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How Relevant is High-Cadence Earth Observation for Maize Crop Phenology Classification?

L. Nieto
Kansas State University, lnieto@k-state.edu

R. Houborg
Planet Labs Inc., San Francisco, CA

A. Zajdband
Planet Labs Inc., San Francisco, CA

See next page for additional authors

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Abstract

Crop phenology can be defined as the study of biological processes such as emergence, flowering, and senescence that are associated with and affected by environmental growing conditions. The ability to reliably detect crop phenology and its spatial-temporal variability is critical for farmers, policymakers, and government agencies, since it has implications for the entire food chain. Currently, two methods are the most used to report crop phenology. Land surface phenology provides insight into the overall trend, whereas USDA-NASS weekly reports provide insight into the development of specific crops at the regional level. High-cadence earth observations may be able to improve the accuracy of these estimations and bring more precise crop phenology classifications closer to what farmers need. The use of robust classifiers (e.g., random forest, RF) to manage large data sets is required to successfully achieve this goal. This study compared the output of an RF classifier model using weather, two different satellite sources (Planet Fusion; PF and Sentinel-2; S-2), and ground truth data to improve maize (*Zea mays* L.) crop phenology classification during the 2017 growing season in Kansas. Our findings indicate that high-cadence (PF) data can enhance crop classification metrics (f1-score = 0.94) as compared to S-2 (f1-score = 0.86). This study emphasizes the significance of very high temporal resolution (daily) earth observation data for agricultural crop monitoring and decision-making tools.

Keywords

high-cadence, maize, phenology, classification

Cover Page Footnote

This report is an adaptation of the recently published study: “Impact of High-Cadence Earth Observation in Maize Crop Phenology Classification” Remote Sensing 14, no. 3: 469. https://doi.org/10.3390/rs14030469”.

Authors

L. Nieto, R. Houborg, A. Zajdband, A. Jumpasut, P. V. Vara Prasad, B. J. S. C. Olson, and I. A. Ciampitti

How Relevant is High-Cadence Earth Observation for Maize Crop Phenology Classification?

L. Nieto, R. Houborg,[1] A. Zajdband,[1] A. Jumpasut,[1] P.V. Vara Prasad, B.J.S.C. Olson,[2] and I.A. Ciampitti[3]

Summary

Crop phenology can be defined as the study of biological processes such as emergence, flowering, and senescence that are associated with and affected by environmental growing conditions. The ability to reliably detect crop phenology and its spatial-temporal variability is critical for farmers, policymakers, and government agencies, since it has implications for the entire food chain. Currently, two methods are the most used to report crop phenology. Land surface phenology provides insight into the overall trend, whereas USDA-NASS weekly reports provide insight into the development of specific crops at the regional level. High-cadence earth observations may be able to improve the accuracy of these estimations and bring more precise crop phenology classifications closer to what farmers need. The use of robust classifiers (e.g., random forest, RF) to manage large data sets is required to successfully achieve this goal. This study compared the output of an RF classifier model using weather, two different satellite sources (Planet Fusion; PF and Sentinel-2; S-2), and ground truth data to improve maize (*Zea mays* L.) crop phenology classification during the 2017 growing season in Kansas. Our findings indicate that high-cadence (PF) data can enhance crop classification metrics (f1-score = 0.94) as compared to S-2 (f1-score = 0.86). This study emphasizes the significance of very high temporal resolution (daily) earth observation data for agricultural crop monitoring and decision-making tools.

Introduction

Crop phenology examines how the biological processes of emergence, flowering, and senescence respond to environmental factors (Liang et al., 2011). Several studies have attempted to address crop phenology using earth observations (remote sensing) (Rulm and Vulic, 2005; Henebry and de Beurs, 2013) or mathematical models supported by weather data (Rezaei et al., 2018). Crop phenology depicts the more agronomically important stages, which are linked to critical phases when management measures can and should be applied.

[1] Planet Labs Inc., San Francisco, CA.

[2] Division of Biology, College of Arts and Sciences, Kansas State University, Manhattan, KS.

[3] This report is an adaptation of the recently published study: "Impact of High-Cadence Earth Observation in Maize Crop Phenology Classification" Remote Sensing 14, no. 3: 469. https://doi.org/10.3390/rs14030469".

A weekly survey of regional extension agricultural agents provides official phenology crop progress estimates in the United States (Gao and Zhang, 2021). Crop development is summarized by agricultural district (as determined by the U.S. Department of Agriculture), and some developmental stages are combined into broader categories. As a result, the data may not accurately represent a county, district, or even a single farm (Gao et al., 2017). This study investigates whether high-cadence satellite data affects crop phenology classification for agronomic purposes. This study compares the output of an RF classifier model using two independent satellite data sources with different temporal and spatial resolutions, along with weather data.

Procedures

The current study was performed in the state of Kansas (US), specifically in the Southwest (SW) area, over the counties of Morton, Stanton, Grant, and Stevens, and the Central (CK) region, which encompasses the counties of Stafford and Pratt (Figure 1).

Crop Quest Inc. provided us with valuable ground-truth data compiled during a five-year period, from 2013 to 2017, by making repeated visits to each farmer field to monitor changes in maize crop phenology throughout the growing season. Each field was visited an average of five times over the season, though frequency varies across the large database of field observations. The final dataset included crop phenology measurements per field, and geolocated fields for both regions.

This analysis used the following remote sensing products:

1. Planet Fusion images on daily basis (3-meter resolution, R, G, B, NIR bands),
2. Sentinel-2 images (only images with less than 20% clouds, 10-meter resolution, same bands), and
3. Weather data.

Different vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Green Chlorophyll Vegetation Index (GCVI), Chlorophyll Vegetation Index (CVI), and Normalized Green Index (NGI) were calculated based on the spectral bands from both products (PF and S-2). From PRIMS layers (https://prism.oregonstate.edu/) we extracted precipitation, mean, maximum and minimum temperature, and vapor pressure deficit.

The Random Forest (RF) classifier was implemented with the Scikit-Learn library (Pedregosa et al., 2011), in a Python 3.8 environment. Further details related to the analysis and model evaluation are described in Nieto et al., 2022.

To test the performance of the model, the metrics used were overall accuracy, precision, recall, and f1-score, since these are the most suitable for classification purposes.

Results

Best Combination of Variables

The NIR band, EVI, minimum temperature, maximum temperature, vapor pressure deficit, and day of the year were related with the highest scores in the southwest region dataset. The best f1-scores were 0.94 for the southwest region and 0.93 for the central region when the factors were included. Also, to test additional model options, numerous combinations were attempted (only spectral data; only weather parameters; EVI and weather; NIR and weather, etc.). As an example of this, the model's f1-scores were 0.79 for SW and 0.76 for central regions when only weather variables were included in the evaluation.

Model Performance Using PF Data in Both Regions

The model comprising NIR, EVI, minimum temperature, maximum temperature, vapor pressure deficit, and day of the year resulted in f1 values of 0.94 for SW and 0.93 for central region (Figure 2 a, b). A confusion matrix depicts the classification results for each crop phenological stage, with the correct components along the main diagonal and the results for precision and recall along the X and Y axes. In the southwest area, most stages had recall and precision scores between 1.0 and 0.75, but R1, R3, and V15 had weak metrics ranging from 0 to 0.66. In the central region, most stages had recall values between 1.0 and 0.87, although some (R2, V10, V11, V12, and V13) had recall values below 0.67. Precision ranged from 0.76 to 1.0 for all stages.

Model Performance Using Sentinel-2 Data

The same model used for S-2 data yielded results inferior to those reported before. Due to the season duration, the first dataset only comprised three crop phenological stages. Overall, the classification produced a high f1-score (0.86) but uneven metrics for each stage. For the VT stage, recall and precision were both zero (Figure 3, a). A second analysis included an enlarged dataset with data from 3 days before and after the field data collection. The overall f1-score was lowered to 0.74, although the dataset included more phenological stages. Finally, the search was extended from 3 to 10 days before and after the field data collection. Overall performance was consistently weaker when the S-2 dataset was used instead of the PF output (Figure 3).

Final Considerations

Combining satellite-based (NIR band surface reflectance, EVI), weather data (maximum and lowest temperatures, VPD), and day of the year data, a random forest model could accurately classify maize crops in two distinct production zones for maize crops in Kansas. The study emphasizes the necessity of high-quality ground truth data and high-cadence earth observation.

Currently available agricultural phenology solutions rely on broad measurements and large geographic regions. While these are useful tools for policymakers and governments, there is still room for improvement in terms of farmer solutions. Confusion and wrong inferences may come from the mismatch between reported and field events. Enhancing crop phenology classification and reporting has a significant impact on every step of the food production chain, enabling precise, proactive, rather than reactive, regional, and field-level policies.

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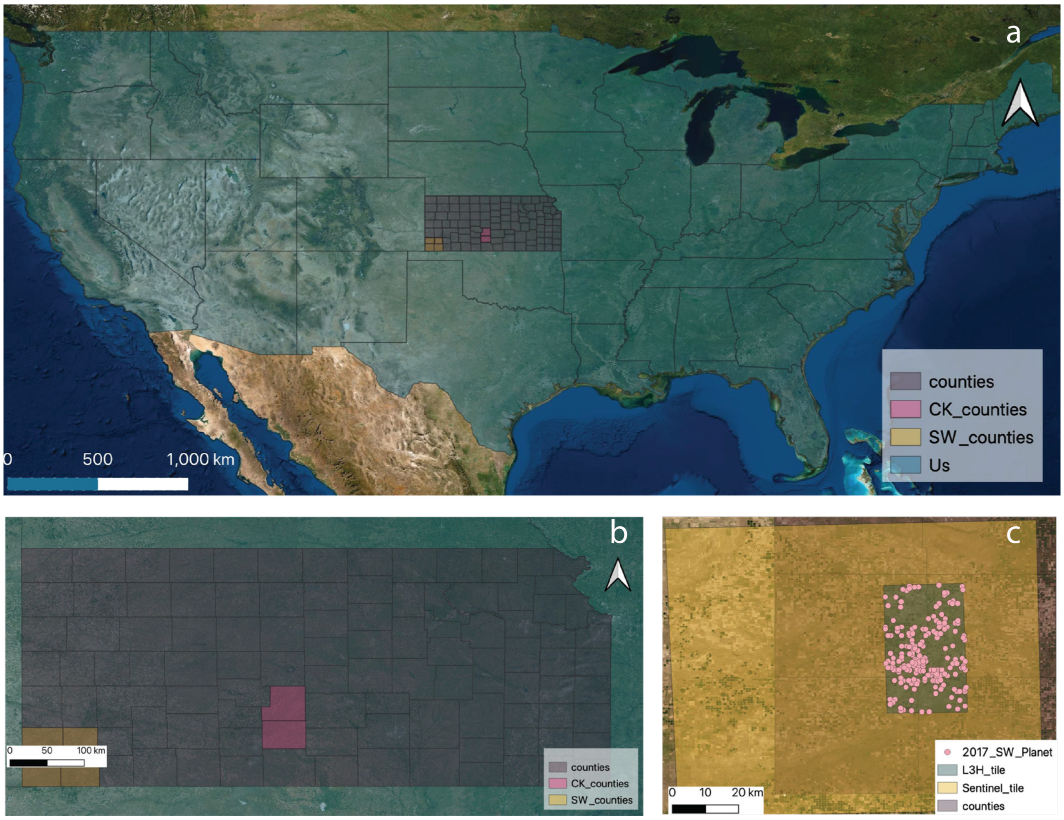

Figure 1. Area of study a) state of Kansas (US); b) Southwest (SW) region and Central (CK); c) large orange rectangle represents the Sentinel-2 tile covering the area. The green rectangle corresponds to the Planet fusion (PF) tiles over the area; and pink dots represent ground truth field data collection sites.

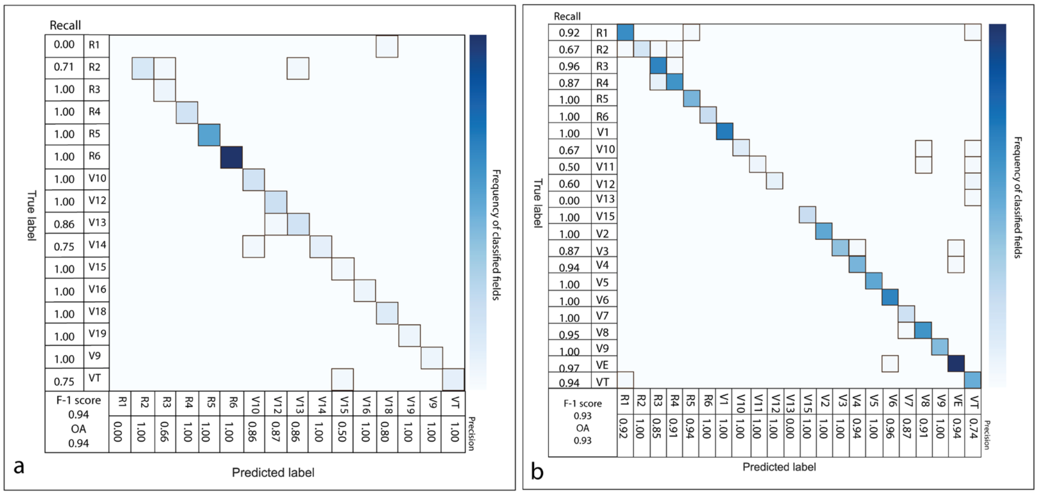

Figure 2 (a) Confusion matrices with PF-based classification results for the Southwest region (SW) and for (b) Central KS region (CK), including recall and precision for each crop phenology stage, and f1-score and overall accuracy (OA).

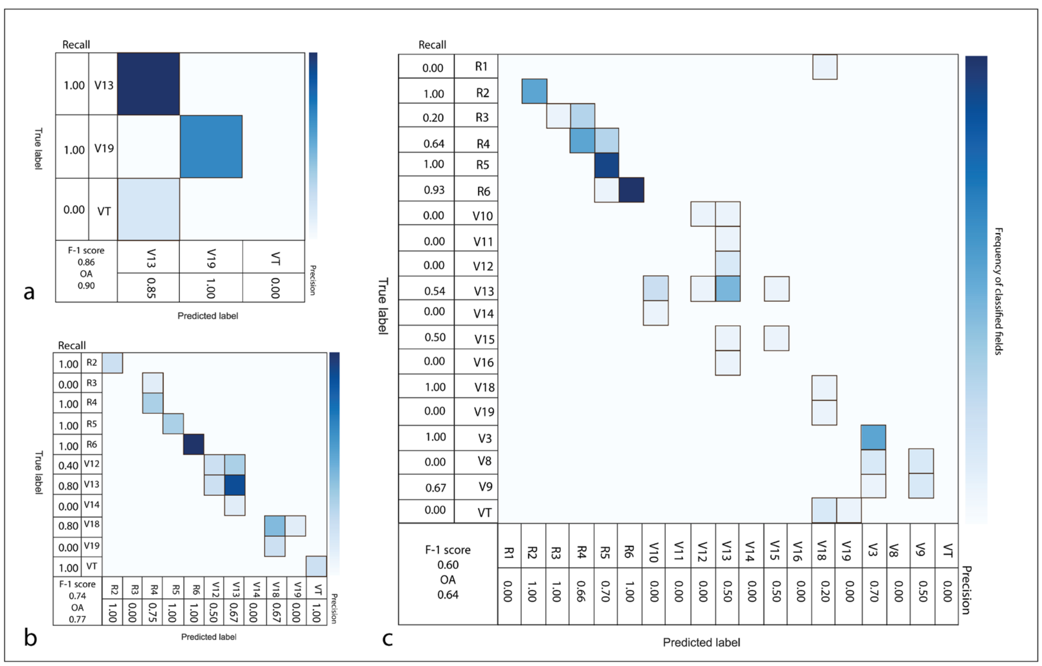

Figure 3. Confusion matrices with S-2-based classification results for the Southwest (SW) region, (a) including imagery on the date of data collection, (b) including data within 3 days before and after, (c) including data within 10 days before and after. All matrices include recall and precision for each crop phenology stage, and f1-score and overall accuracy (OA).