Feasibility of using the FAO-Agricultural Stress Index System (ASIS) As a Remote Sensing based Index for Crop Insurance

Oscar Rojas, Ph.D.
Natural Resources Officer, NRC, FAO
oscar.rojas@fao.org

Shukri Ahmed, Ph.D.
Senior Economist, GIEWS, FAO
shukri.ahmed @fao.org

In recent years, weather index insurance has gained significant international attention. Multilateral agencies and donors are supporting the development of index insurance products. In June 2012 an initial consultation workshop with the purpose of implementing the *G8 Global Action Network to Accelerate the Availability and Adoption of Agricultural Index Insurance* held in Rome. The participating institutions (FAO, FERDI, IFAD, IFPRI, ILO, IRI, JICA, SYNGENTA, SWISS-RE, UCDAVIS, USAID, University of Athens and WFP) agreed that the Action Network would enhance the understanding of agricultural index insurance and promote its availability and adoption where appropriate; as part of broader risk management strategies.

Weather index-based insurance can help secure the income of smallholders who are particularly vulnerable to climate variability. It can improve rural livelihoods and reduce food insecurity. One of the aims is also to improve access to credit by lowering the risk of default for financial institutions. The weather-based index insurance can be likened to contingency insurance in that a specific event can trigger an insurance payment. A commonly used weather-based index is rainfall data from local weather stations; however, other measures can also serve as weather-based indexes. For example, the Normalized Difference Vegetation Index (NDVI), which is derived from data collected by satellites, gives an indication of vegetation health and thus potential crop yields, and has been used to provide index-based drought insurance. Another index insurance product uses sea surface temperatures (SST) as a predictor of extreme flooding in northern Peru. The SSTs used are indicative of extreme El Niño events, the primary cause of catastrophic flooding in that region.

Weather stations have traditionally been the primary data source for weather index insurance programs. However, in many developing countries the number of weather stations is often very limited and their distribution in relation to the agricultural areas poor. Furthermore, spatial interpolation techniques that can be used in some situations to solve the problem of low density of stations prove to systematically underestimate the extreme values; precisely those extreme events that the insurance program intends to cover. Due to this fact, a potential alternative could be the use of rainfall estimates from satellite data or climate simulation models. However, rainfall estimates when compared with ground measurements (rain gauges) generally over or under estimate rainfall amounts quite significantly depending of the geographical position and topography of the area under analysis. Up to the present, these difficulties in estimating rainfall have prevented the development of weather index based insurance.

One feasible alternative for developing countries could be the use of vegetation indices even if those indices still have some technical limitations that can affect the accuracy of the data captured by satellite (amount of humidity in atmosphere/soil, position of satellite relative to earth surface and the time series is composed of data from several different sensors). The use of NDVI has so far been applied mainly in pastoralist areas, nevertheless, it offers a high potential for use also in cropping areas if analysis is restricted to the growing period and the areas where crops are believed to be grown. Improvement of land use maps to better define agricultural cropping areas could contribute to produce much better results with this technique.

The Global Information and Early Warning System (GIEWS) and Climate, Energy and Tenure Division (NRC) of FAO aim to develop an "Agricultural Stress Index System" (ASIS) for detecting agricultural areas with a high likelihood of water stress (drought) on a global scale. This system is being implemented on behalf of FAO by the Flemish Institute for Technological Research (VITO-TAP) with the technical support of the Monitoring Agricultural Resources (MARS) unit of the Joint Research Centre of the European Commission (JRC). The ASIS is based on the Vegetation Health Index (VHI), derived from NDVI and developed by Felix Kogan from the Center for Satellite Applications and Research (STAR) of the National Environmental Satellite, Data and Information Service (NESDIS). This index was successfully applied in many different environmental conditions around the globe, including Asia, Africa, Europe, North America and South America. VHI can detect drought conditions at any time of the year. For agriculture, however, we are only interested in the period most sensitive for crop growth (temporal integration), so the analysis is performed only between the start (SOS) and end (EOS) of the season (see Figure 1).

In order to directly identify the administrative units affected by agricultural drought, the percentage of each unit's agricultural area having a VHI value below 35 during the crop season is calculated. This calculation can be performed on the thirty years of NDVI data that already exists and assuming that drought events are independent, it is possible to obtain the probability at administrative level of having a given percentage of the agriculture area affected. Figure 2 shows the probabilities of exceeding the threshold of 30% of the total agricultural area affected by drought.

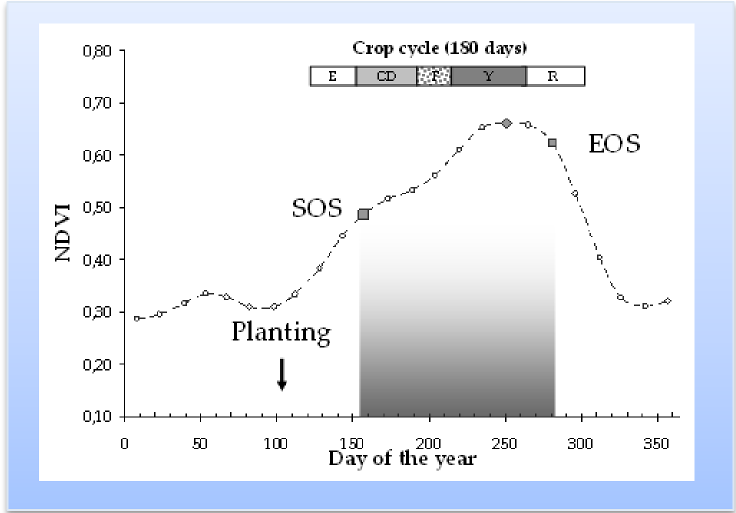

Figure 1: NDVI profile showing the period of analysis defined by the start of the season (SOS) and the end of season (EOS). The crop cycle is divided into 5 development stages: E: establishment, CD: crop development, F: flowering, Y: yield formation or grain filling and R: ripening stage. Stages CD, F and Y are the most sensitive to water deficit

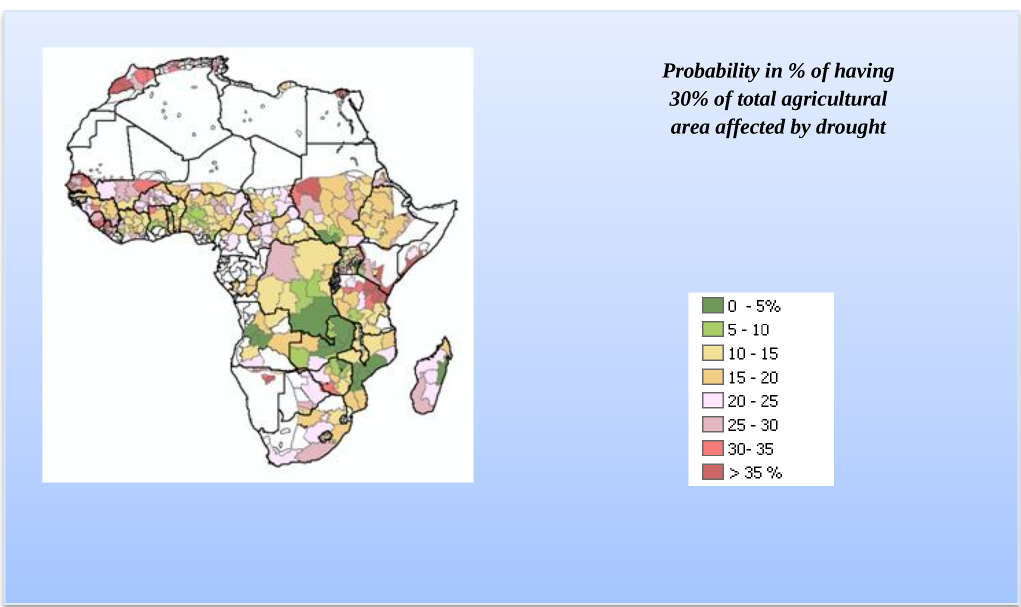

Figure 2. Probability by administrative unit of having more than 30% of the agricultural area affected by drought during the first crop season.

From analysis of the time-series results, it is possible to establish a threshold level for each administrative unit, representative of a "catastrophic drought event," which could be used to trigger insurance payoff. Figure 3 shows a hypothetical case of payoff at sub-national level for Kenya using as an index, the agricultural area affected by drought in percentage. In this case, the line of payoff was arbitrarily fixed at 70% of the agricultural area affected by water stress. Thus, insurance would have paid off in 1984 and 2000 to the farmers in the Central, Eastern and Rift Valley; in 2002 only to the Coast province and in 2009 to the Coast, Eastern and Rift Valley provinces. In the time series analyzed, Eastern and Rift Valley provinces have a higher probability of being affected by drought than the Central and Coast provinces. The Nyanza province would not be interested to sign a contract at the 70% line of pay-off. The insurance contract for Nyanza province could use a lower threshold such as 40% of agricultural area affected by drought; in which case farmers would have been paid off in 1992 and 2004. The crop insurance could adjust with the percentage of area affected by drought and the premium of the insurance to reach an agreement with the farmers of each province.

Conclusion

The proposed remote sensing index bases on ASIS has potential to be used for a crop insurance scheme in developing countries, but the ASIS would need to be carefully calibrated at country level locally and tested before becoming operational. Capacity building among local stakeholders would also be necessary. The proposed remote sensing index will work better in countries with semi-arid conditions where water stress is the main limiting factor of agriculture production.

With respect to weather station-based indices, a remote sensing-based index presents the advantage of exhaustive ground coverage. On the other hand, rainfall estimates derived from remote sensing or general climate circulation models present the disadvantage of over/underestimating rainfall; in this case, we prefer to consider the NDVI as a proxy for assessing the crop condition (which itself depends on the water available to the crop). However, there are some well-known limitations to remote sensing as the NDVI is affected by soil humidity and surface anisotropy. Composite products used in most applications tend to limit these effects that cannot be ignored completely.

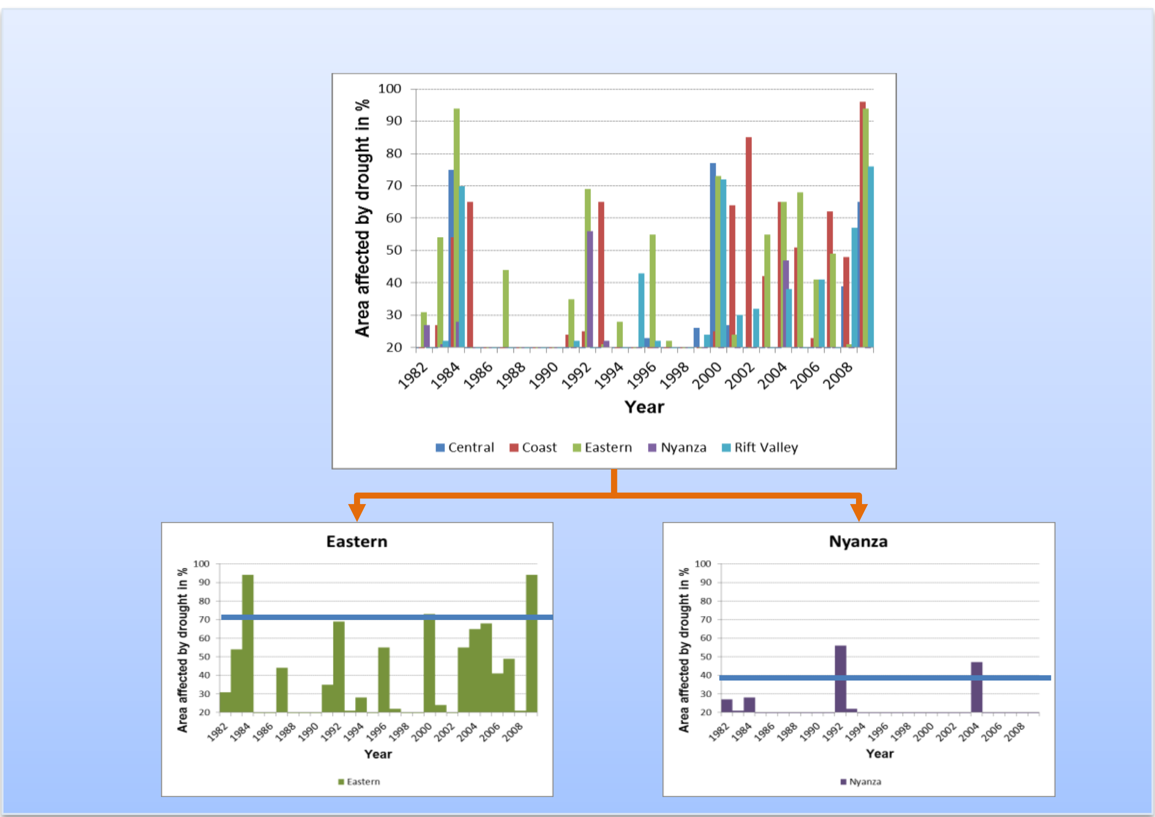

Figure 3. Hypothetical case of payoff at province level, using the line of 70 and 40% of agricultural area affected by drought in Kenya (1982-2010).

References

Doorenbos, J., & Kassam, A. (1979). Yield response to water.FAO Irrigation and Drainage Paper No. 33. Rome: FAO 200 pp.

Evans, M., Hastings, N., & Peacock, B. (2000). Statistical distributions, 3rd ed. New York: John Wiley and Sons (Chapter 6).

Genovese, G., Vignolles, C., Nègre, T., & Passera, G. (2001). A methodology for a combined use of normalized difference vegetation index and CORINE land cover data for crop yield monitoring and forecasting. A case study on Spain. Agronomie, 21(1), 91−111.

Kogan, F. (1986). The impact of climate and technology on Soviet grain production.: Delphic Association Rep. 174 pp.

Kogan, F. (1994). Droughts of the late 1980's in the United States as derived from NOAA polar-orbiting satellite data. Bulletin of the American Meteorological Society, 76(5), 655−668.

Kogan, F. (1995). Application of vegetation index and brightness temperature for drought detection. Advances in Space Research, 15, 91−100.

Kogan, F. (1997). Global drought watch from space. Bulletin of the American Meteorological Society, 7(4), 621−636.

Kogan, F., Yang, B., Guo, W., Pei, Z., & Jiao, X. (2005). Modelling corn production in China using AVHRR-based vegetation health indices. *International Journal of Remote Sensing*, 26(11), 2325−2336.

Rojas, O., Vrieling, A. Rembold, F. (2011), 'Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery', *Remote Sensing of Environment*, 115:343-352.

Unganai, L., & Kogan, F. (1998). Drought monitoring and corn yield estimation in Southern Africa from AVHRR data. *Remote Sensing of Environment*, 63, 219−232.