Authors' Response to Reviews of

A comprehensive assessment of in situ and remote sensing soil moisture data assimilation in the APSIM model for improving agricultural forecasting across the U.S. Midwest

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RC: ***Reviewers' Comment***, AR: Authors' Response, ☐ Manuscript Text

1. Reviewer #2

RC: ***General comments***

The study "A comprehensive assessment of in situ and remote sensing soil moisture data assimilation in the APSIM model for improving agricultural forecasting across the U.S. Midwest", M.Kivi, N.Vergopolan, H.Dokoohaki comprises of a set of new approaches and techniques of data assimilation for improving agricultural forecasting. In this study authors integrated in situ and remote sensing soil moisture observations with APSIM model through sequential data assimilation and assessed the extent to which soil moisture data assimilation can improve APSIM model forecasts. Therefore, paper addresses relevant scientific questions within the scope of HESS. The scientific methods and assumptions present are valid. The title clearly reflects the contents of the paper and abstract provides a complete summary of the research.

The work showed that assimilation of in situ surface soil moisture is not as powerful as the assimilation of in situ root-zone soil moisture in terms of model constraint. It is shown that high temporal resolution due to multisensor satellite availability and accurately estimated observation uncertainty are critical components for optimal system performance. More frequent assimilation helps mitigate the impact of such model errors and improve overall crop model predictions by correcting errors more often. Assimilating in situ observations, the accuracy of soil moisture forecasts in the assimilation layers was improved by an average of 17% for 10 cm and 28% for 20 cm depth soil layer across all site-years and the crop yield was improved by an average of 23%.

Specific comments There are a number of questions:

RC: ***In this study, APSIM's daily forecasts of agricultural variables were transformed and used as inputs into the PROSAIL model to compute the spectral reflectance. Would it be the source of errors in future predictions?***

AR: We appreciate your comment. On a daily basis, the APSIM model passes soil moisture and Leaf Area Index (LAI) measurements to the PROSAIL model in order to simulate canopy reflectance and derive spectral indices. While it is true that inaccurate estimation of LAI and soil moisture can lead to inaccurate estimates of spectral indices, we utilized this to assess the improvement of spectral indices through the assimilation of soil moisture. Furthermore, the soil moisture error in APSIM model is included in the Kalman gain computation, such that assimilation accounts for errors in the model when computing the Kalman gain (how much we will let our satellite observations update the model).

RC: ***There are a number of crops used in the study, which have different spectral signatures, biomass, stages of***

development, nutrient uptake, water use and water stress effect etc. Therefore, in order to reduce errors of agricultural forecasting would it be better to use different optimized variables for each crop?

AR: Thank you for your question. The APSIM model accounts for the differences in crop growth and development between corn and soybean explicitly through the use of two different crop growth models. The maize module, developed from a combination of the CM-KEN (Keating et al., 1991, 1992) and CM-SAT (Carberry et al., 1989; Carberry and Abrecht, 1991) models of maize (both derivatives of CERES-Maize, Jones and Kiniry, 1986) with some features of the maize model of Wilson et al. (1995), is used to describe the growth and development of maize in APSIM. For soybean, the generic plant module is used, which currently includes crops such as chickpea, mungbean, cowpea, soybean, pigeonpea, stylosanthes, peanut, faba bean, lucerne, canola, weed, mucuna, lupin, wheat, and navybean. Also the SDA at each site was performed independently, such that the system is already designed for optimal assimilation considering each site crop-specific characteristics.

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- Wilson, D. R.; Muchow, R. C. and Murgatroyd, C. J. 1995. Model analysis of temperature and solar radiation limitations to maize potential productivity in a cool climate. Field Crops Research, 43: 1-18.

RC: ***Some references should be revised in text and in the list of References.***

AR: Thank you for the comment. The following references were fixed in the main manuscript. Akhavizadegan et al (2021); Archontoulis et al (2014, 2020); Balboa et al (2019); Crane-Droesch (2018); Das et al (2020); Dietze et al (2013); Dietzel et al (2016); Flathers and Gessler (2018); Guerif and Duke (2000); Hoffman et al (2020); Jeong et al (2016); Kang et al (2020); van Klompernburg et al (2020); Leng and Hall (2020); Li et al (2014); Martinez-Feria et al (2019); Pasley et al (2021); Puntel et al (2016); Shahhosseini et al (2021); Spijker et al (2021); Wallach et al (2021), Vergopolan et al (2021), Chakrabarti et al (2014)