Assimilation of Leaf Area Index Measurements Into a Crop Model: Performance Comparison of Two Assimilation Approaches

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Background and Methodology

Introduction

- There is great potential in the application of dynamic crop simulation models for precision agriculture purposes
- Assimilation of spatially dense, repeated leaf area index (LAI) measurements could help to capture within-field heterogeneity of crop growth in the simulation
- Performance of data assimilation approaches (such as the Ensemble Kalman Filter) based on a Monte Carlo setup depends on selection of ensemble generation variables (Ines et al., 2013)

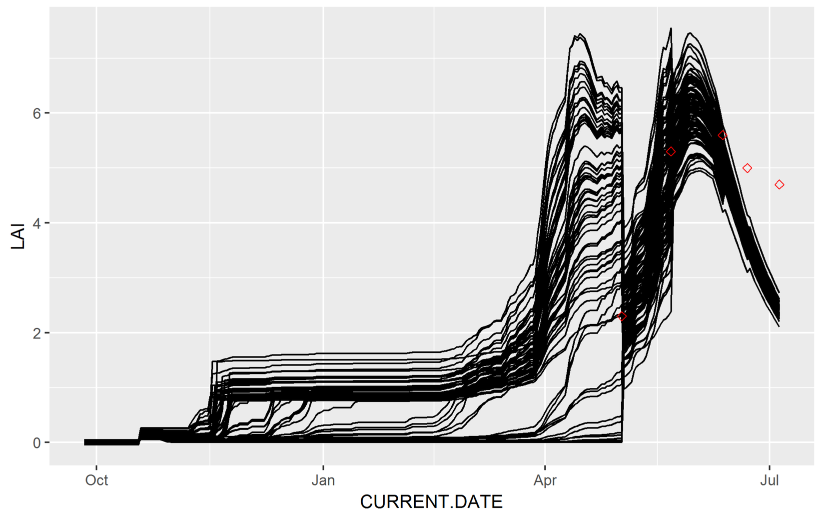

Figure 1: Example of assimilation of LAI observations into an ensemble of model runs using the Ensemble Kalman Filter

Data

- Winter wheat grown on 14 fields across Germany, France and Netherlands during growing seasons (GS) 2016-2017 and 2017-2018
- Daily weather data from weather stations installed adjacent to the fields
- One commercially available cultivar per field
- 40 to 60 sampling points per field with measurements of:
  - LAI using the LI-COR LAI-2200C Plant Canopy Analyzer (LI-COR Inc., Nebraska, USA) five times during GS
  - Soil texture for 0-30 cm, 30-60 cm, 60-90 cm soil depth
  - Growth stages according to BBCH scale
  - Dry weight of total aboveground biomass and grain yield around maturity

Crop Model

- Crop model LINTUL5 (Wolf, 2012) implemented in the modeling framework SIMPLACE (www.simplace.net) in combination with SlimWater and SlimRoots
- Soil hydraulic properties based on HYPRES (Wösten et al., 1999) pedotransfer function
- Daily phenology data provided by xarvio™ in-house developed growth stage model (based on cultivar, accumulated thermal temperature, vernalisation and photoperiod)
- Water stress only growth-inhibiting factor considered
- Assimilation of LAI measurements collected before anthesis

Data Assimilation

- Ensemble Kalman Filter (EnKF) in combination with two sets of ensemble generation variables:
  Crop Component Set (CC) and combinational set of soil and crop components (SCC):

CC	ScaleFactorSLA	Scales development stage dependent specific leaf area
	ScaleFactorRUE	Scales development stage dependent radiation use efficiency
	RGRLAI	Maximal relative increase of LAI during juvenile stage of plant
SCC	SoilWaterInit	Scales soil water content at simulation start
	MaximalRootDepth	Scales maximal rooting depth
	ScaleFactorSLA	Scales development stage dependent specific leaf area

- Run of SIMPLACE<LINTUL5,SLIM> in daily time steps in combination with EnKF and each set of ensemble generation variables
- Evaluation based on comparison of measured and simulated total aboveground biomass and grain yield at harvest day
- Analysis of Ensemble Mean (EM, no data assimilation) and model's standard run (no ensembe, no assimilation) to evaluate potential benefit of data assimilation

Results

Total Aboveground Biomass at Harvest

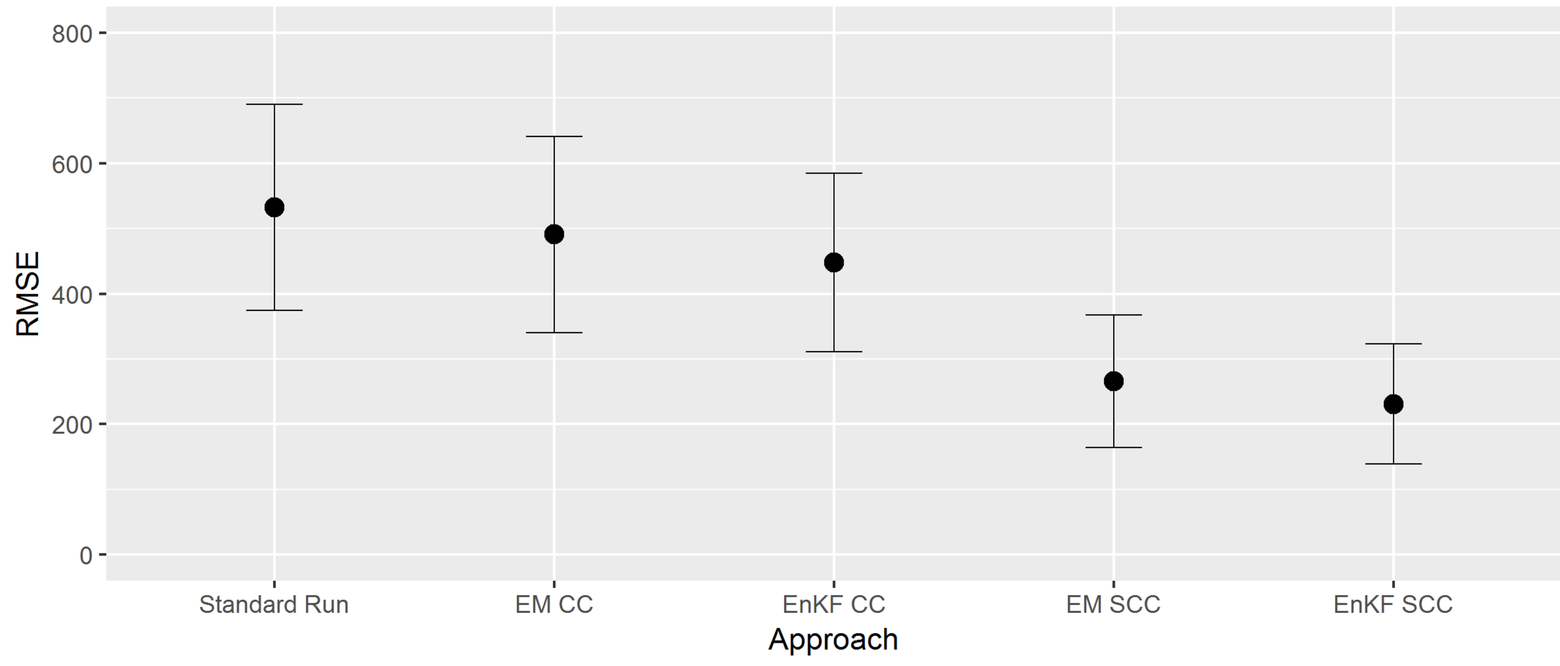

Figure 2: Mean and standard deviation of root mean squared error (RMSE) of total aboveground biomass for tested approaches. SR: Standard Run, EnKF: Ensemble Kalman Filter, EM: Ensemble Mean, CC: Crop Component Set, SCC: Soil and Crop Component Set. All values in g m^{-2}.

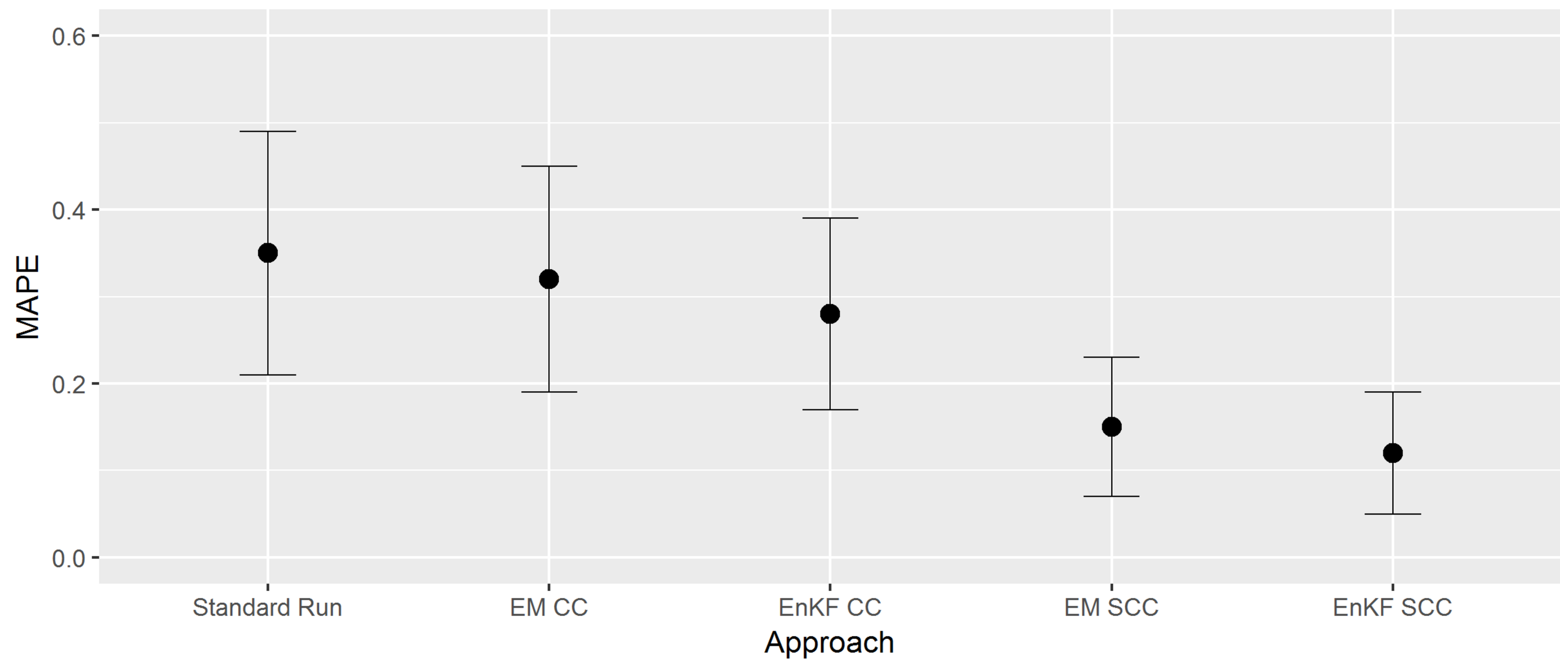

Figure 3: Mean and standard deviation of total aboveground biomass mean absolute percentage error (MAPE in decimal-%) for tested approaches. SR: Standard Run, EnKF : Ensemble Kalman Filter, EM: Ensemble Mean, CC: Crop Component Set, SCC: Soil and Crop Component Set.

Grain Yield

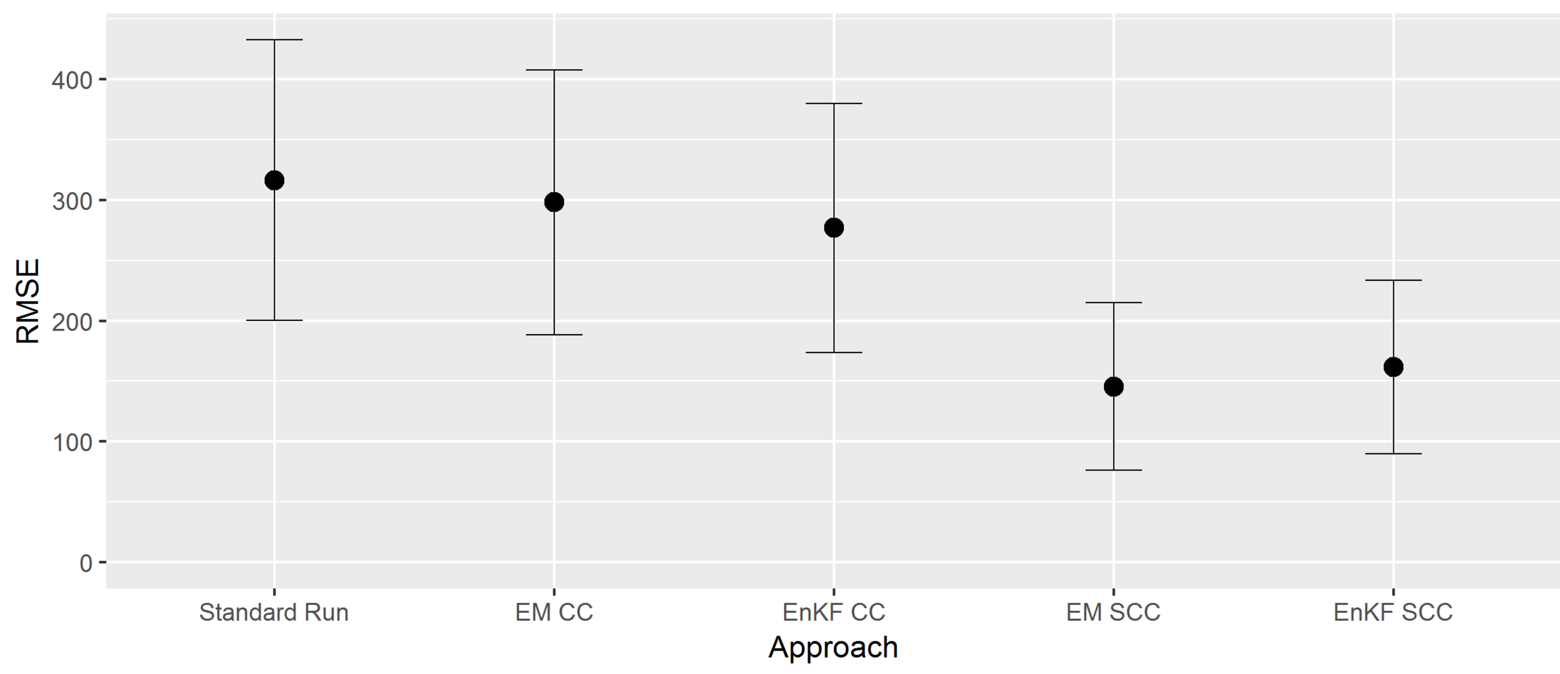

Figure 4: Mean and standard deviation of grain yield RMSE for tested approaches. SR: Standard Run, EnKF: Ensemble Kalman Filter, EM: Ensemble Mean, CC: Crop Component Set, SCC: Soil and Crop Component Set. All values in g m^{-2}.

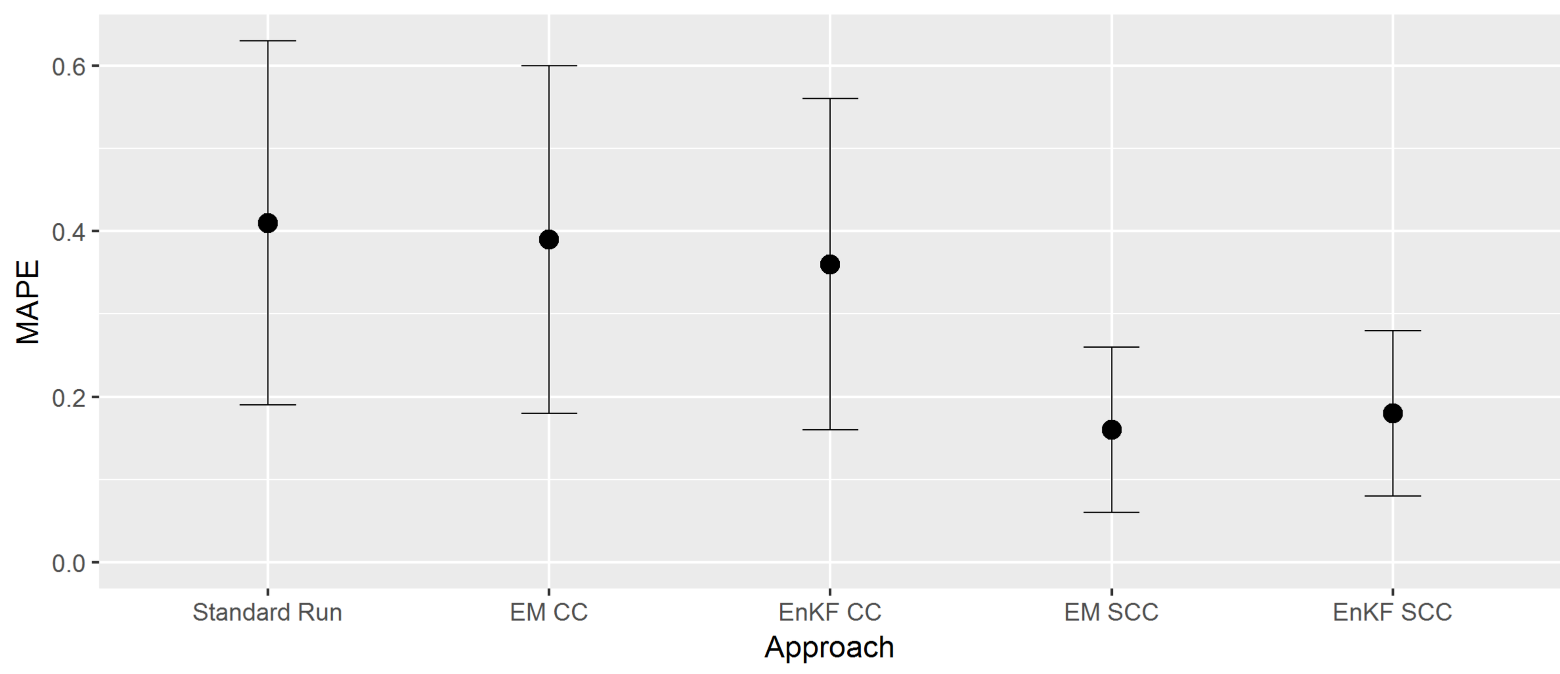

Figure 5: Mean and standard deviation of grain yield MAPE for tested approaches (in decimal-%). EnKF: Ensemble Kalman Filter, EM: Ensemble Mean, CC: Crop Component Set, SCC: Soil and Crop Component Set.

Conclusion and Outlook

- On average across all sites, standard runs showed worst performance
- EnKF SCC outperformed the EnKF CC approach for both total aboveground biomass and grain yield prediction
- EnKF SCC shows best performance for total aboveground biomass prediction, Ensemble Mean SCC for grain yield prediction
- Estimations of aboveground biomass better than estimations of grain yield
- Need for approach that does not violate integrity of the model runs (EnKF only updates small part of the model states)
- Incorporation of data sources with greater level of uncertainty (e.g. soil data from large-scale databases)

References

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