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The Use of NIR/NUTBAL, PHYGROW, and APEX in a Meta-Modeling Environment for an Early Warning System to Monitor Livestock Nutrition and Health.

Jerry W. Stuth[1], Paul Dyke[2], Abdi A. Jama[1] and John Corbett[2]
[1]Ranching Systems Group, Department of Rangeland Ecology and Management
and
[2]Integrated Information Management Laboratory, TAES- Temple
Texas A&M University System

Introduction

A major concern of organizations responsible for monitoring the well-being of pastoralists and their livestock in East Africa is making timely and informed decisions with sufficient lead time to allow policy-makers to design strategies to mitigate emerging crises. Traditional indicators of animal well being and associated forage supply have focused on body condition of animals, human/animal movement patterns, water supply, and broad assessment of forage supply.

The problem with these indicators is that of timeliness of observations and limited quantification of emerging conditions. For instance, body condition is a reflection of past nutrition of the animal as expressed to the human eye in terms of skeletal features either hidden or revealed through fat deposition or mobilization, respectively. A small-framed East African Zebu cow weighs approximately 350 kg at maturity with average fatness. A drop in one condition score results in a weight loss of 36 kg or about 10% of their body weight. Most well-trained observers are capable of visually appraising about 0.25 body condition score changes or about 9 kg. The average observer has a difficult time observing 0.5 body condition score changes or 18 kg in this case.

East African Zebu cows in low body condition such as a 3 (on 1 to 9 system with transverse processes and short ribs showing in lower back, pronounced “V” effect in the hip between hook and pins, with distinct rib cage), a weight loss of 1.0 kg/d day is not uncommon in dry periods, particularly if the animal is lactating. What would this animal look like in 30 days when viewed again? Essentially, they would loose 30 kg or be in body condition score of 1.8 or near emaciation. By the time the monitor returned, appraised the situation, met with key people in government/organization/agency and the responsible entity took action, this animal would be at high risk of death before mitigation could be implemented. The question is how can an enumerator or monitor look at a relatively thin animal today, and determine the rate of change in the body condition of the animal to predict future body condition and potential problems before they visibly express themselves?

Adequacy of forage supply to meet potential dry matter demand of animals is another consideration. Appraisal of current and future forage supply to sustain dry matter intake of animals requires a mechanism to determine standing crop, species composition, preference by the herbivores present and the population density of the animals utilizing a landscape. Predicting when a problem will arise due to either forage quality or supply is a daunting task for monitoring organizations.

Pastoralists are mobile and react to changing water supplies as well as forage conditions. Therefore, adequacy of water supply to meet water needs of animals and human populations determine whether livestock can be sustained in an area, even if forage conditions are sufficient to sustain the animals.

The main issue is to design a set of technologies that can be applied to large landscapes in a systematic manner which are capable of capturing the necessary information in a timely manner, analyzing the data and providing it at the policy and local levels in a form that allows proactive decision making. A research program is currently being initiated in East Africa by the Global Livestock Collaborative Research Support Program (GL-CRSP) which is organizing a network of scientists in Eritrea, Ethiopia, Kenya, Tanzania and Uganda committed to the design, testing and implementation of a livestock early warning system. The purpose of this paper is to provide an overview of the monitoring and modeling technologies that are being used to build this monitoring and analytical system. A companion paper, in this conference, covers the application of GIS spatial analysis techniques of the system that will be briefly covered in this paper.

Establishing a Framework of Monitoring

The Livestock Early Warning System (LEWS), currently under development, in East Africa involves linkage of several new technologies capable of predicting the current nutritional status of free-ranging animals and the impact of weather on forage supply and crop production among a carefully selected set of households reflecting a variety of effective environments across diverse landscapes of East Africa. The first tool to be used is the Spatial Characterization Tool (SCT) which allows stratification of large regions into units of similar environments called "effective environments". The regional extent of the target human population is then defined based on known attributes of environments that are occupied, in this case the pastoral regions of East Africa.

The first task is to sample these environments in a manner that establishes modality of the variety of landscapes in these effective environments. Household bomas, schools, watering points, stock trails, and markets are targeted as potential sampling sites. Access is critical and requires an overlay of the road system to determine what routes could be taken to best sample representative or modal units. A subgrid is overlayed on the clusters and samples collected in each with a road passing through the subgrid. For each sampling point, the landscapes are classified into virtual landscapes or typical plant community/crop combinations characteristic of the region. The proportion of plant community/crop and the modal composition of plant species growing in each ecological unit are defined.

Once a sampling point has been defined (georeferenced) and virtual landscape characterized for that area, herd populations are estimated based on the sample of the household herd and known livestock population densities in the grazing radius of the household. This information is augmented through interviews with local extension agents and NGO working in the area. These interviews set the demand from the livestock within the effective grazing zone of a sampling point. Also,the type of crop and the date planting for these areas are determined in the same manner.

Critical to the process is matching weather information with each of the selected sampling sites (households). A WMO station or active and reporting station is assigned to each of the effective environments and sampling locations. If a WMO station is not available, there is a recording and reporting mechanism established in a central location to acquire rainfall information and extrapolate temperature and radiation data from other reporting stations. The logistics of locating the most appropriate site for a rain gauge and assuring a rapid reporting presents a major challenge to the program. To overcome this problem, rainfall estimates are derived from predictions based on cold cloud cover analyzed by USAID-FEWS and FAO-GIEWS.

Finally, a systematic sampling route will be established that will be run every 30 days for a given zone according to the infrastructure available from governmental (i.e. NARs, Extension, schools), NGO and PVO entities. At each sampling date, a fecal sample is collected from a composite of at least 3 animals for each of the livestock species (cattle, sheep, goats). The number of deaths, sales, purchases, gifts and loans of livestock will be acquired from each individual to get some estimate of population changes (demand function). The enumerator, then, forwards the samples to a central processing facility for drying and shipment to a regional NIRS fecal profiling lab. Initially, this will be in Addis Ababa, Ethiopia but eventually labs will be established in each country (Kenya –1998-99, Uganda –1998-99, Tanzania –1999-2000 and Eritrea –2000-2001) at a location where it can best serve the project. The results are received at the lab, ground through a 1-mm screen in a cyclone mill and scanned with a FOSS NIRS machine. The resulting predictions of dietary crude protein and digestible organic matter are entered into a nutritional balance analysis model (NUTBAL) preset for each sampling site. Changes in body weight and condition are predicted in 30-day increments over a 90-day projection period. An estimate of loss in body condition, by animal breedtype and class, allows assessment of emerging trends towards malnutrition, disease, parasites and drought loss.

Predicted intake demand of the herds is passed to a grazingland production model (PHYGROW) where spatially referenced 10-day increment weather data is being fed to the system and runs are made of forage production under grazing. The models are run for the next 90-day projection with current demand and projected temperature under no rain and high probability events derived from historical weather data. Projections of future forage balance are determined. If crops are located at the sampling point, then the APEX crop simulation model is run as well to make projections on emerging crop yields and potential failures.

The households and strategic WMO and site-specific rain gauges offer a mechanism to sample large regions. Given the fact that the sampling points are representative of a specific area but need to be extrapolated to other areas of similar effective environments. Predicted problem areas in terms of animal condition, forage balance and human activities are mapped and then weather and nutrition data are projected to other areas assumed to have similar effective environments to predict likely outcomes for those areas. The cold cloud cover predictions of present precipitation are critical to the usefulness of the system where we do not sample. We are under negotiation with Foreign Agricultural Service of the United States Department of Agriculture to access their 20 * 25 mile weather grid of the world for East Africa.

Hot spots or emerging areas that are not part of the sampling routes are then investigated by rapid deployment teams to verify if critical conditions are truly emerging and warrant alert status. For those areas identified as alert status, a reporting mechanism is activated to link the information with existing early warning systems such as FEWS, GIEWS and the Climate Prediction Center of USGS as well as direct reporting to governmental entities responsible for policy making concerning disaster relief in each country. Initially, the USAID Famine Early Warning System (FEWS) and FAO Global Information and Early Warning System (GIEWS) 10-day reporting system will be used to predict rainfall amounts based on a complex calculation of elevation, distances to known rain gauges and remotely sensed cold-cloud cover. Predictions from the LEWS project will be fed back into the FEWS and GIEWS reporting systems and the ASARECA Crisis

Mitigation office as it comes on line. Reporting mechanism with IGAD will be coordinated through ASARECA.

The LEWS scientists in East Africa are placing a high priority on watching with their respective governments to assure that information flows to the right people and that it is placed in context of other information sources that policy makers may content with.

Developing a Spatial Sampling Frame for the Monitoring System

Corbett et. al 1998 (see this proceedings) have provided an overview of the Spatial Characterization Tool (SCT) and how it is used to establish a spatial sampling frame for selection of early warning monitoring sites and allocation of fiscal and human resources with maximum impact. Critical to the success of the monitoring phase of an early warning system in pastoral environments is the establishment of geo-referenced locations where monitoring personnel can track trends in emerging conditions in a time-efficient manner.

In the case of the livestock early warning system described herein, the focus is on accessible pastoral households distributed throughout a region, which share common climatic, edaphic and production system attributes, referred to as effective environments. The SCT system provides a gridded (1 km x 1 km, 4 km x 4 km) georeferenced database of a wide array of climatic attributes, soil types, human populations, road networks, livestock density, etc. Using principle component and cluster analysis, it is possible to classify landscapes into units which meet the specified constants or attributes selected to define the geographical extent and subdivision of a problem area. In the case of the LEWS project, we are focusing on the extent of pastoral grazing in five East African countries with sub-delineations within the geographical boundary. Sampling within the clusters assures that time and funds are targeted for maximum impact and representative of variations across the region. When roads are layered with the livestock population density data, it is possible to devise sampling routes which best represent variation in landscapes and human conditions, i.e. Sample where environments shift and the livestock live.

The SCT system also serves as a visual reporting system for emerging trends and potential hot spots. As modeling results come on line, this information can be displayed and provide additional information to allow an effective tool to visualize emerging problems electronically via the internet or CD-ROM or in paper in the form of newsletters, market reports or simple village fliers.

Linking NIRS Fecal Profiling Technology with the NUTBAL DSS

A major limitation to supporting nutritional management decisions, is the inability of managers and advisors to determine diet quality under field conditions where animals graze freely across diverse landscapes or complex pasture mixes. However, recent advances in near infrared reflectance spectroscopy (NIRS) have made it possible to detect fecal by-products of digestion and relate these constituents to dietary crude protein (CP) and digestible organic matter (DOM) (Stuth et al. 1989, Lyons and Stuth 1991, Stuth et al. 1991, Lyons and Stuth 1992, Leite et al. 1992, Lyons et al. 1993, Pearce et al. 1993, Leite and Stuth 1994, Lyons and Stuth 1995, Whitley and Stuth 1996, Showers 1997). Prediction equations are developed from fecal samples of intact animals and extrusa of esophageal fistulated animals sharing the same landscape over a wide array of forage conditions or controlled stall-feeding. Lyons and Stuth (1992) developed a prediction equation that predicted dietary CP and DOM at similar levels of accuracy as standard wet chemistry laboratory analyses for cattle. To date, dietary prediction equations for cattle appear to be reliable across a broad spectrum of forage types including subtropical shrublands, temperate and tropical pastureland, temperate and sub-tropical grasslands, desert shrublands, desert grasslands, Mediterranean annual grasslands, hardwood forests, coniferous forest, marshland, and mountain meadows in the USA. Recently, Coates (1998) demonstrated its viability in the tropics of Northern Australia and Ossiya (1998) in Sub-saharan Africa.

Principles of NIRS

The physical basis for NIRS is the irradiation of molecules of a substance with light from an outside source. Varying proportions of light energy are absorbed by, reflected by, or transmitted through the substance in ways discussed fully by Norris (1985a,b) and Birth and Hecht (1987). Few substances fail to absorb in the NIR band. The pattern of absorbance spectra through the NIR band conveys chemical information of a sample (Murray and Williams 1987). The amount of absorbance/reflectance that takes place will differ at different wavelength points, thereby creating a spectral pattern. The shape of the spectrum in terms of “peaks and valleys” of absorbance is characteristic of all of the absorbing molecules present in the sample (Murray and Williams 1987).

The most critical part of the NIRS system is the selection of the correct wavelength to measure (Williams 1987a). The three main types of wavelengths selected are: 1) wavelengths that correspond to known absorbencies of specific constituents to be determined, 2) wavelengths that correspond to an absorber on a constituent that is inversely related in concentration to the constituent to be determined, and 3) wavelengths that occur when the optimum wavelength for measurement of a constituent corresponds to an area of least interference from other constituents, rather than to a band caused by a specific absorber (Williams 1987a).

Wavelength selection is the most time consuming and potentially the most critical aspect of calibration development (Westerhaus 1985a). A calibration is established by using a set of samples of known composition (a reference set) and correlating them to NIR measurements of log (1/reflectance) values for those samples (Hruschka 1987). NIRS relies heavily on the collection of an appropriate set of reference samples, representing a diverse set of conditions in the population of interest, for calibration and choosing the best mathematical treatments to obtain the most accurate calibration (Shenk and Westerhaus 1991).

Application of NIRS

Coleman et al. (1989) and Stuth et al. (1989) suggested fecal monitoring with NIRS was a potentially useful tool to assess diet quality of free-ranging herbivores. Similar results have been obtained with elk (Brooks et al. 1984) and white-tailed deer (Gallagher 1990; Showers 1997). Lyons and Stuth (1992) suggested that dietary CP and DOM of free-ranging cattle can be predicted with NIRS fecal analysis to a degree of precision equivalent to conventional laboratory diet analyses. Leite and Stuth (1995) concluded that NIRS is a viable tool for predicting diet quality of free-ranging goats. Whitley and Stuth (1996) indicated NIRS can be used effectively to determine protein partitioning in the gastro-intestinal tract of free-ranging cattle.

Calibration requires correlation of a reference set of known values to spectra generated by NIRS scans of corresponding samples (Hruschka 1987). In the case of predicting diet quality from feces, chemistry values are obtained from diet samples and NIR spectra are generated from feces obtained from animals consuming those diets.

The first step in calibration is subjecting the calibration file to various mathematical treatments of the data (Hruschka 1987). Optical data recorded by NIR spectrophotometers are obtained from the sample in the form of the log of the inverse of reflectance, or log (1/R) (Williams 1987a). Derivatized log (1/R) optical data are commonly used to address problems associated with overlapping peaks and large baseline variations (Hruschka 1987). Math treatments involve selecting a first, second, or higher derivative to conduct the calibration procedure rather than the original spectra (Hruschka 1987). The mathematical treatment also allows for selection of the gap over which the derivative will be calculated and degree of smoothing for the calibration. Gap size is important in calibration sensitivity to system noise (Williams 1987b). Although a large gap may render the calibration inefficient due to lower sensitivity to sample variation, a small gap could produce the opposite effect and make the calibration sensitive to variations resulting from sample noise. Smoothing is used to reduce instrument and/or sample noise and is performed by multiplying points along the NIR spectrum with a weighting function, increasing values at low frequency points and decreasing values at high frequency points (Hruschka 1987, Williams 1987b).

Multi-term linear regression is used in the development of calibrations to isolate effects of a single absorber and normalize the baseline (Hruschka 1987). The optical data generated from fecal scans are the dependent variables and the diet chemistry values are the independent variables (Williams 1987b). Wavelengths are selected using the modified- stepwise regression approach (Westerhaus 1985a). One wavelength (term) for every 10 samples is recommended as maximum terms allowable for an equation (ISI 1992), hence, providing a stopping criterion for regression runs. Calibrations using fewer wavelengths perform most effectively (Williams 1987b). After calibrations are subjected to various mathematical treatments and modified-stepwise regression, sample outliers are eliminated where this is justified (Martens and Naes 1987). Calibration datasets are subjected to two outlier elimination passes before completion (ISI 1992).

Stable equations are selected by evaluating calibration regression statistics and interpretation of important wavelengths. Each math treatment results in a separate equation, the value of which is determined by considering standard error of calibration (SEC), coefficient of determination (R^2), wavelength coefficient magnitude, F-statistic, and biological interpretation of wavelengths.

The SEC describes the degree of fit achieved in the calibration regression (Westerhaus 1985b). Although lower SEC values indicate better fit, overfitting can occur when calibration regression addresses spectral features not representative of samples used in the calibration set. Higher SEC values suggest poor fit due to occurrence of erroneous laboratory data or NIRS cannot be used to predict the variable of interest. Generally, SEC should be between 1 and 2 times standard lab error (SEL) (Westerhaus 1985b). However, this relationship between SEC and SEL is used for a direct relationship between laboratory and NIRS analyses; in other words the sample used for laboratory analysis is the sample used for NIRS analysis. In the case of an indirect relationship, such as laboratory analysis of diet samples correlated to NIRS analysis of fecal samples, individual animal variation may introduce error not encountered in direct measures. Thus, a 2:1 relationship between SEC and SEL may be too critical for indirect determinations. The SEL is measured by standard deviation of chemistry values between duplicate samples from the reference or standard set (Hruschka 1987).

Second, the coefficient of determination (R^2) is important in selecting equations. The R^2 is the proportion of variability in the log (1/R) spectra that is accounted for by the standard (chemistry) values (Ott 1993). R^2 values close to 1 indicate high correlation between spectra and standard values.

Third, the magnitude of the wavelength coefficients should be optimal for the constituents under consideration (Williams 1987b). In other words, the wavelengths are biologically explainable as they pertain to the parameter of interest. Regression coefficients are used to multiply the energy signal obtained from a sample in order to interpret sample information at the optimum wavelengths (Williams 1987b). As a wavelength proceeds further from the optimum point, the associated regression coefficient changes and compensates for the wavelength difference (Williams 1987b). Large coefficients tend to be sample sensitive and lead to an increase in frequency of large errors within a calibration (Williams 1987b). Hence, equations with large coefficients should be avoided where possible.

Fourth, it is important to choose an equation with a high F-statistic. Low values serve to fit random errors and cause problems of multi-collinearity; therefore, equations containing low F-values should not be considered (Westerhaus 1985b). Wavelength importance is determined directly by the magnitude of the F-statistic.

Finally, wavelengths in equations of interest should be examined for biological interpretation. Wavelengths should correspond to known absorption peaks in the NIR spectrum for the constituent being predicted (Westerhaus 1985b, Hruschka 1987); in this case fecal constituents as indicators of dietary composition.

Once a series of candidate equations has been selected, their stability should be evaluated with a validation trial derived from materials outside of those used in the reference set. In this way the equation can be tested for applicability to samples from the population of interest (Fearn 1997). This step is critical to the evaluation process as several equations can emerge with nearly identical statistics but focusing on different areas of the spectra and(or) weighting the influence of the same wavelengths in a different manner.

Effectiveness of predicting unknowns from the population of interest with an equation can be ascertained through examination of the standard error of performance (SEP) for the validation (Williams 1987a). SEP's should be less than 0.15-0.20 times the SEC of the equation. Additionally, the coefficient of correlation should be above 0.8 (or $> R^2=0.64$) for the NIR equation to be effective (Williams 1987a). Another useful statistic in equation validation is slope of the regression line (Westerhaus 1985c). Slope relates the NIR determinations to chemistry values of the standards and should be near 1.0. Slopes deviating from 1 indicate high and low values will be regularly under or over predicted.

A final step that should be performed is to ascertain the level of spectral integrity across a diverse set of seasons and geography among the group of potentially viable equations. Experiences of the USA National Service Lab, GAN Lab, have indicated that a group of equations meeting the above criteria should be ranked according to performance in the validation trial and then reranked after running them against a large population of fecal samples from the target region(s). This second ranking should be based on the number of spectral outliers. GAN Lab has found that it is best to work with a series of equations that focus on different parts of the spectral but perform similarly in terms of statistical validation. Generally, when the “best” equation fails, one of the secondary ranked equations will focus on another part of the spectrum and successfully predict the values. This allows for a more geographically robust application of the technology.

NUTBAL – Nutritional Balance Analyzer

The NUTBAL software enables the estimation of crude protein (CP) and net energy for maintenance (NEm)/gain (NEg) balance of cattle, CP and NEm balance of sheep and goats, and CP and digestible energy balance of horses. When coupled with estimates of dietary CP and digestible organic matter (DOM) of the diet of free-ranging animals via fecal scans using NIRS of fecal samples from cattle, sheep, and goats, the user of the NIRS/NUTBAL nutritional management system can provide projections of weight gain/loss and resulting body condition score.

The NUTBAL system uses a combination of published modeling systems including the NRC's 1984, 1987 basic nutrient requirement formulas, the Fox et al. (1988) adjustments to the NRC (1984) equations, McCollum's (1995) rumen degradable protein thresholds and DOM/CP ratio concepts and Moore and Kunkel's (1995) concept of intake change rate and modification of metabolizable energy due to associative effects in growing animals. Where NUTBAL deviates from other nutritional intake models is in the application of a modified, metabolic-fill system to predict dry matter intake of the animal from dry fecal output. The system is based on early work by Conrad et al. (1969), Forbes (1980, 1984), Kartchner (1981), and Fisher et al. (1990). Use of this approach allows modeling of fecal output processes, considering more than just the digestion process. Impacts of forage availability, appetite drive and associative effects can be characterized in both fecal output as a proportion of fat-corrected body weight and the metabolizability of ingested forage. Many of the baseline values of fecal output expressed as a percentage of fat-corrected body weight are derived from literature review, expert opinion and unpublished data extrapolated from prior studies. Basal fecal output factors of mature animals in NUTBAL are relatively less complex than those of growing animals which reflect differences in the sexes, impact of DOM/CP ratio, threshold rumen protein degradability and associative effects. Perhaps the greatest weakness of NUTBAL today is the inability to account for requirements of degradable intake protein (DIP) and digestible undegraded protein (DUP). Recent research in the prediction of these variables via NIRS fecal profiling will make it possible to monitor them and include them in current versions of NUTBAL under development (Whitley and Stuth, 1996).

Modeling Forage Supply

The SCT system allows the spatial representation of any of the analyses performed within the LEWS program. As mentioned one of the first information sources is the projected changes in body condition by kind and broad class of livestock. This addresses issues of nutrition. However, adequacy of forage supply is another concern.

The estimated population density and computed forage demand (kg/d) will be input into the PHYGROW modeling system to determine adequacy of forage supply for the projected livestock population. PHYGROW is a hydrologically based, grazingland forage production model capable of represent georeferenced, complex plant communities with a selectively grazing herbivore population. Weather, soils, plant communities and herbivore populations are specified for each virtual landscape defined for the SCT analysis. Updated intake inputs and estimates of livestock density are input into the model every 30-days and model runs of the grids for the entire region are run at 10-day intervals, corresponding to the 10-day reporting structure of the FEWS and USGS systems.

PHYGROW is capable of projecting how a known population of animals is selectively grazing available forage responding to environmental conditions, representing a complex of individual species. The resulting standing crop by species of the major modal plant communities in a virtual landscape is then subjected to a series of probabilistic projections reflecting the statistical characteristics of historical weather relative to current conditions. Forecasts can be made in the form of probability distributions of potential inadequacy in 30, 60 and 90-day projections and reported via the SCT and FEWS systems.

The human decision-making process can be incorporated into PHYGROW's destock/restock rule base. Critical standing crops of available forage can be specified at be specified at critical decision points and destock/restock levels, allowing the model to project how animal demands may be adjusted.

APEX Cropping Systems Model

Crop mixtures increase as long-term annual rainfall of a pastoral region increases or favorable soil-slope position allows cropping in normally drier regions. Where appropriate, the principle crops, maize/wheat/teff/millet/sorghum, will be simulated from the same weather data, soil data and on-site recording of planting dates to project crop yields and or failures in a spatially explicit manner. APEX is a hydrologic-based model, which allows projection of crop yields given differences in cultivation practices, soils, weather, and fertility regime. APEX will be fed the same weather data as PHYGROW from the reporting network and projections made from the 10-day reporting mechanism mentioned in the PHYGROW section. Crop vulnerability projections will be made in the SCT environment and report through the FEWS system.

Building In-Country Analytical Capacity

Finally, the primary goal of the LEWS project is to leave in place the analytical capacity and human resources to sustain the monitoring and early warning system linked to key policy or agency personnel capable of taking actions to mitigate crises emerging from poor nutrition, inadequate forage supply, loss of water, disease outbreak or social disruption due to security issues. It will be critical to the success of the LEWS program to involve key decision-makers at the right level of government in the early phases of the project to insure that the reporting mechanisms achieve maximum communicative capacity. We see the emergence of the ASARECA Crisis Mitigation program as a key component to this process given the ties to a broad network of governments in East Africa and the commitment of the participating NARs and University to the idea of an early warning system for livestock. We envision a network of highly skilled people in each country conducting the analyses, reporting the results to the proper people and providing insights into potential mediation actions that could be taken to dampen the negative impact of emerging stress conditions. Strong linkages with international monitoring systems such as FEWS will also insure that the world and affected governments are well aware of emerging problem areas and help focus resources in a proactive manner to help alleviate major losses of assets of pastoralists due to drought stress, disease outbreak or social unrest.

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