter, bare ground or rock. If a basal area of a grass species was encountered, this was recorded as a “hit”. Within a 5 x 5 cm quadrat around each point, each presence of a unique forb species was defined as a “hit”. If a shrub or tree canopy intersected an upward, perpendicular line from the point, the shrub or tree species was recorded as a “hit”. A total of 250 to 500 points were sampled with the number of points sampled varying depending on vegetation cover and plant spacing. The “hits” of grass, forbs, and shrub/tree species were divided by the total possible hits and these values were entered as the plant community composition variable in the PHYGROW model.

Herbaceous biomass at each transect was measured at the time of transect establishment and in subsequent years after monitoring site establishment. A 0.25 or 0.50 m^2 quadrat was placed at equal increments along the transect (n = 10 samples per transect) and the herbaceous biomass (grass and forbs) was clipped to a 1-cm stubble height (Photo 12.2). If shrubs were located within the quadrat and they were palatable to livestock, the current year’s growth was clipped from the stems of the shrub. The clipped biomass was placed in paper bags, taken back to the laboratory and dried in a forced air oven at 60 °C for 48 hours. After drying, the samples were weighed with a digital scale. The sample weights were then multiplied by the appropriate plot factor in relation to the quadrat size to convert the forage biomass to kg/ha units. The 10 samples were averaged and the mean was used for calibration and validation of the simulation model output.

For the soil components in PHYGROW, a 1:1 000 000 scale soil map was acquired from the Mongolia National Soil Laboratory. Using a GIS, the soil series information was extracted from the soil map and soil parameters were entered into the PHYGROW model. If soil data were not available for a site, a soil pit was dug and characterized during visits

Photo 12.2
Clipping of a quadrat at a Gobi Forage LEWS monitoring site

to the monitoring site. Soil samples were retrieved from the layers and sent to the National Soil Laboratory for analysis. Soil scientists were consulted to assist with soil classification. When texture parameters were the only information available for a soil, model parameters were estimated from texture percentages using a soil parameter estimation tool (Saxton *et al.*, 1986).

Stocking rate information was calculated from *sum*[13] (district) censuses of livestock that were conducted during each year of the study. The total number of each kind of livestock was divided by the land area of the *sum* and this number was used as the stocking rate parameter in PHYGROW. Seasonal dry matter intake for each kind of livestock was determined through consultation with ruminant nutrition scientists at the Mongolian Agriculture University Research Institute for Animal Husbandry (RIAH).

12.4.3 Simulation model parameterization

Soil, plant and grazer data were entered into the PHYGROW centralized database that contains a relational table structure to store parameter data for each of the monitoring sites. Soil parameter data entered included soil depth for each layer, bulk density, water holding capacity variables, slope and water runoff parameters. Plant parameter data for the plant community characterization included basal area and canopy cover information collected from field visits. Species-specific and functional group-specific plant growth parameters were also entered and these included leaf area index, relative growth rate, leaf/wood turnover variables, rooting depth, plant height, and optimal growth and suppression temperatures. Species and functional group plant growth parameter data were acquired

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[13] Each aimag is divided into a number of sums (districts).

from published literature and online databases such as EcoCrop (FAO, 1994) and the Global Leaf Area Index Database (Scurlock *et al.*, 2001). When no information could be found for a species, an expert judgment was made based on the plant genus, functional group and information on growth characteristics gathered from plant experts in Mongolia.

Grazer data were entered to characterize the density of livestock grazing, the monitoring site and the general characteristics of livestock management for the area where the monitoring site was sampled. Grazer parameters include a maximum and minimum stocking rate, dry matter intake of the grazer and grazing preferences for the plants that occupy the site. Preferences were entered for each species and functional group and represent whether the grazer considers the species as preferred, desirable, undesirable or non-consumable for different plant growth stages such as rapidly growing, dormant or dead.

Climate data were downloaded on a daily basis from the NOAA servers and stored on the PHYGROW servers. Maximum and minimum temperature and bias-corrected rainfall were extracted from the NOAA data using the latitude and longitude of the monitoring site and stored in the PHYGROW database for use in the simulation model run for each site.

12.4.4 Near real-time simulation for monitoring sites

After all sites had been parameterized, PERL[14] scripts are used to extract the parameters from the database and the parameter files needed by the PHYGROW model are built for each monitoring site. Prior to near real-time simulation, each of the monitoring sites was calibrated. This involved running the model with the climate data and comparing the simulated forage biomass output to that measured during the transect establishment and subsequent biomass clipping at later dates. If the model output fell within ± 1 standard error of the mean for the forage biomass measured on the monitoring site transect, the model was considered calibrated for that data collection period. If the model output fell outside ± 1 standard error of the measured data, parameters were adjusted in an attempt to move the modelled biomass estimate to within the standard error. This process was repeated for each time period for which data were collected until the model was considered calibrated. Model parameter adjustments for calibration were limited to species maximum rooting depths, green and dead leaf turnover rates, and soil layer thickness at the surface[15] parameters. After the model was considered calibrated, the model parameters for a site were no longer adjusted and the runs were established in the queue to run on a near real-time basis.

The near real-time simulations are run on a distributed computing system. The system consists of central server connected to 20 nodes with a capacity of 80 central processing units. The central server uses the PERL scripts to extract the parameter files with the most recent weather for the 247 monitoring sites from the PHYGROW database and stores them in the run queue. The queued runs are sent to the various processing nodes and the simulations and forecasts are run. Once completed, selected outputs are stored in the PHYGROW database. Individual site outputs are made available via the project web portal at http://glews.tamu.edu/mongolia. PERL scripts extract the total forage available data from the database and prepare them for use in the forage mapping.

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[14] PERL is a high-level, general-purpose, interpreted, dynamic programming language.

[15] Soil layer thickness at the surface influences the depth of soil water evaporation.

12.4.5 Integration of model output with remotely-sensed data

To prepare the data for forage mapping, a weighted average of total forage available data for all grazers is extracted from the database for all of the monitoring sites. Total forage available represents the forage available to specific grazers based on their preferences and the amount of biomass present at the monitoring site. The PHYGROW model will output total forage available for each grazer; however, an integrated total forage available dataset is created where a weighted average of the total forage available for the grazers is calculated on the basis of forage intake and stocking rate (i.e. total forage demand) of the grazers at the monitoring site. The integrated total forage available is output every 15 days with the latitude and longitude for each of the monitoring sites. The total forage available data are then co-located with NDVI data for the project region. The resulting file is used for the co-kriging interpolation to create forage maps. Long-term average total forage available and the 60-day forecast total forage available are also extracted from the database. The long-term average total forage available data are co-located with the long-term average NDVI for the same time period to create a co-kriging file in order to produce a long-term average forage map. The 60-day forecast total forage available data are co-located with a forecast NDVI image to create the 60-day forecast forage map.

12.4.6 Regional mapping of forage biomass and anomalies

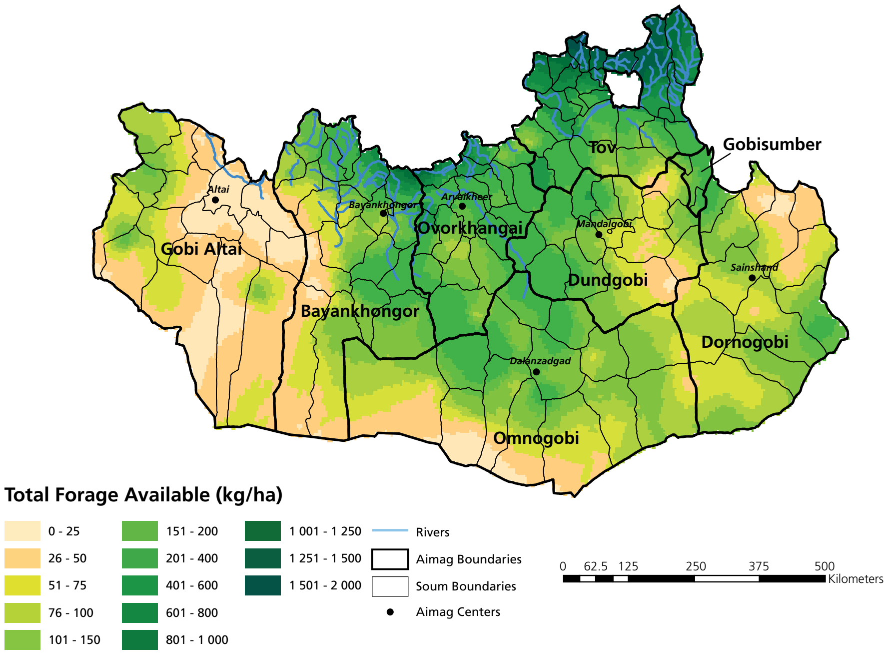
The geostatistical procedure of co-kriging (see Isaaks and Srivastava 1989 for a discussion of co-kriging) to produce landscape maps of forage production uses the co-located forage output and NDVI data. The co-kriging procedure not only uses the positive relationship between the forage biomass and the NDVI, but also accounts for spatial autocorrelation[16] to create interpolated maps of forage biomass. Co-krigings were conducted using the Geostatistical Analyst extension in the ArcGIS 9 software (ESRI, 2005).

To assess how well co-kriging predicted forage biomass, cross-validation was conducted using the ArcGIS software. Cross-validation involves dropping out data for one of the monitoring points and then running the co-kriging procedure and predicting the forage value for the point that was left out. This procedure is repeated for all the monitoring points and then the observed and predicted values can be compared via regression to assess statistically how well the co-kriging procedure performed for estimating unsampled points. The results of this exercise for forage mapping during the summer months of 2005 to 2007 indicated that the co-kriging procedure generally did a reasonable job of predicting forage biomass ($r^2 = 0.58$ to 0.69). The co-kriging procedure had a tendency to slightly underpredict forage biomass by 1 to 4 percent (Angerer, 2008).

Total forage available maps representing current forage conditions are produced bimonthly (Figure 12.3). To provide a spatial representation of forage anomalies, a forage deviation map is also produced (Figure 12.4). This is calculated by performing a standardized deviation between the current forage map and the long-term average forage map for the period of interest. The deviations are categorized into early warning indicators to delineate areas of drought intensity (Figure 12.4). A 60-day forecast map of projected forage conditions is produced to provide information for assessing drought risk (Figure 12.5).

[16] Spatial autocorrelation refers to the "rule" that items closer together in space are generally more similar than those farther apart.

FIGURE 12.3
Map of total forage available for Gobi Forage LEWS project area between 1 and 15 September 2007



12.4.7 Information dissemination

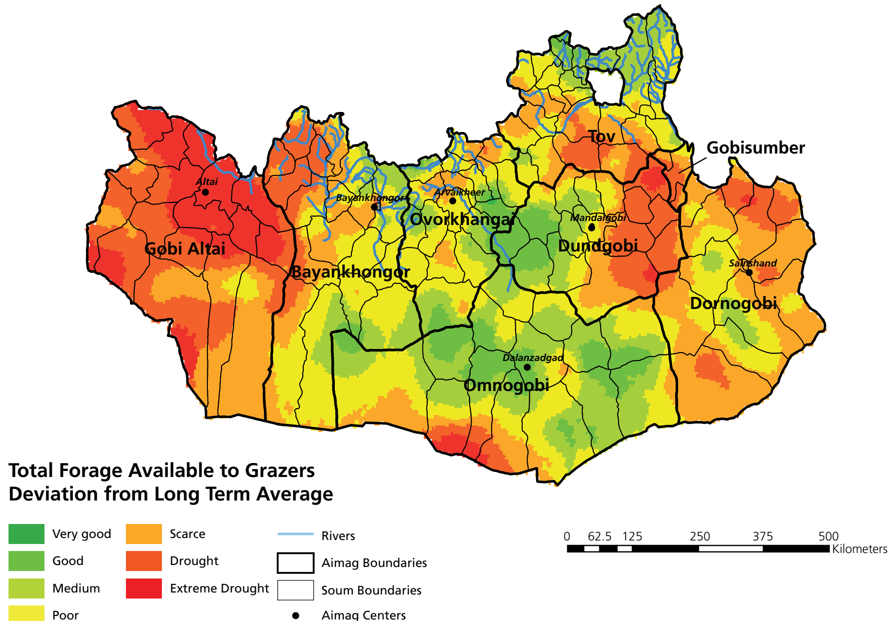
Current, forecast and long-term deviation forage maps are produced bimonthly and are distributed via the internet (http://glews.tamu.edu/mongolia) and email. The maps are also printed in colour and mailed to *sum* governments for local government use and for posting on the local government bulletin boards. Maps are also provided to regional and national government officials. A situation report, representing an interpretation of the forage maps by a rangeland specialist, is produced and mailed to regional and national government officials. This report is also used to produce radio bulletins that are reported on Mongolian National Public Radio.

12.4.8 Training on use of Gobi Forage products

Training programmes for herders, government personnel, NGOs and other interested stakeholders in the use and interpretation of the LEWS products were developed. Gobi Forage personnel travelled to *sums* across the region and conducted training sessions for herders and local government personnel to introduce them to the Gobi Forage products and to provide instruction on interpretation of Gobi Forage maps (Photo 12.3). Training was enhanced by the production of a set of DVD videos that were distributed, as well as shown, at the training sessions. These videos proved to be very effective tools for introducing potential users to the Gobi Forage programme by providing a description of both the LEWS meth-

FIGURE 12.4

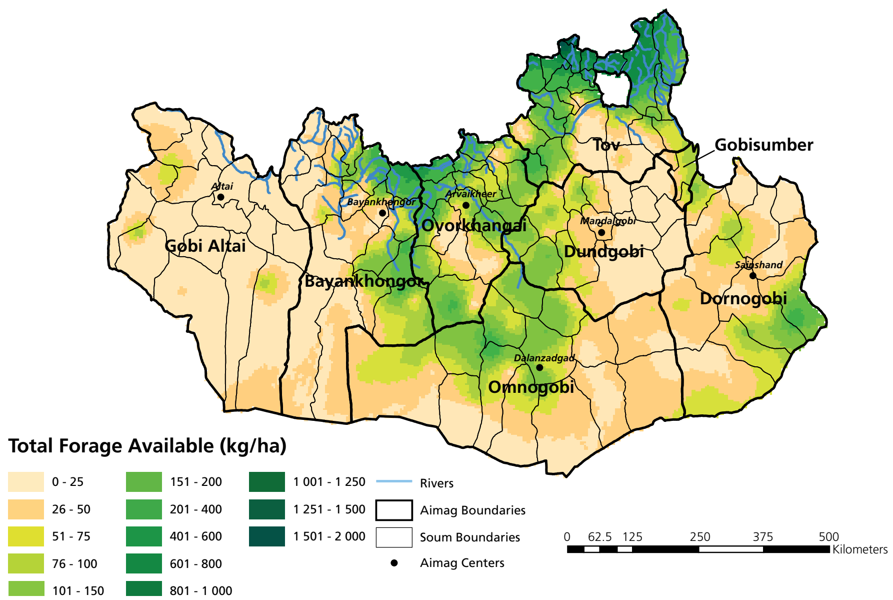
Map of total forage available deviation from long-term average for Gobi Forage LEWS project area between 1 and 15 September 2007



Note: Deviation categories represent early warning indicators on severity of drought – observe the severity of drought in east Dundgobi and northern Gobi Altai aimags.

FIGURE 12.5

Map of total forage available projected 60 days into future for Gobi Forage LEWS project area between 1 and 15 September 2007



Note: Forage amounts represent the forecast biomass available for 1-15 November 2007.

Photo 12.3
Training sessions held for herders and local government officials to introduce them to Gobi Forage maps and to assist them in using maps for risk management decision-making

odology and products. Brochures, calendars and descriptive maps were also produced for distribution after training sessions to improve retention of information by trainees.

A survey conducted during 2008 in the region indicated that the Gobi Forage programme was well received, with over 70 percent of herders having some degree of familiarity with Gobi Forage products. Almost half of the surveyed herders reported that they had used Gobi Forage information to guide livestock movements (51 percent), provide supplemental feed (49 percent) or change their grazing strategy (40 percent). An overwhelming majority (93 percent) of government officials found Gobi Forage products to be "very useful" in advising herders on grazing management and livestock movement. One provincial governor described how the system helped him manage the influx of almost 50 000 herders and their families from a neighbouring drought-stricken *aimag* and prevented conflict with local herders.

12.5 UPDATING THE FORAGE INVENTORY

Because of the early warning nature of the Gobi Forage LEWS programme, the forage inventory is updated continuously with the bimonthly processing of monitoring site data and the production of forage maps. Subsets of the monitoring sites throughout the region are visited periodically to collect forage biomass data to verify model predictions. In addition, vegetation transect data are collected periodically (every 3 to 5 years) for monitoring vegetation change and to update monitoring site parameters in the model if vegetation conditions have changed.

After USAID funding for the project ended in 2008, funding for continuation of the programme was received from the World Bank's Sustainable Livelihoods Programme in Mongolia. With the World Bank funding, the monitoring area has been expanded to include all of Mongolia and has since been renamed as the Mongolia Livestock Early Warning System. Forage mapping for the entire country will be initiated by mid-2012. By 2013, the system will be institutionalized at the Mongolia National Agency for Meteorology, Hydrology and Environment Monitoring (NAMHEM).

12.6 REFERENCES

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13. Livestock feed inventory on the Tibetan Plateau by remote sensing and *in situ* observation

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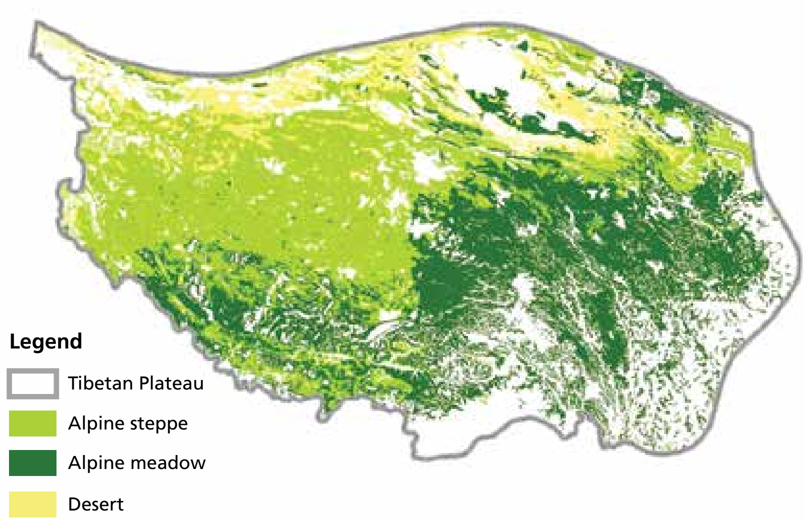
13.1 THE NEED FOR A LIVESTOCK FEED INVENTORY ON THE TIBETAN PLATEAU

The Tibetan Plateau, also known as the Qinghai-Tibetan Plateau, is the largest and highest plateau in the world (Figure 13.1). It covers an area of 2.5 million km^2, with an average elevation of 4 500 m above sea level, and is often called "the roof of the world". The Plateau includes the Tibetan Autonomous Region (TAR), Qinghai Province of China, and parts of Sichuan, Gansu and Yunnan provinces. The population of the Tibetan Autonomous Region increased from 1.23 million in 1959 to 2.93 million in 2010. This increased population has brought great demand and pressure on natural resources and the environment.

FIGURE 13.1
Grassland types of Tibetan Plateau including alpine steppe and alpine meadow



Due to the extreme climatic conditions on the Tibetan Plateau, its alpine meadow, alpine steppe, desert and forest ecosystems are fragile. With a total area of 1.5 million km^2 of pasture, the major livestock on the Plateau are yak and sheep, and its livestock population has doubled over the last 40 years. The total number of livestock in Qinghai and Tibet provinces in 2004 was 8735×10^4 standard sheep (yak was converted into sheep for uniform unit).

Primary production and aboveground biomass of natural grasslands has substantial seasonal and inter-annual fluctuations because of changing weather and climate. The field data show that the grassland primary productivity in the Three River Sources Region has a cyclical fluctuation over 3–5 years (Fan *et al.*, 2010). The feedstock yields in the region have shown an increasing trend over the last few years, particularly in the alpine grassland steppe, but it is likely to be a short-term phenomenon. The overall effects of climate change on grassland ecosystem productivity are likely to be negative over a long-term period on the Plateau (Fan *et al.*, 2010).

Climate change and increasing human activities will continue to increase the uncertainty and instability of grassland ecosystems. Drought on the Tibetan Plateau and overgrazing by livestock have accelerated grassland degradation (Liu *et al.*, 2008). Many regions on the Plateau have experienced environmental pollution and ecological damage (Cheng and Shen, 2000). Land desertification on the Plateau has increased substantially, particularly in a large area of Qinghai Province, which now accounts for approximately 21 percent of the total area of desertification in China. Soil erosion has also increased, in particular along the Hengduan Mountains where deforestation and other man-made disturbances occurred extensively. Biodiversity has decreased rapidly due to environmental degradation, over-excavation and hunting.

A livestock feed inventory can provide information on feed availability over time and space, which is critically needed to support feedstock management of individual herders and livestock industry. It is of great significance for utilizing and managing grassland, as well as improving ecological balance and environment. On the Tibetan Plateau, natural grassland is the only feed resource for livestock. An effective feed inventory system with a focus on grasslands will be very helpful for the livestock industry and ecosystem protection. Remote sensing could play an important role in the feed inventory at the regional level. Field investigations on the Tibetan Plateau region are difficult because of low oxygen levels and remote locations, so ground data are very limited. Our strategy is to integrate remote sensing-based modelling and flux tower-based *in situ* observations to develop a real-time system of monitoring gross and net primary production on the Tibetan Plateau. Regional aboveground biomass and forage will also be estimated with a remote sensing-based approach. The flux towers will provide data needed to validate our results. The workflow is shown in Figure 13.2.

In this document, we focus on the methods and procedures for estimating gross and net primary production, aboveground biomass and edible forage for livestock in grasslands of the Plateau (Figure 13.2). The first part of the document introduces methods and procedures for estimating gross and net primary production of grasslands from a satellite-based approach. We will briefly discuss the satellite-based Vegetation Photosynthesis Model (VPM) as a diagnostic model for estimating gross and net primary production of terrestrial ecosystems (Xiao *et al.*, 2005a; Xiao *et al.*, 2005b; Zhang *et al.*, 2005; Zhang *et al.*, 2006). The second part of the document discusses satellite-based approaches for estimating aboveground biomass, which include using data from optical sensors such as Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) (Friedl *et al.*, 1994; Ikeda *et al.*, 1999; Hirata, 2000; Weiss *et al.*, 2001; Schino *et al.*, 2003; Benie *et al.*, 2005; Xu *et al.*, 2008; Yang *et al.*, 2009a; Yang *et al.*, 2009b)

13.2 GROSS AND PRIMARY PRODUCTION OF GRASSLANDS

13.2.1 The Vegetation Photosynthesis Model (VPM)

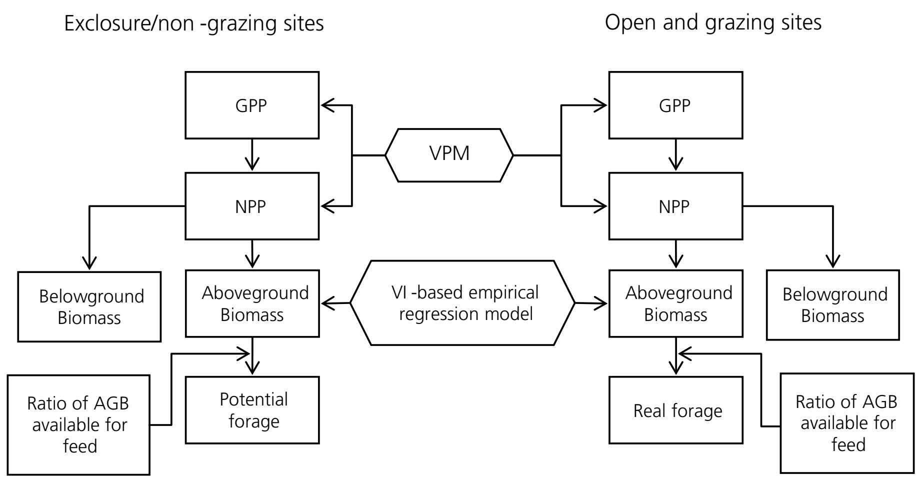
From a biochemical perspective, vegetation canopies are composed of chlorophyll (chl) and non-photosynthetic vegetation (NPV). The latter includes both canopy-level (e.g. stem, senescent leaves) and leaf-level (e.g. cell walls, vein and other pigments) materials. Therefore, $FPAR_{canopy}$ should be partitioned into the fraction of photosynthetically active radiation (PAR) absorbed by chlorophyll ($FPAR_{chl}$) and the fraction of PAR absorbed by NPV ($FPAR_{NPV}$) (Xiao *et al.*, 2004a; Xiao *et al.*, 2004b; Xiao *et al.*, 2005a):

$$Canopy\ (g/m2) = chlorophyll\ (g/m2) + NPV\ (g/m2) \qquad (1)$$

$$FPAR_{canopy} = FPAR_{chl} + FPAR_{NPV} \qquad (2)$$

Plant photosynthesis starts with light absorption by leaf chlorophyll. The PAR absorbed by chlorophyll (product of $FPAR_{chl} \times PAR$) is responsible for photosynthesis or gross primary production (GPP). Based on the conceptual partitioning of chlorophyll and NPV within a leaf and canopy, the VPM was developed for estimating GPP over the photosynthetically active period of vegetation (Xiao *et al.*, 2004b). The VPM is briefly described as the following:

FIGURE 13.2
Feed inventory system based on remote sensing and *in situ* observation on the Tibetan Plateau



$$GPP = \varepsilon_g \times FPAR_{chl} \times PAR \quad (3)$$

In the first version of the VPM, $FPAR_{chl}$ within the photosynthetically active period of vegetation is estimated as a linear function of Enhanced Vegetation Index (EVI), and the coefficient *a* is set to be 1.0 (Xiao *et al.*, 2004a; Xiao *et al.*, 2004b):

$$FPAR_{chl} = a \times EVI \quad (4)$$

Light use efficiency (ε_g) is affected by temperature, water and leaf phenology:

$$\varepsilon_g = \varepsilon_0 \times T_{scalar} \times W_{scalar} \times P_{scalar} \quad (5)$$

where ε_0 is the apparent quantum yield or maximum light use efficiency (μmol CO_2/μmol PPFD[17]), and T_{scalar}, W_{scalar} and P_{scalar} are the scalars for the effects of temperature, water and leaf phenology on the light use efficiency of vegetation, respectively. The full description of the VPM is given elsewhere (Xiao *et al.*, 2004c; Xiao *et al.*, 2005a).

The VPM has been evaluated over several major biome types, including tropical rain-forest (Xiao *et al.*, 2005b), temperate deciduous broadleaf forest (Xiao *et al.*, 2004b; Wu *et al.*, 2009; Wu *et al.*, 2010), evergreen needleleaf forest (Xiao *et al.*, 2004a; Xiao *et al.*, 2005a), alpine tundra (Li *et al.*, 2007b), grassland (Wu *et al.*, 2008; Wang *et al.*, 2010b), winter wheat, and corn croplands (Yan *et al.*, 2009). The VPM model was also applied to estimate GPP on the Tibetan plateau (Li *et al.*, 2007b), and the results showed that the VPM-predicted GPP agreed reasonably well with the estimated GPP from three CO_2 eddy flux tower sites in alpine meadow, alpine wetlands and alpine grasslands. These results demonstrated the potential of the satellite-driven VPM model for scaling-up the GPP of alpine grassland ecosystems.

13.2.2 Satellite images and climate data for simulations of the VPM model

The VPM model uses the EVI and Land Surface Water Index (LSWI), derived from imagery from optical sensors such as MODIS on board the Terra and Aqua satellites. MOD09A1 MODIS products are downloaded from the USGS EDC data centre[18], which includes surface reflectance values of bands 1–7 at 500 m resolution and an 8-day temporal resolution.

The VPM model also uses air temperature and PAR as input data. The air temperature data is derived from the China Meteorological Data Sharing Centre. The daily air temperature was combined into an 8-day average and interpolated to produce wall-to-wall gridded data coverages. PAR was derived from the Total Ozone Mapping Spectrometer (TOMS) ultraviolet reflectance data in point format. The PAR was calculated using the method of Eck and Dye (1991) and Li *et al.* (2007A), and then the PAR point data was interpolated into grids.

[17] Photosynthetic photon flux density.

[18] Earth Resources Observation and Science (EROS) Center.

13.2.3 *In situ* observations from CO2 flux tower sites for evaluation of the VPM model

There are three CO_2 flux towers available in Maqu, Haibei and Damxung on the Tibetan Plateau, which collect data for alpine meadow, alpine meadow and alpine steppe-meadow, respectively. All the three flux towers (Table 13.1) provide observational data for parameter calibration in models and validation.

The Maqu flux measurement site is located in Maqu county, Gansu province, China (37°52.77′ N, 102°09.27′E), on the eastern, protuberant edge of the Tibetan Plateau. A number of different ecosystems are present in this area. The climate of this region is cold and humid, which is typical in alpine areas. The mean annual temperature of this site is 1.1 ℃. There are only 19 days without frost throughout the year. Mean annual precipitation is 560 mm. Vegetation in this area is typically alpine meadow, dominated by gramineous species. The main soil types are alpine meadow soils and swamp soils.

The Haibei flux observation site is located at the Haibei Alpine Meadow Ecosystem Experimental Station (37°29′ ~ 37°45′N, 10112′ ~ 101°23′E), geographically situated in the northeastern part of the Qinghai-Tibetan Plateau. The altitude of this area ranges from 3 200 m to 3 600 m. The climate of this region is highly continental, and has been termed "plateau continental". Mean annual temperature is around -1.7 °C. Annual precipitation is about 600 mm with most precipitation occurring in summer. Vegetation in this area is the typical alpine vegetation of the Northern Qinghai-Tibetan Plateau. The main soil types are alpine meadow soils, alpine scrubby meadow soils and swamp soils.

The Damxung flux measurement site is located north of the Lhasa municipality and near to the southern edge of the Nyainqntaglha Mountains (91°05′E, 30°25′N) with an elevation of 4 333 m. The experimental site is categorized as plateau monsoon climate with strong radiation, low air temperature, large diurnal variation and small annual differences. Mean annual temperature is 1.3 °C and mean annual precipitation is 476.8 mm. Mean annual evaporation is 1 725.7 mm and average wetness coefficient is 0.28. The vegetation at the Damxung site is alpine steppe-meadow, with *Kobresia* meadows typical of the northern Tibetan Plateau. There are two typical meadows at the site. One is marsh meadow dominated by *Kobresia littledalei*, associated with *Blysmus sinocompressu, K. microglochin* and *K. littledalei*. The other is dominated by *K. parva*, with subdominants species such as *K. Humilis* and *Stipa purpurea* and occasional tussocks of *Kobresia* and forbs.

TABLE 13.1
The three CO_2 flux tower sites on the Tibetan Plateau

Station name	Location	Ecosystem types	Manager
Maqu	102.15°E 37.88°N	Alpine meadow	Shihua Lv
Haibei	101.33°E 37.66°N	Alpine meadow	Xinquan Zhao
Damxung	91.08°E 30.41°N	Alpine steppe-meadow	Peili Shi

13.2.4 Net primary production of grassland

When monitoring the C^{13} isotope and effects of CO_2 doubling on the photosynthesis of sunflowers, Cheng *et al.* (2000) found that the ratio between net primary productivity and gross primary productivity was constant. Here we assume that plant respiration is proportional to gross primary productivity; and therefore, net primary production is calculated as: NPP = GPP×α.

13.3 ABOVEGROUND BIOMASS OF GRASSLANDS

Grasslands in the Tibetan Plateau are dominated by alpine steppe and alpine meadow, which cover more than 60 percent of its area. The total aboveground biomass of alpine grasslands was estimated to be approximately 77.6 Tg (1 Tg = 10^{12} g), accounting for about one-quarter of total aboveground biomass storage in China's grasslands (298.0–323.1 Tg) (Ni, 2004; Yang *et al.*, 2009b).

13.3.1 Estimation of aboveground biomass from remote sensing

There have been a limited number of studies on grasslands on the Plateau. Most of them have focused on net primary productivity and few of them have specifically examined aboveground biomass or estimated forage (Piao and Fang, 2002; Zhou *et al.*, 2004; Chen, 2009). In recent years, with government investment, some regions such as the Three River Sources region have attracted more attention, resulting in more data collection of aboveground biomass and feedstock in the grasslands.

Aboveground biomass is often estimated using simple regression models that are based the correlations between aboveground biomass and vegetation index. The correlations between *in situ* aboveground biomass measurements, various spectral bands and vegetation indexes have been established by using statistical methods (Friedl *et al.*, 1994; Ikeda *et al.*, 1999; Hirata, 2000; Weiss *et al.*, 2001; Schino *et al.*, 2003; Benie *et al.*, 2005; Xu *et al.*, 2008). Simple regression models of the following general form were widely used:

$$\textit{Aboveground biomass} = f(VI) \qquad (6)$$

A recent study has evaluated six statistical models to estimate aboveground biomass, using *in situ* biomass data in Southern Gansu Province, Northeastern Tibetan Plateau (LIANG *et al.*, 2009): a linear model, an exponential model, a growth model, a logarithm model, a power model and a polynomial model. Their results showed that the power model has better estimation accuracy, and EVI has better performance than NDVI. The best-fit simple regression model is: $AGB\ (kg/ha) = 13583 \times EVI^{1.665}$, where AGB is aboveground biomass, EVI is the value of MODIS-EVI.

Another study has evaluated eight vegetation indices for estimating aboveground biomass (Shen *et al.*, 2008), and the results showed that all the eight vegetation indices have the ability to provide good estimation of aboveground biomass. The vegetation index based on universal pattern decomposition (VIUPD) is the best predictor of aboveground biomass among simple regression models. Moreover, both VIUPD and the soil-adjusted vegetation index (VI) could provide accurate estimates of aboveground biomass with dummy variables integrated in regression models.

A recent study has reported *in situ* aboveground biomass data from 675 plots in 135 sites (i.e. five plots from each site) measured on the Tibetan Plateau during the summers (July and August) of 2001–2004); and a simple regression model between aboveground biomass and growing season EVI during the period of 2001–2004 (Yang *et al.*, 2009a; Yang *et al.*, 2009b) was developed (see equation 7). That study investigated the allocation between above- and belowground biomass in alpine grasslands and its relationship with environmental factors using field data, proving that the median values of the ratio of below-ground biomass and aboveground biomass is 5.8 on the Tibetan plateau. This ratio was significantly higher in temperate grasslands than in alpine grasslands (Wang *et al.*, 2010a).

$$AGB = 334.39 \times EVI + 10.051 \qquad (7)$$

Here we use the simple regression model from Yang *et al.* (2009a,b) for estimating aboveground biomass. The EVI is calculated as the following:

$$EVI = G \times (\rho_{nir} - \rho_{red}) / (\rho_{nir} + (C1 \times \rho_{red} - C2 \times \rho_{blue}) + L) \qquad (8)$$

where G = 2.5, C1 = 6, C2 = 7.5 and L = 1; ρ_{nir}, ρ_{red} and ρ_{blue} is reflectance of blue, red and near infrared bands.

13.3.2 *In situ* aboveground biomass data for calibration and validation

A series of plots nearby the three flux towers (see section 13.2.3) needs to be sampled every year in order to provide validation data. The clipping and weighing method is a very tedious, but also the most accurate method for estimation of aboveground biomass (dry matter). First, suitable plot locations are selected; usually around five plots should be clipped in one sample but more plots are needed if the pastures are variable spatially. Second, grasses above the soil surface in a given area (usually one square metre or one square foot) are clipped and collected in paper bags. Third, the samples are dried in an oven and weighed for dry matter biomass.

13.4 FORAGE BIOMASS OF GRASSLANDS

Forage availability concerns farmers most. Forage yield is part of the aboveground biomass for livestock feed. Usually, the forage yield is based on the hypothesis that grazing is in the reasonable range of the ecosystem's self-regulation. That is, pasture is used fully without grassland degradation. The ratio of forage to biomass is a key parameter for forage estimation. However, few previous studies have referred to this parameter. Therefore, a field survey must be conducted to calculate the fraction of feed in aboveground biomass.

$$Forage = AGB \times Ratio \qquad (9)$$

According to the above equation, the ratio is the key for estimating forage amount. The forage yield is affected by many factors, such as grassland types, utility period, utility type, grassland degradation situation and disasters. These factors are classified as shown in Table 13.2 (Liu, 2005).

TABLE 13.2
Ranking factors and their values for forage estimation on the Tibetan Plateau

Grassland types	Alpine steppe	Alpine meadow		
	0.48*	0.58*		
Utility period	Growing season	Wither period	Avoid grazing period	
	1.0	1.2	0	
Utility type	Grazing	Cradle		
	1.0	1.4		
Grassland degradation	No	Slight	Middle	Severe
	1.00	0.85	0.7	0.55
Disasters	No	Slight	Middle	Severe
	1.00	0.85	0.70	0.55

* These values are revised from the previous study (Liu, 2005)

Therefore, the ratio of forage to aboveground biomass can be calculated using the following equation:

$$Forage = AGB \times f(x1) \times f(x2) \times f(x3) \times f(x4) \times f(x5) \quad (10)$$

where *AGB, x1, x2, x3, x4, and x5* are aboveground biomass, grassland type, utiliization (grazing) period, utility type, grassland degradation status and disasters, respectively.

13.5 SUMMARY

In this report, we describe a basic and simple framework for a feed inventory system on the Tibetan Plateau that integrates remote sensing and *in situ* observations. The main workflow comprises:

1. calculation of GPP and NPP on a regional scale, using a satellite-based VPM model, climate data and MODIS data at 50 m spatial resolution
2. estimation of aboveground biomass on a regional scale, using existing algorithms or from statistical analysis of field survey data; in addition, we can calculate below-ground biomass according to net primary production and aboveground biomass data
3. calculation of available forage for feedstock from aboveground biomass according to previous studies or related results from fieldwork on the Plateau.

It is very feasible to use such a remote-sensing methodology to update a livestock feed inventory on a regular basis.

13.6 ACKNOWLEDGEMENTS

The literature review and writing of this document were supported by research grants from the US National Science Foundation (NSF) EPSCoR programme (NSF-0919466) and the US National Aeronautics and Space Administration (NASA) Land Cover and Land Use Change Program (NNG05GH80G).

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