INTEGRATION OF HUMAN PARTICIPATORY SENSING AND ARCHIVES OF REMOTE SENSING OBSERVATIONS FOR FIELD LEVEL CROP PHENOLOGY ESTIMATION

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ABSTRACT:

The rise in global population has increased food and water demand thereby causing excessive pressure on existing resources. In developing countries with fragmented land holdings there exists constant pressure on available water and land resources. Obtaining field scale crop specific information is challenging task. Advent of open freely available multi-temporal remote sensing observations with improved radiometric resolution the possibilities for near real / real time applications has increased. In this study and an attempt has been made to establish operational model for field level crop growth monitoring using integrated approach of crowd sourcing and time series of remote sensing observations. The time series of Sentinel 2 (A and B) satellite has been used to estimate crop growth related components such as vegetation indices and crop growth stage and crop phenology. In initial stage high valued cereal crop Wheat has been selected. The field level information (i.e. 108 Wheat fields) collected using mobile based agro-advisory platform mKRISHI® has been used to extract time series of Sentinel 2 observations (44 scenes for year 2016 and 2018). The moving average has been used for filling gaps in the time series of vegetation indices. The BFAST and GreenBrown package in R were used for detecting breaks in vegetation index time series and estimating crop growth stages. Analysis shows that the estimated crop phenology parameters were in better agreement with the field observations. In future more crops from different agro-climatic conditions will be considered for providing field level crop management advisory.

1. INTRODUCTION

The rise in global population has increased food and water demand thereby causing excessive pressure on existing resources. In developing countries with fragmented land holdings there exists constant pressure on available water and land resources. Obtaining field scale crop specific information is challenging task. Wheat is an important cereal crop grown across all regions of the world. In India Wheat production is severely affected by various biotic (pests and diseases) and abiotic (temperature, rain, water stress, etc.) stresses. Changing weather conditions such as increase in temperature causes early senescence in the Wheat (Lobell et al., 2012). Also, irrigation schedule has effect on crop growth and production (Dhillon and Fisher, 1994).

The field level operational crop water balance models require agro-meteorological, soil and crop parameters on near-real time spatio-temporal scale. To estimate irrigation schedule on spatial scale there is a need for point based crop growth stage, available soil moisture, crop evaporative fraction / crop coefficient (i.e. the ratio of actual crop ET to potential ET) and soil depth information. Studies have found that crop coefficient (Kc) varies with the crop growth rate, planting density and management practices. FAO-56 based generic Kc curves often don't match with actual crop water use therefore there is need for site specific Kc estimates (Glenn et al., 2011). Studies have shown that satellite derived canopy cover and Vegetation Indices (VI's) have strong correlation with Kc (Tasumi et al., 2014; Er-Raki et al., 2007; Mateosa et al., 2013).

The VI's such as, Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI) and Transformed Soil Adjusted Vegetation Index (TSAVI) are widely used for ETa estimation (Glenn et al., 2011; Choudhury et al., 1994). The eddy covariance based energy flux towers, lysimeters and actual soil moisture measurements are used for validating the relationship between observed and estimated Kc for selected crops (Dugo et al., 2013; Galleguillos et al., 2011; Mateosa et al., 2013). Glenn et al., (2011) demonstrated the use of RS based crop VI's for estimation of crop water requirement on field-by-field basis. Also, attempts are being made to develop reflectance-based Kc's for numerous individual crops such as Corn (Maize), Wheat, Alfalfa, Cotton, Potato, Sugar-beet, Vegetables, Grapes and other orchard crops (Glenn et al., 2011). As variable rate of irrigation is required for different regions in the field spatial resolution of available ET products (Mu et al., 2007) is large and not suitable for small to medium agriculture areas (i.e. sizes ranging between 1 and 5 ha.). Therefore, there is a need for continuous crop monitoring and growth based irrigation scheduling for yield improvement.

Satellite based earth observation (EO) platforms have proved capability to spatio-temporally monitor changes on the earth surface. United States Geological Survey (USGS) Landsat program is one of the oldest sources of optical EO datasets (EarthExplorer, 2018). Also, European Space Agency (ESA) has opened optical high resolution satellite observations of Sentinel 2A and 2B from Copernicus mission (ESA, 2018).

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These historical and near-real time EO archives are rich source of information to understand the seasonal changes in the horticultural crops (Sawant et al., 2016). With increase in the availability of satellite observations in regular interval it's possible to monitor the crop growth conditions across the cropping cycle (Sentinel 2 and Landsat 8 with return period of 12 and 15 days respectively). The field specific crop growth stages and vegetation index based Kc values are necessary for determining the precision irrigation schedules. Also, there is need for ground level information from stakeholders (farmers, agriculture extension officers, etc.). The main objective of this study is to establish operational model for field level Wheat crop growth monitoring using integrated approach of crowd sourcing and time series of RS observations.

Further, information on study area, detailed methodology, datasets used and overall framework for crop phenology mapping is described in Section 2. Details about the data analysis approach and results are covered in Section 3. The last section covers summary and future prospects of the study.

2. MATERIALS AND METHODS

The proposed framework combines all necessary processes to calibrate and validate field scale Wheat crop growth stages. The study area comprises of field observations collected from three districts (i.e. Amravati, Wardha and Nagpur) of Maharashtra, India (Figure 1 a). The region falls under semi-arid tropics and faces acute shortage of water during summer months (March to June). In the study area horticultural crop Mandarin / Citrus is cultivated on larger scale. The groundwater is a main source of irrigation during post-monsoon season and there exists competition for extracting the groundwater source for both Citrus and Wheat. Hence, there is a need for understanding the crop growth stages for conservation and judicious use of available water resource.

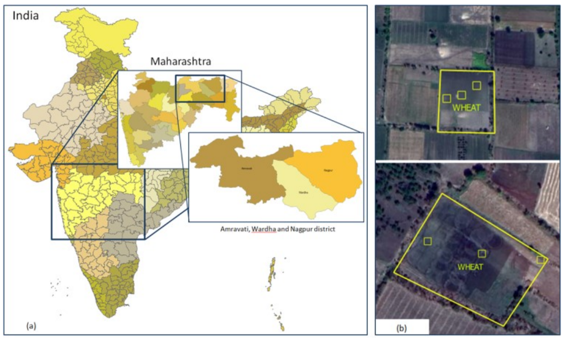

Figure 1. a) Study Area and b) Example of selected Wheat fields and pixel locations. The field boundary (i.e. vector layer) is overlaid on high resolution satellite image.

In the study area Wheat is cultivated during post-monsoon season (i.e. Nov. to Feb. locally called *Rabi* / winter season). The availability of cloud free satellite images and short duration subsistence irrigated crop are the main reasons to select *Rabi* / winter Wheat crop. The field level information such as field GPS boundary, farmer / cultivator name, crop name, date of sowing and date of harvest are collected using mobile based agro-advisory platform mKRISHI® (Pande et al., 2009). For each Wheat field three pixels are randomly selected and time series of Sentinel 2(A and B) was extracted for year 2016 to 2018 (i.e. total 44 satellite passes and 108 fields) using Google Earth Engine (GEE) interface (Gorelick et al., 2017). The sample Wheat fields and selected pixels are shown in the Figure 1 (b). The extracted time series has been used to estimate the crop growth related components such as vegetation indices, crop growth stage and crop phenology (Figure 2).

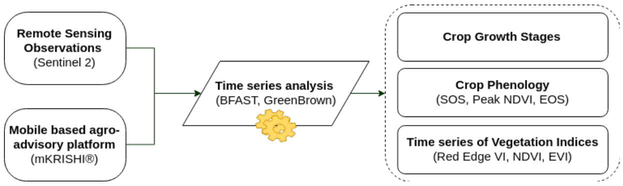

Figure 2. Overall framework

The time series for selected pixels was filtered for cloud cover and Enhanced Vegetation Index (EVI), Normal Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) are calculated (Bausch and Neale, 1987; Huete et al., 1999). The Vegetation Index (VI) time series data was smoothened using logistic regression based smoothing algorithm used in BFAST (Verbesselt et al., 2012; Verbesselt et al., 2010). The field wise average NDVI time series was analyzed for understanding the seasonality in the Wheat crop. Methodology for analysis of land surface phenology provided by Forkel et al. (2013) has been used to identify the Wheat crop growth stages. The estimated crop growth stages were compared with the actual Wheat crop growth stages collected using mKRISHI® platform.

3. RESULTS AND DISCUSSIONS

The estimated VI’s are aggregated on monthly scale for Wheat crop cultivated in year 2017-18 (Figure 3). The rise in VI shows the crop growth season starting from Nov. 2017 to Apr. 2018. The mean values of EVI, NDVI and SAVI are 0.5, 0.45 and 0.36 respectively. Further, NDVI time series has been selected for all calculations.

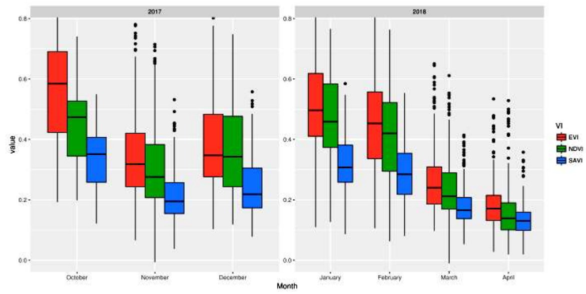

Figure 3. Monthly Variation in EVI, NDVI and SAVI

Figure 4 shows the raw NDVI (non smoothed) time series for selected representative Wheat fields. It is observed that NDVI time series has uneven spikes and gaps due to cloud cover.

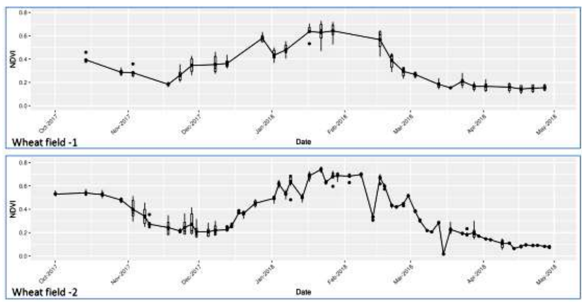

Figure 4. Raw NDVI time series observed over sample Wheat fields

The results of Wheat crop growth stage detection algorithm estimates day of year (DOY) for Start of Season (SOS), End of Season (EOS), Length of Season (LOS), Position of Trough (POT), Mean Spring value (MSP) and Rate of Spring Greenup (RSP). The complete cycle of phenological changes in citrus crop canopy are captured in Figure 5. The cropping season starts from month of Nov. to Dec. and ends during next year Feb. to Mar.

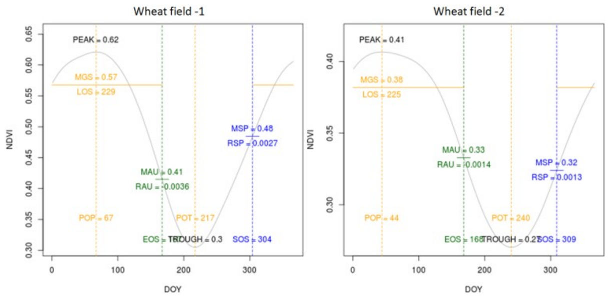

Figure 5. Crop growth stages for sample Wheat fields

The field wise estimated and actual mean of SOS, EOS and LOS are shown in Table 1.

SN	Growth Stage	Actual DOY	Estimated DOY
1	Start of Season	307	240
2	End of Season	83	123
3	Length of Season	141	157

Table 1. Actual and estimated crop growth stages

The estimated mean SOS is less than actual SOS and estimated mean EOS is greater than actual EOS, this is due to the poor identification of minimum NDVI smoothed over daily scale. There is a need for further investigations for identification of minimum NDVI and identify the potential application of EVI and SAVI for crop growth stage estimation. The actual and estimated mean LOS has better match as different cultivars / varieties of Wheat are aggregated.

4. SUMMARY AND CONCLUSIONS

In dynamic semi-arid cropping systems, every season crops change and it’s challenging to estimates crop growth stages for short duration crops due to cloud cover in monsoon season. In this study and an attempt has been made to establish operational model for field level crop growth monitoring using integrated approach of crowd sourcing and time series of remote sensing observations. The time series of Sentinel 2 (A and B) satellite has been used to estimate crop growth related components such as vegetation indices and crop growth stage. Analysis shows that the estimated crop growth stages were in better agreement with the field observations. However, there is a need for further investigations using VI’s such as EVI and SAVI to achieve precise estimates of crop growth stages. The proposed VI based crop growth stage estimation methodology can be further evaluated for field level crop water requirement estimation. The integrated approach of mobile based human participatory sensing (crowd sourcing) and RS based time series analysis of VI’s has potential to continuously monitor crop growth stages for optimal crop resources (i.e. water, soil, fertilizer, etc.) management.

5. FUTURE SCOPE

The local variation in Wheat crop growth stages is caused mainly due to the crop management practices. The feasibility of EVI and SAVI will be evaluated for short duration crop growth stage estimation. Crop growth stage adjusted VI based Kc values are needed for field level irrigation scheduling. In future RS based crop growth stage estimation method will be evaluated for more crops from different agro-climatic conditions. An attempt is being made to integrate the proposed approach for personalized field level crop management advisory using mobile based agro-advisory platform mKRISHI®.

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