Synergetic Use of Passive Microwave and Visible to Near Infrared Data Improves Monitoring of Cropland Dynamics in Major Grain Production Areas of Russia, Ukraine, and Kazakhstan

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1. Introduction
To increase global food security we need a comprehensive understanding of cropland dynamics for major commodities. Increased and sustained recent crop production recovery in Russia (RU), Ukraine (UA), and Kazakhstan (KZ), after two decades of decline, may be an opportunity to address growing demands for grains in the coming decades (1).

Many studies have used vegetation indices (VIs) derived from visible and near infrared (VNIR) sensors to study land surface phenology (LSP) in terms of day of year [2-4]. However, crops strongly depend on insolation and air temperature for growth and development. Other studies have demonstrated the efficacy of modeling LSP in terms of thermal time [5-7]. Here we use air temperature from microwave data with VIs from VNIR data to characterize cropland dynamics.

2. Data and Methods
We used the following variables from the AMSR-E enhanced land surface parameter dataset (Daynight, 25km [8]) & MODIS (8-day: 0.05°–0.06 km) land products [9]:
* AMSR-E twice daily air temperature (tA)
* Land Surface Temperature (LST) (MOD11C2 & MYD11C2)
* Combined Nadir & Forward Reflectance (NBAR) (MOD09A1/2/C)

We used 8 years (2003-2010) of data, which is the maximum available data for the AMSR-E sensor full functional years. An 8-day moving average filter was applied to the AMSR-E data to align it with the MODIS data minimize data gaps due to orbit and swath width.

Growing degree-day (GDD): daily mean temperature increase above a temperature threshold of 0 °C (2°C = 15 K).

\[ \text{GDD} = \frac{tA_{m} - tA_{th}}{2} \]

Where GDD is the accumulated GDD from April 1st to October 31st, to avoid the frozen season when no microwave data are available. GDD in mid- and high-latitude can be well approximated using quadratic functions of GDD (6, 10). And thus, as a function of GDD was fitted with a convex quadratic (CQ) model:

\[ \text{GDD} = \alpha + \beta tA_{m} + \gamma tA_{m}^2 \]

The intercept \( \alpha \) is the start of observation period GDD value, the linear parameter \( \beta \) affects the slope, and the quadratic parameter \( \gamma \) controls the curvature. As our model is convex quadratic in shape, the sign of \( \gamma \) is positive while \( \gamma \) is negative.

Residual plots from the CQ model was done for model performance check and to see if there is some kind of pattern in GDD over the course of a growing season. Two phenometrics were calculated from the fitted parameter coefficients of the CQ model:

Peak thermal time to peak (TPP): \( \frac{\beta}{2\gamma} \)

Thermal time from peak (TTP) = \( \frac{1}{2\gamma} \)

NDVI and EVI were calculated from the MODIS NBAR data.

3. Results: Land Surface Seasonality of GDDs
Given that mid-latitudes are temperature-limited, this quasi-parabolic relationship during the frost-free period is expected and the coefficients of determination are uniformly high (r²=0.88–0.98) [6, 10]. The fits for the two datasets exhibit strong similar seasonalities (Fig. 2). However, GDD residual plots revealed the AMSR-E data were better fitted to the CQ model compared to that of the MODIS data.

GDD difference by latitude was evident (Fig. 2). GDD at the beginning and end of growing season for the study period was well above zero and with larger accompanied AGDD (> 4000 °C) in the lower latitude sites (Fig. 2a & b), while it was closer to zero and with smaller AGDD (“3000 °C) in the higher latitude sites (Fig. 2c).

4. Results: Land Surface Phenology of VIs
A. Cropland seasonality: Sites exhibiting a bimodal growing season are associated with cultivation of winter & summer crops (Fig. 4a); those exhibiting an unimodal growing season were associated with spring crops (Fig. 4b). Two phenometrics were calculated from the fitted parameter coefficients of the CQ model:

Peak thermal time to peak (TPP) = \( \frac{\beta}{2\gamma} \)

Thermal time from peak (TTP) = \( \frac{1}{2\gamma} \)

NDVI and EVI were calculated from the MODIS NBAR data.

5. Discussion: Changes in Seasonality of Cropping
Based on changes in cultivation practice, we divided our sites into three groups– sites with no change (36), one change (6), or two changes (7). Northern sites displayed no change in cultivation practice, only southern sites showed any change in seasonal cropping dynamics (Fig. 6). Sites that showed no change in the seasonality of cropping were unimodal.

6. Discussion: Growing Degree-Day Residuals vs. Vegetation Indices
Negative residuals from the CQ models of GDD correspond to times near peak VIs: cooler air temperatures resulting from higher latent heat flux due to evapotranspiration. Positive residuals occurred earlier and later in the growing season during times of lower VI: warmer air temperatures resulting from higher sensible heat flux (Fig. 7).

Averaging across sites with the same land cover, we can compare the LSps from croplands with spring planting with the longer growing season in a cropland/natural vegetation mosaic (Fig. 7a). Note that in each instance the GDD residuals go negative between AGDD 1000 and 2200. In the croplands these negative GDD residuals correspond to NDVI exceeding “0.45; in the cropland/natural vegetation mosaic the NDVI exceeds 0.45 before AGDD=1000, before the GDD residuals go negative. However, there is a sharp increase in the magnitude of the positive GDD residuals corresponding to the NDVI exceeding “0.40. For croplands dominated by winter grains, averages of unimodal years show a weaker inverse relationship between the NDVI and GDD residuals (Fig. 7b).

7. Next Steps
Comparative analysis of LSps using GDD & VOD from AMSR-E and MODIS VIs for the same study sites.

Extending the approach and knowledge gained in the mid-latitudes to tropical croplands of East Africa.

East Africa is known for rainfed agriculture, highly fragmented farmlands, rainfall variability, food insecurity, sparse meteorological data, and heavy cloud cover during the growing season. Major grains in (a) Ethiopia: teff, wheat, barley, maize, sorghum; (b) South Sudan: sorghum, maize, millet, rice, and (c) Tanzania: maize, rice, wheat, sorghum. We will use microwave and VNIR data to model LSps and LSs in the region. However, the CQ model of GDD will not work due to the limited seasonality of GDD in the tropics.

Comparing grain production and yield statistics with models of GDD, VOD, NDVI, and EVI in East Africa.

8. References

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