Analyzing Agricultural Stress Index over Pakistan with Phase Change of Oceanic Nino Index in 2015–16 El Niño Episode

Ahmad, B., S. A. A. Bukhari, H. Naveed, M. Haroon

Abstract

Agricultural stress index (ASI) is analyzed over Pakistan with phase change of Oceanic Nino Index in 2015–16 El Niño Episode in this study. FAO's established Agricultural Stress Index System (ASIS) is employed to analyse its sensitivity to water stress conditions attributed to a strong 2015–16 El Niño episode. In addition to the ASIS, states of auxiliary drought monitoring indices e.g. Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Vegetation Health Index (VHI) and precipitation anomaly are examined to establish attributions to the episode. This article explains the effect that the 2015–16 El Niño episode has had on key crop production provinces converging on wheat cereal in Pakistan. Results reveal that positive El Niño picked up by warm phase of Oceanic Nino Index (ONI) reached its highest value of 2.6 above normal during the episode. Signal of the NDVI anomaly was exceptionally high in Jan–2016 with a decrease of up to 60% over the water stress regions. Severity of the VCI and the VHI was also evident by its weak value of less than 0.15 especially in Jan–2016. In essence, the warm ONI phase attributed to more than 80% decrease in precipitation over parts of the region forced the drought monitoring indices to reach severity and hence, affected more than 8% of crop areas over parts of the region.

Keywords: NDVI, VCI, VHI, ONI, ASI, drought, El Niño, Pakistan.

Introduction

Drought distresses more communities than any other form of natural catastrophe and is ravaging to sources of revenue, particularly in emerging states. Current trends show that droughts are intensifying in scale and rigour, upsetting lives and food security, and causing damages that may be suffered considerably in drought– shaken zones. Observing crop growth round the globe is vital to estimate production and offer timely caution of conditions where crop damages could lead to food scarcities. Agricultural yield is vastly reliant on climate variability in several parts of the globe. For instance, drought may well rigorously diminish crop produces, hypothetically disturbing food accessibility at local, regional, and global levels. The Food and Agriculture Organization of the United Nations (FAO) runs the Global Information and Early Warning System (GIEWS) that watches global food supply and demand. One of the significant tasks is to acquire synoptic data on a frequent and timely basis regarding drought– moved agricultural sectors. This is required to rapidly detect zones entailing abrupt response. The Agricultural Stress Index System (ASIS), created on imagery from the Advanced Very High Resolution Radiometer (AVHRR) sensors on the project of the National Oceanic and Atmospheric Administration (NOAA) and Meteorological Operational Satellite (METOP) satellites, was explicitly built to encounter this demand.

Concurring to the World Meteorological Organization (WMO, 2014), research performed over modern spans has casted substantial stress on the significant part enacted by exchanges linking troposphere and marinas in the tropical stretch of the Pacific Ocean in changing global weather and climate forms. In the course of El Niño events, for instance, sea temperatures at the exterior in the central and eastern tropical Pacific Ocean get markedly greater than average. On the other hand, in the course of La Niña episodes, the sea surface temperatures in these zones befall lesser than average. These temperature deviations are intensely associated with main climate variations around the world and, once begun, such occurrences can persist for 12 months or more. The intense El Niño episode of 1997–1998 was followed by a sustained La Niña period that protracted from mid-1998 to early 2001. El Niño/La Niña events alter the prospect of specific climate patterns all over the globe, but the consequences of each occurrence are by no means precisely identical. Additionally, even though there is normally a correlation concerning the global effects of an El Niño/La Niña episode and its strength, there is forever ability for an episode to render severe impressions in a few areas regardless of its force. There is an agreement between climatologic corporations concerning the common effects of El Niño around the world. From an agronomic and food security perspective, implying only to cereal yields, it is imperative to recognise the prospective influences of El Niño.

To measure the effect of drought, the FAO Agriculture Stress Index (ASI) is employed as a statistic. ASI is developed on remote sensing information that shows up atypical vegetation growth and impending drought environments in arable soil all through a known cropping season (Rojas et al., 2011). The foremost risk to crops is drought. Nevertheless, El Niño might fabricate other climatic effects, including flash floods or forceful cyclones that might affect the crop season, upsetting agricultural pursuits and harming crops. ASI is unable to measure the damaging effect of flash floods or cyclones, but only the productive ones, if in the least, owed to the upsurge of water disposal subsequent to extreme precipitation.

Any phase (neutral, warm and cold) of Oceanic Nino Index (ONI) could be linked with droughts in global cropping zones. From a climatic and oceanic perspective, there are cycles where consecutive years are under the influence of a warm or cold phase. In fact few years are under the influence of only one specific El Niño phase; most years are characterized by a transition phase. The cycles dominated by El Niño are associated with more area affected by drought at the global agricultural level. Owing to the said hypothesis it is investigated whether transition of phase occurred and with what magnitude over the course of 2015–2016 El Niño episode. Moreover implications of prefaced ASI index on wheat yield over targeted regions is explored.

Data

The ONI has turned out to be the effective benchmark that the NOAA exploits to detect El Niño (warm) and La Niña (cool) occurrences in the tropical Pacific. It is the three month mean SST anomaly for the El Niño 3.4 region (i.e., $5^{\circ}N-5^{\circ}S$, $120^{\circ}-170^{\circ}W$). Episodes are delineated as five successive intersecting three month cycles at or exceeding the +0.5°C anomaly for warm (El Niño), episodes and at or receding the -0.5°C anomaly for cold (La Niña) episodes. The tolerance is additionally classified into Weak (with a 0.5 to 0.9 SST anomaly), Moderate (1.0 to 1.4) and Strong (≥ 1.5) occurrences. For an episode to be considered as weak, moderate or strong, it should have met or surpassed the limit for no less than three successive coinciding three month cycles.

The Agriculture Stress Index (ASI) is an FAO statistic that underlines unusual vegetation growth and possible drought in arable terrain for the duration of a set cropping period http://www.fao.org/giews/earthobservation/. ASI was programmed with the backing of EU/FAO Improved Global Governance for Hunger Reduction Programme. http://www.fao.org/europeanunion/eu-projects/global-governance/en/. ASI assimilates the Vegetation Health Index (VHI) in two aspects that are significant to measure a drought occurrence in agriculture: temporal and spatial. ASI evaluates the temporal strength and length of dry intervals and computes the fraction of arable terrain distressed by drought. Pixels with a VHI value less than 35 percent – are classified as crucial in earlier papers to measure the scope of the drought (Kogan, 1994; Unganai and Kogan, 1998). The entire managerial expanse is categorized corresponding to the fraction of arable zone distressed by drought environments (Rojas, et al. 2011). ASI however, cannot assess the impacts of flash floods.

The routine is based on an approach established by Rojas, Vrieling, and Rembold over the African region. This methodology has been altered and improved to the worldwide level to create an agricultural stress index (ASI) denoting, per managerial unit, the percentage of cropland (or paddock) regions distressed by drought round the growing period. The vegetation health index (VHI), built on normalized difference vegetation index (NDVI) and temperature differences, is utilised as a drought gauge. A merged time series of AVHRR data from METOP and NOAA is employed to create a steady time series of VHI at 1 km resolution. International phenology atlases, signifying the figure of growing seasons and their onset and expiration dates, are developed from a multi–annual image set of SPOT–Vegetation (1999–2011). The VHI time series and phenology records are then pooled to generate the ASI for the selected El Niño years. This granted assessment of the aptness of the ASIS to detect drought using past information and supplementary data.

Methodology

ASIS (Agriculture Stress Index System) observes foliage indices across international crop zones all through the growing season and can identify hotspots all over the sphere where yields may be distressed

by drought. It is built on the Vegetation Health Index (VHI), descended from NDVI and remodelled by Kogan from the Center for Satellite Applications and Research (STAR) of the National Environmental Satellite, Data and Information Service (NESDIS). This index was effectively employed in several diverse environmental states around the world, comprising Asia, Africa, Europe, North America and South America. ASIS manipulates satellite–based remote sensing data to identify agricultural zones (cropland or grassland) with an eminent probability of water stress (dry periods and drought). ASIS sustains FAO's global staple food supply and demand watch, particularly in the perspective of the Global Information and Early Warning System (GIEWS). Since 2016, Country–level ASIS has been put into operation in Bolivia, Nicaragua, the Philippines and Central America (Dry Corridor) and is presently being applied in Peru (Puno Province), Panama, Paraguay, Pakistan and Viet Nam.

VHI can sense drought situations along any stretch of the year. For agriculture, nevertheless, we are only concerned with the phase highly subtle for crop growth, so the investigation is made only concerning the start (SOS) and end (EOS) of the crop season (time–based assimilation) and limited to crop zones (spatial integration). ASIS measures the acuteness (strength, period and spatial scope) of the agricultural drought and communicates the conclusive outcomes at administrative level providing the option to associate it with the agricultural statistics of the country. Equations 1–3 describe VHI index as follows:

$$VCI = 100 \times (NDVI - NDVI_{min}) \div (NDVI_{max} - NDVI_{min})$$
(1)

$$TCI = 100 \times (BT_{max} - BT) \div (BT_{max} - BT_{min})$$
⁽²⁾

$$VHI = a \times VCI + (1 - a) \times TCI$$
(3)

where NDVI, $NDVI_{min}$, and $NDVI_{max}$ are the seasonal average of smoothed weekly NDVI, its multiyear absolute minimum and its maximum respectively; VCI is the vegetation condition index; BT, BT_{min} , and BT_{max} are values for brightness temperature (Kogan, 2001); TCI is the temperature condition index; a is the weighting parameter. The seasonal statistics are created to permit straightforward detection of regions of cropped land with a high probability of water stress (drought). The indices are built on remote sensing data of foliage and land surface temperature blended with data on agronomic cropping rotations resulting from past data, and a worldwide crop mask. The conclusive records feature unusual vegetation growth, and possible drought, in crop regions for the duration of the growing season. In order to precisely detect the managerial units distressed by agricultural drought, the fraction of every unit's agricultural zone having a VHI value less than 35 for the duration of the crop term is evaluated.

Wheat season in Pakistan:

The wheat crop (Rabi crop) is sown during October–December and is harvested during March– April. The precise scheduling of the Rabi crop fluctuates with the latitude and is impelled with the withdrawal of monsoon, consequently it can be anywhere from September to April (Figure 1). In addition to drought, negative factors affecting wheat production may also include high winds and localized hailstorms. The tall growing cultivars mainly in Punjab and KPK are generally prone to lodging.

Impacts in 2015–16 El Niño

El Niño is a native heating of surface waters that occurs in the whole equatorial region of the central and eastern Pacific Ocean of the Peruvian coast and which influences the atmospheric circulation worldwide (Kiladis and Diaz, 1989). It is a periodic meteorological phenomenon that recurs roughly every two to seven years and ordinarily lasts between 12 and 18 months (Climate Prediction Center, 2005). An El Niño episode is classified by a high Oceanic Niño Index (ONI), which is created on Sea Surface Temperature (SST) digressions from normal along the expanse in the central equatorial Pacific. An El Niño occurrence is related with continued warmer than typical sea surface temperatures and coherent deviations in wind and rainfall precedents (Ropelewski and Halpert, 1992; International Research Institute on Climate and Society, 2013). Regardless of their cyclic and repeated appearances, El Niño events do not have a statistical trend with rigid manifestation cycles and a uniform strength. As a consequence, stochastic archetypes have been advanced to forecast the arrival and the force of El Niño episodes. Nevertheless, whereas the precision of these archetypes in forecasting the inception of an El Niño event is utterly good, the strength is much



Figure 1: SOS (left) and EOS (right) of wheat derived from long term average of NDVI using SPOT vegetation data. (Courtesy of FAO GIEWS).

The intense El Niño in 2015–16 was comparable to episodes in 1997–98 and 1982–83. Major influences linked with the 2015–16 El Niño were expected and suffered across the Pacific Islands expanse, primarily related with below normal rainfall and shrunken sea level in the southwest Pacific. The central Pacific underwent enhanced rainfall and elevated sea level. During 2015–16 El Niño, the ONI picked its highest in NDJ with a value of 2.6 above normal (Figure 2).



Figure 2: Running 3–month Mean ONI values in 2015/16 El Niño.

An NDVI anomaly is the difference between the average NDVI for a particular month of a given year and the average NDVI for the same month over a specified number of years. This approach can be used to characterize the health of vegetation for a particular month and year relative to what is considered normal, which is a good indicator of drought or declining vegetation health. The NDVI anomaly for Nov–2015 to Feb–2016 shows up to 60% decrease from long term average over the trans–provincial boundary of Sindh and Baluchistan province. Signal of the NDVI anomaly is especially high in Jan–2016 (Figure 3).



Figure 3: NDVI anomalies of wheat season (NDJF 2015–16) to long term average (1984–2014) by METOP–AVHRR. (Courtesy of FAO GIEWS).

The present analysis of VCI relates the current dekadal (10 days) NDVI to its long-term minimum, normalized by the historical range of NDVI values for the same dekad. The VCI is designed to separate the weather-related component of the NDVI from the ecological element. Using AVHRR thermal bands, VCI is used to identify drought situations and determine the onset, especially in areas where drought episodes are localized and ill defined. It focuses on the impact of drought on vegetation and can provide information on the onset, duration and severity of drought by noting vegetation changes and comparing them with historical values. As seen through Figure 4 the VCI for Nov-2015 to Feb-2016 show significant patterns of poor vegetation condition especially over trans-provincial region of Sindh and Baluchistan. Severity of the VCI is evident especially in Jan-2016.

VCI and TCI are combined into the so-called VHI. The VHI is the most elementary indicator in the ASIS, derived from EO-observations and available per pixel and per dekad. AVHRR data in the visible, infrared and near-infrared channels are all used to identify and classify stress in vegetation due to drought. The basic idea is the following: the lower the observed VCI (relatively poor green vegetation) and the higher TCI (relatively warm weather), the lower the VHI. Low VHIs are indicative for drought, especially when they persist for longer periods. In the 2015–16 case, both Baluchistan and Sindh provinces suffered with small magnitudes of VHI with as low as 0.15 over several crop areas in the months of January and February (Figure 5). The crop areas of the regions struck with poor VHI values were essentially rain-fed ones which could not bring their requisite soil moisture levels via irrigated means.



Figure 4: VCI of wheat season (NDJF 2015–16) by METOP-AVHRR. (Courtesy of FAO GIEWS).



Figure 5: VHI of wheat season (NDJF 2015–16) by METOP–AVHRR. (Courtesy of FAO GIEWS).

In order to understand severity of VCI and VHI, precipitation patterns in the wheat season are explored using European Centre for Medium Range Weather Forecasting (ECMWF) reanalysis outputs (Figure 6). A straightforward analysis of monthly total precipitation shows insufficient reach of western disturbances to Sindh and Baluchistan provinces. In fact some potentially high rainfall receiving crop areas suffered metrological drought especially in the Sindh province. The month of February 2016 was especially struck with widespread dry conditions both in Baluchistan and Sindh provinces.



Figure 6: Precipitation of wheat season (NDJF 2015–16) by ECMWF. (Courtesy of FAO GIEWS).

Precipitation anomalies with long term averages for the wheat growing season are investigated using ECMWF reanalysis data in order to identify key water stress areas (Figure 7). Monthly anomalies from November 2015 to January 2016 show considerable decrease in precipitation, especially in the Sindh and Baluchistan provinces. The evident decrease in precipitation of more than 80% in the rain–fed areas of the two provinces seems to be the trigger for the water stress conditions of the 2015–16 wheat season.

The production of wheat in Sindh was 92,000 Tonnes less in 2014–16 as compared to that in 2012– 14 (Agricultural Statistics of Pakistan, Ministry of National Food Security & Research). Our analysis of ASI represents the percentage of (land cover specific) pixels within each administrative region, which are affected by drought and defined over the course of the growing season. Owing to the below normal precipitation and corresponding severities of the VCI and the VHI, all three dekads of the ASI show pronounced magnitudes with stresses of up to 70% at conjunction of the Sindh and the Baluchistan provinces (Figure 8). Moreover impact associated with precipitation anomaly in third dekad of Jan–2016 is also shown by ASI in the KPK region. Furthermore, more than 8% and 6% of crop areas in Baluchistan and Sindh faced water stress as per values of ASI data in 2016 (Table I).



Figure 7: Precipitation anomalies of wheat season (NDJF 2015–16) to long term average (1989–2015) by ECMWF. (Courtesy of FAO GIEWS).



Figure 8: Top row: Mean VHI by METOP–AVHRR from start of wheat season to all three dekads of January 2016. Bottom row: ASI by METOP–AVHRR representing percentage of cropland area affected by drought from start of wheat season to all the three dekads of January 2016. (Courtesy of FAO GIEWS).

46

COUNTRY	PROVINCE	CROP_MASK	YEAR	ASI	UNIT
Pakistan	ALL	Crop land	2016	3.33	VHI % below 35
Pakistan	ALL	Crop land	2015	2.57	VHI % below 35
Pakistan	Balochistan	Crop land	2016	8.74	VHI % below 35
Pakistan	Fata	Crop land	2016	1.69	VHI % below 35
Pakistan	Islamabad	Crop land	2016	0.27	VHI % below 35
Pakistan	KPK	Crop land	2016	1.27	VHI % below 35
Pakistan	Punjab	Crop land	2016	2.4	VHI % below 35
Pakistan	Sind	Crop land	2016	6.97	VHI % below 35
Pakistan	Balochistan	Crop land	2015	4.5	VHI % below 35
Pakistan	Fata	Crop land	2015	1.18	VHI % below 35
Pakistan	Islamabad	Crop land	2015	0.41	VHI % below 35
Pakistan	KPK	Crop land	2015	2	VHI % below 35
Pakistan	Punjab	Crop land	2015	1.89	VHI % below 35
Pakistan	Sind	Crop land	2015	5.08	VHI % below 35

Table 1: ASI values for VHI below 35%

Conclusion:

Drought is the earth's highly devastating environmental threat that has had overwhelming impressions on food security and food production. Events of drought grew in rate of recurrence and strength over the former two decades as a consequence of climate change, and this trend is anticipated to last. Well–timed and consistent knowledge on the state of food crops all over the globe is indispensable for moderating the effect of agricultural drought. FAO's Global Information and Early Warning System (GIEWS) was employed for identifying agricultural zones with a high probability of water stress – drought at regional level.

The ONI/ASI investigation exposed the extents where El Niño adversely affected agriculture triggering drought conditions, with consequent declines in agricultural production and impending food security implications. In these regions, governments should instrument mitigation packages to upsurge resilience of growers in the course of El Niño episodes. Moreover, the results of this analysis present new challenges to scientific community in establishing teleconnections of local droughts with regional atmospheric/oceanic indices.

References:

World Meteorological Organization (WMO), 2014: El Niño/La Niña background. http://www. wmo.int/pages/prog/wcp/wcasp/enso_background.html.

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. doi:10.1016/j.rse.2010.09.006.

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.

Unganai, L. & Kogan, F., 1998: Drought monitoring and corn yield estimation in Southern Africa from AVHRR data. Remote Sensing of Environment, 63; 219–232.

Kiladis G., & Diaz H., 1989: Global climatic anomalies associated with extremes in the southern oscillation. Journal of Climate, 2: 1069–1090.

Climate Prediction Center. 2005: ENSO FAQ: How often do El Niño and La Niña typically occur? National Centers for Environmental Prediction. http://www.cpc.ncep.noaa.gov/.

Ropelewski, C. F. & Halpert, M. S., 1992: Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. Mon. Wea. Rev., 115: 1606–1626 (1992).

International Research Institute on Climate and Society (IRI). 2013: Schematic effects of ENSO. http://iri.columbia.edu/climate/ENSO/globalimpact/temp_precip/region_elnino.html.

Kogan, F. N., 2001: Operational Space Technology for Global Vegetation Assessment. Bull. Amer. Meteor. Soc., 82(9), pp. 1949-1964.