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Supporting decision-making in agricultural water management under data scarcity using global datasets – chances, limits and potential improvements

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ABSTRACT

Assessing alternative agricultural water management strategies requires long-term field trials or vast data collection for model calibration and simulation.

This work aims to assess whether an uncalibrated agro-hydrological model using global input datasets for climate, soil and crop information can serve as a decision support tool for crop water management under data scarcity.

This study employs the Cool Farm Tool Water (CFTW) at eight eddy covariance sites of the FLUXNET2015 dataset. CFTW is tested using global (CFTWglobal) and local (CFTWlocal) input datasets under current and alternative management scenarios.

Results show that the use of global datasets for estimating daily evapotranspiration had little effect on the median Root Mean Square Error (*RMSE*) (CFTWglobal: 1.70 mm, CFTWlocal: 1.79 mm), while, however, the median model *bias* is much greater (CFTWglobal: −18.6%, CFTWlocal: −4.3%). Furthermore, the periods of water stress were little affected by the use of local or global data (median accuracy: 0.84), whereas the use of global data inputs led to a significant overestimation of irrigation water requirements (median difference: 110 mm). The model performance improves predominantly through the use of more representative local precipitation data, followed by local reference evapotranspiration and soil for some European growing seasons.

We identify model outputs that can support decision-making when relying on global data, such as periods of water stress and the daily dynamics of water use. However, our findings also emphasize the difficulty of overcoming data scarcity in decision-making in agricultural water management. Furthermore, we provide recommendations for enhancing model performance and thus may increase the accessibility of reliable decision support tools in the future.

1. Introduction

Securing food production for a projected 9 billion people by 2050, whilst reducing the associated environmental impact, is one of the major challenges of our age (Foley et al., 2011; Gerten et al., 2020; Godfray et al., 2010).

Water is one of the main limiting factors to agricultural crop production, therefore improving water management at the field level may provide a way to increase food production without increasing other inputs, such as fertilizers or pesticides (Jägermeyr et al., 2016; Mueller et al., 2012; Rosa et al., 2018).

Water yield gaps are particularly pronounced in rainfed agriculture which indicates significant potential to increase production through addressing water constraints. Jägermeyr et al. (2016), for instance, identified water yield gaps of 6% in irrigated and of 29% in rainfed agriculture and modelled that global production could be increased by 41% through improved irrigation management. This is supported by Rosa et al. (2018) estimating a potential increase in global production of

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37%.

On the other hand, water withdrawal from surface water or below-ground aquifers for food production removes water for ecosystems and other water users in the catchment (Davis et al., 2017; McLaughlin and Kinzelbach, 2015). Therefore caution has to be exercised to avoid negative consequences of water use for agricultural production (Rodell et al., 2009; Zaveri et al., 2016).

The merits of alternative water management strategies are often investigated directly using field trials or by employing crop water models with site-specific input data and calibration. Agro-hydrological models have been shown to be effective in supporting irrigation water management at the field level (García-Vila et al., 2009; Multsch et al., 2013; Sassenrath et al., 2013a).

However, the use of such models in optimizing crop water management requires a substantial amount of site-specific data related to management, soil, weather, and crop. These data are not ubiquitously available (e.g. van Wart et al., 2013) which limits the capacity for informed decisions around site-level water management to be made (Mourtzinis et al., 2017; Rasera et al., 2023). Furthermore, agro-hydrological models generally require calibration before use, and such calibration requires additional data and in-depth knowledge, which reduces the accessibility to non-academics and those who are not experts on soil water modelling (Bastiaanssen et al., 2007).

The substitution of local with regional or global datasets for climate, crop and soil in decision support tools for agricultural water management might facilitate the adoption. However, these datasets introduce uncertainties in the model inputs which propagate into uncertainties in the model outputs (Mourtzinis et al., 2017; Rasera et al., 2023) and thus require thorough testing and sensitivity analysis before deployment.

While global datasets are frequently tested, in particular, climate datasets using local weather station data (Blankenau et al., 2020; de Leeuw et al., 2015; Martins et al., 2017; Paredes et al., 2018; Srivastava et al., 2020; Szczypta et al., 2011), studies testing model outcomes at field level based on these datasets are less prevalent. Recent research has looked at the use of regional gridded datasets in the absence of field-level observations for crop growth modelling (Dias and Sentelhas, 2021; Mourtzinis et al., 2017; Rasera et al., 2023). Although some studies show promising results using gridded datasets, they often highlight the constraints for field-level applications. Mourtzinis et al. (2017), for example, emphasize that gridded datasets are no suitable replacement for weather station data, in particular for yield and water balance modelling. The authors advocate increasing the density of weather station networks (Mourtzinis et al., 2017).

To our knowledge, there is no published or active research using global datasets to model daily, field-level water management. Therefore, evaluating the impact of the use of such datasets on the outputs of agro-hydrological models requires more attention (Baroni et al., 2019). If results are sufficiently accurate they allow decision-making for field-level water management under data scarcity.

This paper addresses three research objectives:

i) To quantify the error introduced through the use of global datasets for daily field-level modelling under conditions of data scarcity,

ii), To identify individual measures to improve daily model performance, and

iii), To evaluate the alignment of model outcomes for different irrigation management scenarios using field-level and global input datasets.

This will ultimately inform the ability to support decision-making at the field level through the use of an uncalibrated agro-hydrological model paired with global data.

2. Methods

We address these objectives by assessing the model performance of Cool Farm Tool Water (CFTW) presented in Kayatz et al. (2019a). CFTW is an online tool for performing growing season-specific water footprint assessments based on global soil, climate and crop information. This model framework provides reliable estimates for seasonal water footprints compared to field-level observations and state-level assessents produced by the Water Footprint Network. While this may be sufficient for sustainability reporting and strategic decision-making for agricultural supply chains, improving water management at the field level requires reliable performance at a higher time resolution. In addition, such a tool should provide accurate estimates for the comparison of different management practices such as altering irrigation amounts and irrigation intervals (e.g. Irmak et al., 2016).

The following section provides, i) a description of CFTW and the data used to evaluate the impact of different data inputs, and ii) the procedure applied to compare the predictions for varying irrigation management when using different input datasets.

2.1. Cool Farm Tool Water

CFTW is part of the online Cool Farm Tool (CFT) (https://app.coolfarmtool.org), which considers greenhouse gas emissions and crop water use for agricultural production, as well as biodiversity impacts at the farm level (Cool Farm Alliance, 2016; Hillier et al., 2011; Vetter et al., 2018). The tool is tailored for growers and practitioners in agricultural supply chains using only such data as is readily available to users at the farm level and providing default data from alternative sources for the remaining inputs.

As part of the Cool Farm Tool, CFTW is a water assessment tool for the evaluation of seasonal water footprints under current and alternative irrigation management practices. It is, to a large extent, based on FAO56 using the single crop coefficient to determine daily actual evapotranspiration (ET_a) (see Eq. 1) (Allen et al., 1998).

$$ET_a = ET_O * K_c * K_s \tag{1}$$

Reference evapotranspiration (ET_O) is based on the Penman-Monteith Equation deriving temperature, net radiation and surface pressure from the global gridded ERA Interim reanalysis dataset (Allen et al., 1998; Dee et al., 2011).

Crop coefficients (K_c) are taken from FAO56 and are automatically adjusted for climate, soil and crop conditions using the FAO56 methodology (Allen et al., 1998). In particular, during the initial growing stages, K_c is highly dependent on wetting frequency (ERA Interim), ET_O (ERA Interim) and soil (Harmonized World Soil Database), while during later growing phases K_c needs to consider crop height, humidity (ERA Interim) and wind speed (Allen et al., 1998; Dee et al., 2011; FAO et al., 2012).

K_s is the transpiration reduction factor describing crop water stress as defined by Allen et al. (1998) and is determined by the soil water depletion and stress tolerance of the specific crop. CFTW enhances the classical 'tipping bucket' approach presented in FAO56 in four ways: i) The size of the bucket considers the root growth over the growing season, ii) soil water holding capacity considers soil organic carbon using the pedo-transfer function of Saxton and Rawls (2006), iii) CFTW automatically considers crop interception of irrigation and precipitation using Hoyningen-Huene (1983) and Braden (1985) as in the SWAP model (Kroes et al., 2008) and iv) runoff is automatically determined using the LPJmL approach (Jägermeyr et al., 2015). The required input data for these adjustments are derived from the Harmonized World Soil Database (HWSD), ERA Interim and FAO56 among others (Allen et al., 1998; Dee et al., 2011; FAO et al., 2012).

A full model description is provided in Kayatz et al. (2019a) and Kayatz et al. (2019b).

To address the research questions, CFTW using global input data for climate, soil, and crop as described above as well as limited user inputs (CFTWglobal), is compared to an adjusted CFTW using local observations derived from the FLUXNET2015 dataset (CFTWlocal). Both use the CFTW methodology and rely on an uncalibrated agro-hydrological but employ different input data as defined in Table 1. By assessing these two model variants the added value of local input data as well as the most

Table 1
The following table provides an overview of the global and local datasets used for CFTW in this study. Gaps in local observations have been filled using global datasets, as long as the total gap did not exceed 10% of the growing season for each variable. FAO56 refers to data that has been derived from Allen et al. (1998). HSWD refers to the Harmonized World Soil Database (FAO et al., 2012), while ERA Interim refers to Dee et al. (2011). User is data that is currently already defined as user input in CFTW.

domain		CFTWglobal	CFTWlocal
Crop	field location	User	User
	crop type	User	User
	crop yield	User	User
	growing area	User	User
	planting & harvesting date	User	User
	length growth stages	FAO56	FAO56
	default crop factors	FAO56	FAO56
	rooting depth	FAO56	FAO56
	crop height	FAO56	loc. obs.
	leaf area index	FAO56	loc. obs.
Soil	soil texture	HWSD	loc. obs.
	soil organic matter	HWSD	loc. obs.
	initial soil water content	User	User
	readily evaporable water	FAO56	FAO56
	readily available water	FAO56	FAO56
Climate	min. and max. temperature	ERA Interim	loc. obs.
	dew point temperature	ERA Interim	loc. obs.
	net radiation	ERA Interim	loc. obs.
	surface pressure	ERA Interim	loc. obs.
	minimum relative humidity	ERA Interim	loc. obs.
	precipitation	ERA Interim	loc. obs.
	wind speed	Approx. using FAO56	Approx. using FAO56
Management	irrigation amount	User	User
	period irrigated	User	User
	number of irrigation events	User	User
	fraction irrigated	User	User
	irrigation method	User	User

important elements of the data affecting model performance can be determined (See Section 2.3).

2.2. FLUXNET2015 test sites

The analysis is based on 33 individual growing seasons from eight different Tier 1 eddy covariance sites from the FLUXNET2015 dataset (Table 2) (Pastorello et al., 2020). The sites selected for our analysis were those which had sufficient local data available on climate, crop, and soil.

Field-level meteorological input data and observed evapotranspiration for model evaluation in FLUXNET2015 contained minor gaps. We allowed for a gap-filling using ERA Interim data for up to 10% of the growing season similar to Kayatz et al. (2019a). Atmospheric pressure and dewpoint temperature were not observed at all eddy sites. In such cases, ERA Interim data and local observed daily minimum temperature were used as suggested by FAO56 (Allen et al., 1998).

Model results were compared to evapotranspiration derived from corrected latent heat flux following the post-processing of the FLUXNET2015 dataset (Pastorello et al., 2020). To address remaining gaps in daily evapotranspiration we allowed for a gap-filling for a maximum of 5% of the growing season using linear interpolation.

2.3. Model evaluation

We tested the uncalibrated agro-hydrological model driven by global datasets against model results using local input and observations in order to understand how this modelling approach can support decision-making under data scarcity and with limited modelling experience. No soil-, crop- or climate-specific calibration of CFTW was conducted.

The model evaluation focuses on a comparison of daily evapotranspiration, daily water stress, and irrigation water requirements. Daily evapotranspiration supports decision-making for water management as it describes water lost from the soil profile. Water stress derived from soil water depletion and crop stress tolerance informs on time periods when crops are exposed to stress and require irrigation. While irrigation requirements define the amount of water needed to meet crop water requirements.

CFTWglobal and CFTWlocal were both tested against daily observed evapotranspiration using eddy covariance measurements. Since FLUXNET2015 does not provide consistent observations for soil water, no consistent data for water stress and irrigation requirements exist. The model evaluation therefore also included a direct cross-comparison between CFTWglobal and CFTWlocal for crop water stress and irrigation requirements. Here we assumed that modelling results using local information are more accurate, due to the higher accuracy of driving input parameters in particular for climate information.

2.3.1. Daily evapotranspiration

The model performance in terms of bias and variance for daily evapotranspiration were assessed using the percent bias (*bias*) and Root Mean Square Error (*RMSE*), as defined below:

$$RMSE = \sqrt{\frac{1}{n}\sum(obs - sim)^2} \quad (2)$$

$$bias = 100\% * \frac{\sum(sim - obs)}{\sum obs} \quad (3)$$

Where *obs* refers to the daily observed ET_a, *sim* the daily simulated ET_a, and *n* the number of observations and simulations.

2.3.2. Crop water stress and irrigation requirements

CFTWglobal and CFTWlocal were tested for their alignment in predicting crop water stress ($K_s < 1$) as well as irrigation requirement (*IWR*) (see Eq. 4).

Table 2
The table provides an overview of sites, crops and years used to assess CFTW accuracy based on global and local input. The sites listed here are also used to investigate irrigation management based on model input.

site	crops	years	location	country	reference
BE-Lon	winter wheat, potato	2005–2007,	50.6 N, 4.7 E	Belgium	Moureaux et al. (2006)
CH-Oe2	winter barley, potato	2005–2007	47.3 N, 7.7 E	Switzerland	Dietiker et al. (2010) and Emmel et al. (2018)
DE-Kli	maize	2007	50.9 N, 13.5 E	Germany	Prescher et al. (2010)
FR-Gri	winter wheat, maize, winter barley	2006–2008, 2010–2012	48.8 N, 2.0 E	France	Loubet et al. (2011)
IT-BCi	maize	2004, 2005	40.5 N, 15.0 E	Italy	Vitale et al. (2009, 2007)
US-Ne1	maize	2002–2007	41.2 N, 96.5 W	USA	Suyker and Verma (2009)
US-Ne2	maize, soybean	2002–2007	41.2 N, 96.5 W	USA	Suyker and Verma (2009)
US-Ne3	maize, soybean	2002–2007	41.2 N, 96.4 W	USA	Suyker and Verma (2009)

$$IWR = \sum (ET_0 * K_c) - \sum (P_{net} + I_{net}) \tag{4}$$

Where P_{net} and I_{net} are the sum of net precipitation and net irrigation. *IWR* was evaluated by comparing the absolute difference in *IWR* when using CFTWglobal versus CFTWlocal over the full growing season.

The variable $K_s accuracy$ indicates the agreement of both model variants in indicating daily crop water stress ($K_s < 1$) and no crop water stress ($K_s = 1$).

$$K_s accuracy = \frac{TP + TN}{P + N} \tag{5}$$

Where *TP* (true positive) and *TN* (true negative) refer to the days with water stress or without water stress, respectively for both model setups. *P* and *N* are the days with water stress or without water stress respectively, for CFTWlocal.

2.3.3. Understanding model differences using the contribution factor

The contribution factor C_f (see Eq. 6) describes the impact of a model input on the reduction of the *RMSE* or *bias* for ET_a. C_f was assessed by replacing global input data with local information for reference evapotranspiration (minimum & maximum temperature, net radiation, atmospheric pressure), precipitation, soil information (soil type, soil organic carbon), and crop information (leaf area index (LAI), crop height) individually for all 33 growing seasons.

C_f was determined as follows:

$$C_f = \frac{P_{G_f} - P_G}{P_L - P_G} \tag{6}$$

P_G and P_L are the performance metrics (e.g. *RMSE* or *bias*) comparing observations and CFTW outputs with global and local input data respectively. P_{G_f} is analogous but replaces an individual global dataset *f* with local data (for example, using local soil data instead of global soil data). The greater the value of C_f in comparison to the other factors, the more important the model input is in improving model performance.

The same approach was applied for $K_s accuracy$ and *IWR*. As no observations for *IWR* and $K_s accuracy$ were available, CFTWlocal was instead used to determine the performance metrics. For *bias* and *IWR* absolute values were used to estimate the contribution factors.

2.3.4. Assessment of different management interventions

Finally, to support decision-making in agricultural water management, CFTWglobal needs to enable the comparison of different management interventions. This study compares model results using global and local input data under different irrigation management interventions. The interventions were compared in terms of their potential to lower *IWR* and to reduce the number of days (as a fraction of total days) that crops are exposed to stress during the irrigation period.

Irrigation periods were derived from the model outputs of CFTWglobal and CFTWlocal under reported irrigation management. The irrigation period was defined as the longest consecutive period of water stress predicted by either of the two model setups in one growing season. If water stress reoccurred within five days of a previous water stress period it was treated as a single event.

The following two irrigation strategies were investigated:

Changing irrigation amount. Increasing irrigation directly influences available water in the soil profile and therefore water available to the crops. However, too much irrigation triggers runoff and deep percolation, and therefore not all abstracted water used for irrigation may be available to the crop.

Changing irrigation intervals. More frequent irrigation intervals may have multiple effects on crop water availability. Higher wetting frequency can increase evaporation from the soil and canopy surface, in particular at the beginning of the growing season when evapotranspiration is dominated by evaporation. However, if combined with lower application rates it may also lead to less deep percolation and reduced runoff.

Irrigation management is defined by timing, method and irrigation amount. For this study, CFTW is tested using different irrigation amounts and different timing. Specifically, the irrigation amount was altered by applying 10, 20, 30, 40 or 50 mm for each irrigation event. The interval was changed by applying irrigation every 2nd, 4th, 6th, 8th or 10th day. The selection of intervals and amounts was done to cover a wide range of potential management scenarios. These management options as well as their different combinations were applied to CFTW using local data input and global data input. Existing irrigation management was disregarded for these model comparisons.

3. Results

3.1. Comparing daily **ETa** estimates using local and global model input to observations

Fig. 1 displays the model *bias* and the *RMSE* for CFTW with local and global input data.

The median *RMSE* for ET_a across all growing seasons is similar when using global and local input data. At the same time, the variability, determined by the standard deviation (sd) of the *RMSE* across growing seasons, is much greater when using global data (sd CFTWlocal 0.58, sd CFTWglobal 0.79). The model inter-comparison of the *RMSE* shows a high correlation between both model variants (R2 = 0.76, p-value < 0.05).

The median model *bias* across all growing seasons (CFTWglobal: −18.6%, CFTWlocal: −4.3%) is greatly reduced when using local input data, while the variability (sd CFTWlocal: 19.0%, sd CFTWglobal: 20.1%) is only slightly lower when using local data. Both model variants showed a good correlation for the *bias* results (R2 = 0.59, p-value < 0.05), but lower compared to the correlation of the *RMSE*.

The use of global data does not, therefore, reduce the model accuracy for ET_a based on the *RMSE*. However, the *bias* of the predicted ET_a is greatly increased when relying on global data alone. For both performance metrics, the variance of the model performance is reduced using local input data.

Fig. 2 displays the ET_a for individual growing seasons in which shifting from global to local input data showed the smallest and the largest model improvements.

For winter wheat at the FR-Gri site in 2006, CFTW showed only slight improvements for *bias* and *RMSE* using local data, while for maize and soybean at US-Ne3 in 2006 and 2007 the estimate of ET_a was greatly improved using local data. However, the *RMSE* for US-Ne3 in 2006 remains relatively large at 2 mm even when using local inputs, due largely to poor model performance during July and early August and at the end of the growing season.

The poor performance using global data at both US-Ne3 trials is linked to overestimation of relative soil water depletion and thus crop water stress (see App. Fig. 1). This overestimation is linked to a strong negative *bias* for precipitation (2006: −52.1% and 2007: −34.4%) and a slight overestimation of ET_0 (2006: 12.7% and 2007: 4.5%) (see App. Fig. 1). In addition, the local soil information resulted in the estimated maximum water-holding capacity being 22.3% higher than with the global data (using the HWSD) which further increases the risk of water stress. An overview of the comparison between local and global climate data is provided in App. Table 1.

The drivers for the improved *bias* and *RMSE* for modelled ET_a are provided in Fig. 3. The contribution factors ranged from −17.1–12.9 for the *RMSE* and −6.4–9.1 for the *bias*. The reasons for contribution factors outside of the 0–1 range for individual trials were two-fold: i) Using local data resulted in a decrease in model performance and ii) exchanging individual datasets is more effective in improving model results compared to changing all datasets to local observations.

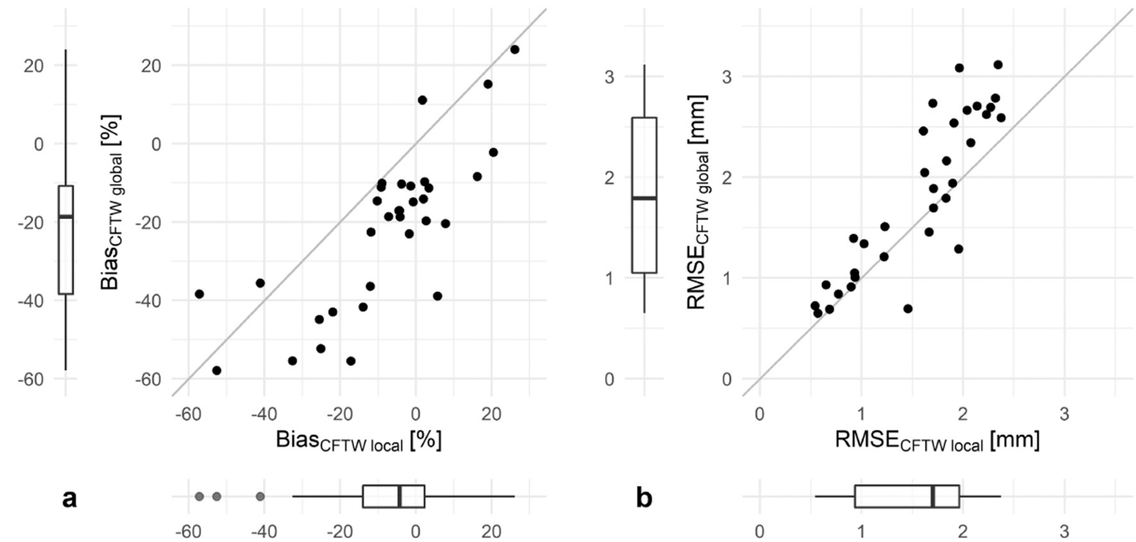

Fig. 1. Comparing model performance of CFTW using global and local input based on 33 seasons from 8 eddy covariance sites. (a) Shows the *bias* for CFTW using global and local input. (b) Shows the *RMSE* for CFTW using global and local input.

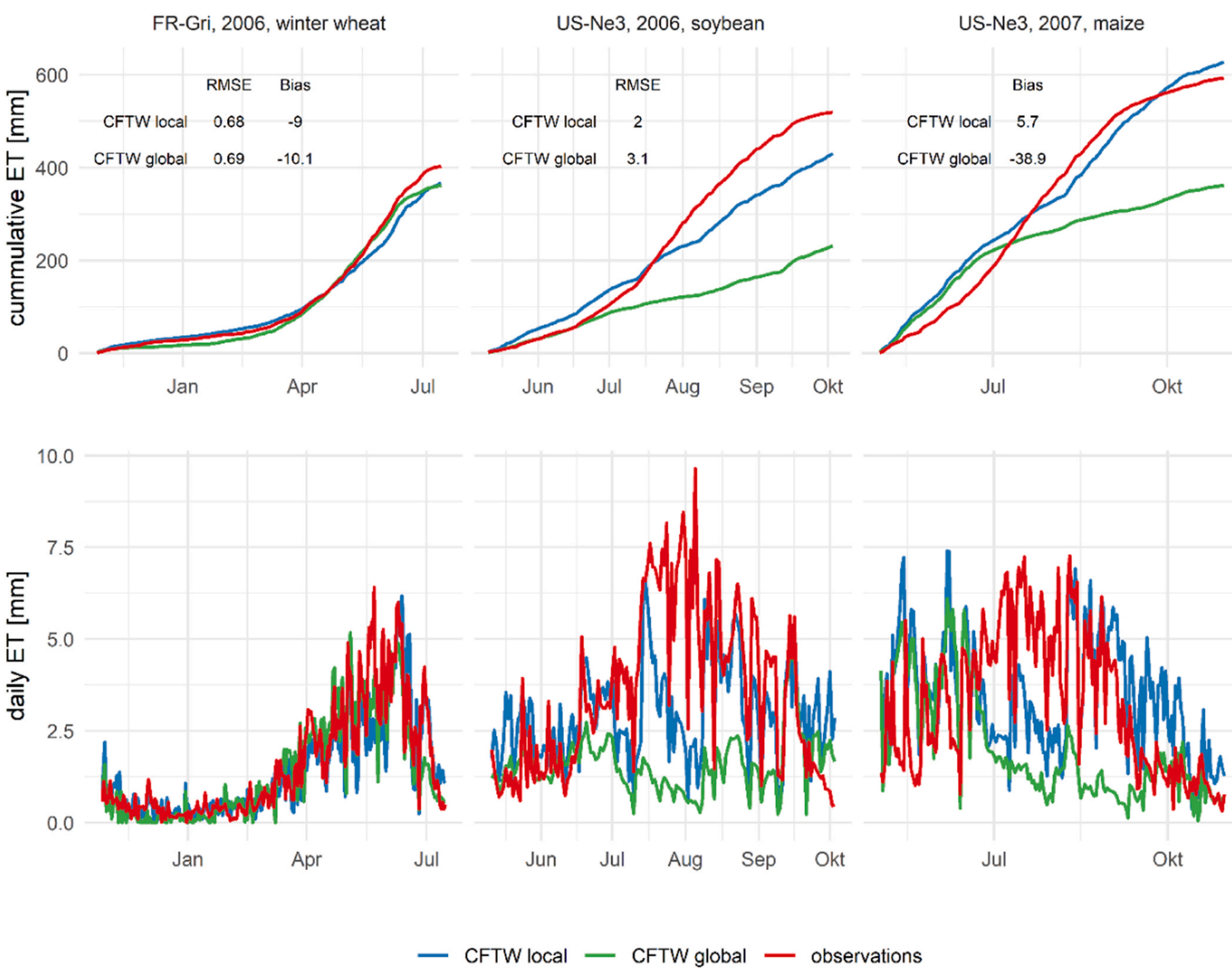

Fig. 2. Daily evapotranspiration simulated with CFTW using global and local input versus observations. FR-Gri in 2006 shows only a very limited increase in performance for *bias* and *RMSE*, while US-Ne3 trials for 2006 and 2007 greatly benefit from using local data, in particular for *bias*.

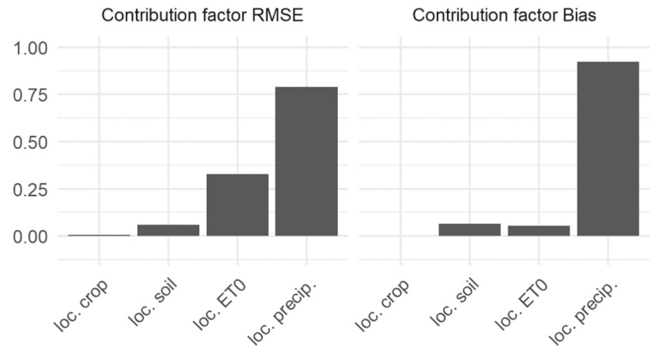

Fig. 3. The barplot displays the median contribution to improved model performance (*RMSE*, *bias*) for actual evapotranspiration ET_a.

Generally the contribution of local crop (median $Cf_{RMSE,crop} = 0.01$) and soil information (median $Cf_{RMSE,soil} = 0.06$) to the reduction of the *RMSE* is low. Perhaps surprisingly, using local crop data (median $Cf_{bias,crop} = 0.00$) resulted in a slight reduction of model performance in terms of *bias*.

The largest value of the contribution factor is observed when replacing global with local precipitation data (median $Cf_{RMSE,prceip} = 0.79$), followed by local ET_0 (median $Cf_{RMSE,ET_0} = 0.33$). For *bias*, the contribution factor of precipitation is even more dominant (median $Cf_{bias,precip} = 0.92$).

The dominance of precipitation is not consistent across all sites and is largely driven by the US-Ne sites. Other sites also show individual seasons where ET_0 or soil information has the highest contribution factor for *bias* and *RMSE*. Individual site results are provided in the appendix (App. Fig. 4 and App. Fig. 5).

These findings are supported by the comparison of observed meteorological site data and ERA Interim (App. Table 1). Precipitation data shows a much weaker correlation and much higher *bias* compared to ET_0.

3.2. Estimating stress periods and irrigation requirements

The cross-comparison of CFTW using global and local input data shows good agreement in terms of detecting periods of both water stress and no water stress (median $K_s accuracy = 0.84$) (Fig. 4). Overall, using global data results in periods of crop water stress being on average (median) 12.6% longer caused by higher relative soil water depletion (see App. Fig. 2 and App. Fig. 3). This is particularly pronounced for the single-season from DE-Kli, where CFTWlocal shows no crop water stress for 92.6% of the season, while for CFTWglobal this value is only 33.1%. This offset is linked to an offset in seasonal precipitation (-29.0% global vs. local) as well as ET_0 (+19.5% global vs. local). In total, $K_s accuracy$ is above 0.75 in 87.9% of all growing seasons.

CFTWglobal overestimates periods of water stress, driven by an overestimation of relative soil water depletion, and irrigation requirements. The median overestimation is 110 mm (40%) (see Fig. 4b, App. Fig. 2 and App. Fig. 3).

This offset shows great variability and ranges from −105 mm (global vs. local, CH-Oe2, 2007, winter barley) to 279 mm (US-Ne3, 2007, maize). Again, DE-Kli is an extreme case, since CFTW does not predict any irrigation need for the entire growing season using local data but estimates an irrigation demand of 108 mm using global data. The largest differences were simulated for all US-Ne sites - ranging from 76 mm to 279 mm.

The factors contributing to the increased accuracy in predicting K_s and the difference in *IWR* are displayed in Fig. 5. The largest contribution factor is for precipitation information (median $Cf_{Ks,precip} = 0.35$). Similarly, for *IWR*, precipitation plays a dominant role in explaining the differences between both model outputs (median $Cf_{IWR,precip} = 0.66$). The

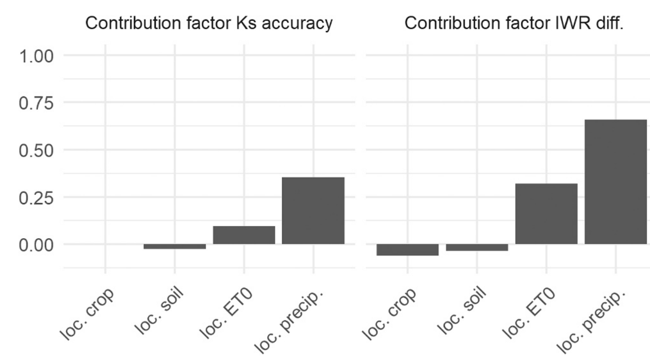

Fig. 5. The barplot shows the median contribution factor to improved model performance based on the model inter-comparison of CFTWlocal and CFTWglobal for *Ks* and difference in IWR.

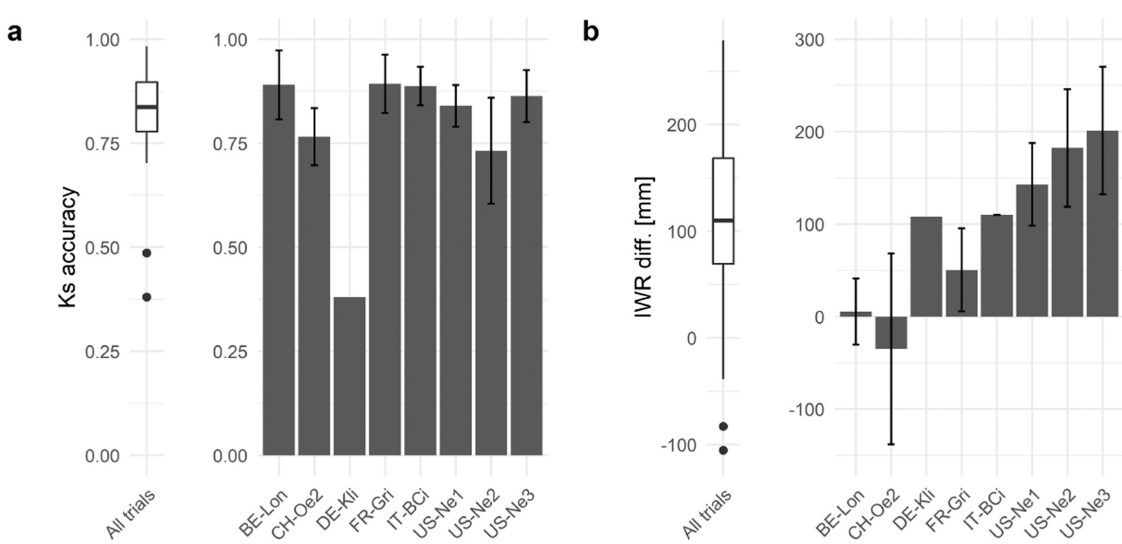

Fig. 4. The barplot displays the agreement of water stress periods and irrigation water requirements of CFTW using local and global input. The error bars of the barplot show the standard deviation across all growing seasons for each location. (a) Shows the temporal agreement of days indicating water stress and no water stress ($K_s accuracy$). (b) Indicates the difference between irrigation requirements (*IWR*) using local data input and global data input.

contribution factor for ET_0 is 0.32, indicating that this is also an important driver for the different model results.

3.3. Identifying improved irrigation management

The following section investigates the agreement of both model variants for different irrigation management practices. The duration of water stress (median correlation = 0.96) and irrigation requirements (median correlation = 0.99) are highly associated with each other for all growing seasons and different irrigation practices (Fig. 6). However, at the same time, the *bias* for the duration of water stress and *IWR* were relatively large, with a median of 25.0% (lower quartile = 10.5%, upper quartile = 53.8%) and 42.0% (lower quartile = 22.2%, upper quartile = 74.4%), respectively. This shows that estimates for both inputs agree in terms of the relative change resulting from a change in irrigation management, albeit there is a substantial difference in absolute terms.

The individual trials revealed three typologies which are displayed in Fig. 7: (i) Duration of water stress changes for only one of CFTWglobal or CFTWlocal when applying different irrigation management (see CH-Oe2, 2005, winter barley or FR-Gri, 2006, winter wheat), ii) high agreement is present regarding water-stressed periods for both input data sets across all irrigation management scenarios (BE-Lon, 2005, winter wheat), and iii) agreement for water-stressed periods is present for some of the irrigation interventions but not all (US-Ne2, 2005, Maize). The last two of these represent 78.8% of the trials. Duration of water stress and *IWR* for all management interventions and trials are shown in the appendix (App. Fig. 6 and App. Fig. 7).

4. Discussion

4.1. Model performance and uncertainty using local field-level data

Numerous studies have compared modelled ET_a or potential evapotranspiration using field-scale meteorological, soil, and crop data with eddy covariance measurements over intervals from hourly to seasonal (Gao et al., 2020; Gharsallah et al., 2013; Kimball et al., 2019; Maes et al., 2019; Wang et al., 2018; Wegehenkel et al., 2017). When *RMSE* for daily ET_a has been reported, it has generally fallen into the lower range of values seen in this study using an uncalibrated model.

For example, Gharsallah et al. (2013) reported an *RMSE* of 0.79 mm d^{-1} for a maize site in northern Italy, while Wang et al. (2018) reported an *RMSE* of 1.13 mm d^{-1} for maize in northern China using a soil-plant model based on FAO56. Anapalli et al. (2019) simulated evapotranspiration for corn, soybean, and cotton showing *RMSE*s ranging from 0.9 mm d^{-1} to 1.4 mm d^{-1} using the Root Zone Water Quality Model v2.0.

In terms of *bias*, other studies have reported on an overestimation of daily evapotranspiration in particular during the mid-season (Maes et al., 2019; Wang et al., 2018). Our study has shown a slight underestimation of ET_a using local input data (see Fig. 1).

This study showed that CFTW can predict daily ET_a using field-scale input data but performs, on average, slightly less well than existing studies. Thus CFTWlocal can support decision making by providing water use based on absolute values (*bias*) and daily dynamics (*RMSE*).

Multiple reasons may have contributed to the slightly reduced performance compared to existing studies:

Firstly, while it may be expected that local calibration improves model performance, this is explicitly not the purpose of CFTW. CFTWs primary aim is to allow for water assessments for decision-making at the global scale without local calibration.

Secondly, the FAO56 single crop coefficient approach is a simple model and is parameterized at the global level in CFTW. For irrigation management, FAO56 recommends using the dual crop coefficient approach, differentiating evaporation and transpiration (Allen et al., 1998). In addition, the coarse spatial resolution of FAO56 default data may reduce the representativity of rooting depth, stress tolerance and crop coefficients. Further, crop coefficients in FAO56 have been established in and before 1998 (Allen et al., 1998). Since this date, atmospheric CO_2 levels have significantly increased which may consequently have increased the water use efficiency of crops (Hatfield and Dold, 2019). This adds uncertainty to the FAO56 approach and the published crop coefficients.

Lastly, the calculation of the soil water balance uses a 'leaky bucket' approach and determines the size of the bucket using the pedo-transfer functions published by Saxton and Rawls (2006) (Kayatz et al., 2019a). This incurs uncertainty regarding the bucket size, the soil water distribution in the rooting depth and ultimately crop water stress.

4.2. Uncertainty with global data and potential improvements

The *RMSE* was primarily analysed to assess the ability of CFTW to capture the daily variability of observed ET_a. The use of global data increased the median *RMSE* by just 5.3% (median *RMSE* CFTWlocal: 1.70 mm, median *RMSE* CFTWglobal: 1.79 mm), while the variability between all trials grew by 36.2% (see Fig. 1). Thus, based on the daily dynamics, CFTWglobal may be equally suitable for decision-making as

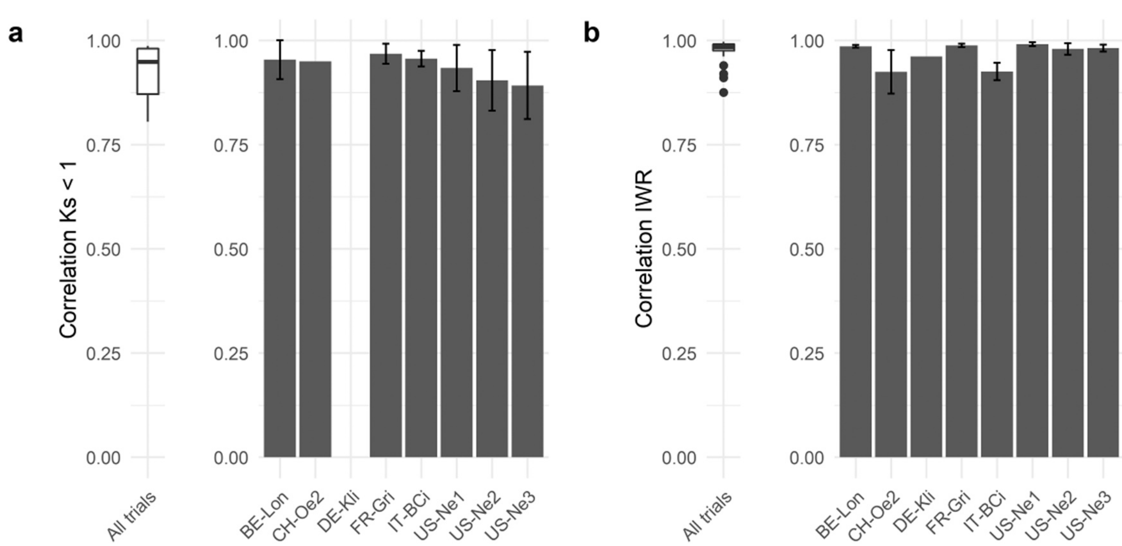

Fig. 6. Correlation of water stress periods (a) and irrigation requirements (b) during the irrigation period of CFTW using local and global input for different irrigation intervals and irrigation amounts. The error bars of the barplot show the standard deviation across all growing seasons for each location.

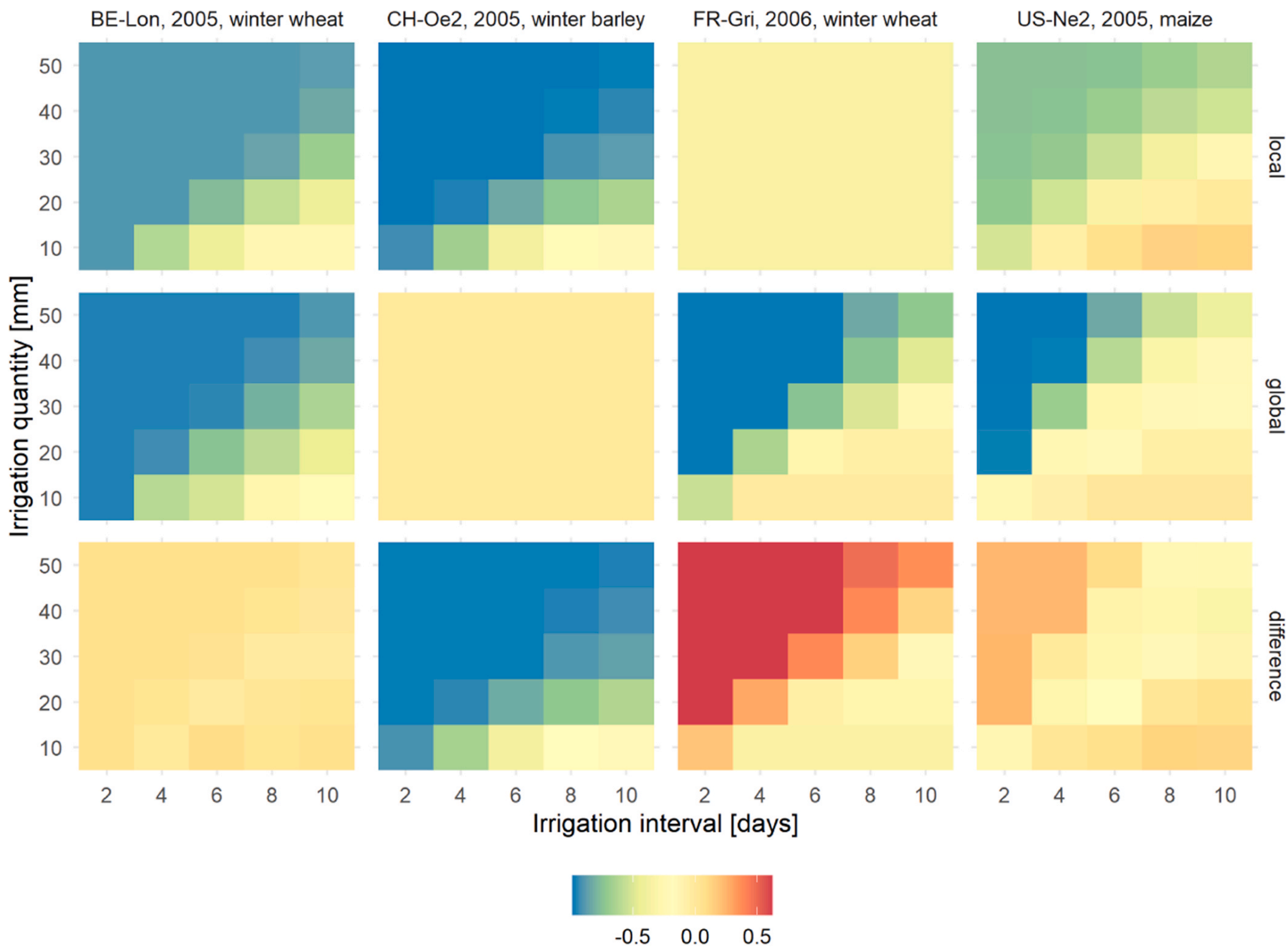

Fig. 7. The tile plot displays the fraction of the irrigation period where the crop is exposed to crop water stress for different irrigation scenarios (irrigation interval - horizontal, irrigation rates – vertical). "local" and "global" display the difference between no irrigation management and the irrigation scenarios. A negative value therefore indicates a reduction of the period exposed to water stress. "difference" displays the delta between CFTW global and CFTW local for different irrigation practices. For the latter, a negative value indicates that crop water stress for CFTWglobal is higher than for CFTWlocal.

CFTWlocal when considering the slightly higher variability.

The median contribution factor identifies precipitation as the main reason for these differences, followed by ET_0 (see Fig. 3). The daily dynamic of ET_a is, in large part, driven by daily ET_0. The much lower contribution factor may therefore be explained by the high quality of ERA Interim-derived ET_0 data using the Penman-Monteith equation by FAO56. ET_0 has the highest median correlation coefficient comparing local observations to global data after temperature and atmospheric pressure (App. Table 1). Precipitation has an indirect effect on daily ET_a dynamics via K_s, and may reduce ET_a to zero when soil water content has reached the permanent wilting point. Crops were exposed to longer periods of water stress ($K_s < 1$) when using global input data. This emphasizes the importance of accurate precipitation data and the high contribution factor.

Bias for ET_a was analysed to gain an understanding of the average offset of observations and modelled data with different input datasets. In stark contrast to *RMSE*, the *bias* increased by 332.6% (median *bias* CFTWlocal: −4.3%, median *bias* CFTWglobal: −18.6%), clearly highlighting the caveats of using global information for daily model results (see Fig. 1). The variability of the *bias* only increased by 5.8%. Therefore, caution is required if using CFTWglobal for decision-making based on absolute ET_a values, due to the significant increase of the *bias*.

The main contribution factor is precipitation, while all other inputs showed either very limited or no contribution to improvements of the modelling results (see Fig. 3). This again is in line with our analysis of meteorological input data, where global precipitation was characterised by a high underestimation (App. Table 1). Replacing precipitation input data with local information, reduces the median *bias* across all trials to 8.5% (see Fig. 3).

The above indicates that the main driver for the difference in model outcomes is the discrepancy in precipitation data. Reducing uncertainty for decision support tools should therefore focus on on acquisition of precipitation at field level.

Similar results have been published regarding yield modelling employing gridded datasets. Menezes et al. (2022) and Dias and Sentelhas (2021) suggest using local precipitation data to improve daily crop growth simulations for rice and sugarcane, respectively, in Brazil. Rasera et al. (2023) compared modelled citrus yields using weather station information and gridded climate datasets. The authors suggest using local precipitation data compared to NASA Power precipitation data due to the high heterogeneity of rainfall (Rasera et al., 2023).

Fewer publications consider agro-hydrological modelling for irrigation management explicitly. Mun et al. (2015) highlight the importance of accurate water inputs for reducing uncertainty in assessing irrigation strategies using the model MIST. In contrast, Sassenrath et al. (2013b) compared modelled soil water deficit using weather station data as well as radar-based gridded National Weather Service precipitation data in the Mississippi Delta. Both model outputs produced comparable results, demonstrating that some gridded precipitation datasets may well be able to compete with weather station data.

The contribution factor of local soil and crop data for improving model performance is for most sites negligible (see App. Fig. 4 and App. Fig. 5). For soil, this is particularly surprising as studies have highlighted the importance of soil information for the modelling of crop growth or irrigation planning (Aggarwal, 1995; Prats and Picó, 2010). Soil information defines the available water capacity in CFTW and therefore the resilience against droughts (Kayatz et al., 2019a). As soil information is relatively easy to obtain, CFTW recommends using local observations. In some of our study sites, soil data did play a dominant role in improving model performance, namely FR-Gri, 2006, winter wheat (*bias*), FR-Gri, 2008, maize (*bias*), IT-BCi, 2005, maize (*bias*) and BE-Lon, 2005, winter wheat (*RMSE*) (see App. Fig. 4 and App. Fig. 5). However, these seasons belonged to the best performing sites for ET_0 and precipitation based on the *RMSE*, except for IT-BCi, 2005, maize. This emphasizes that global soil information can be the main driver for model differences and may play an important role if not dominated by errors of other input variables.

Local crop data played only a minor role in explaining the differences between both model variants (see Fig. 3, App. Fig. 4 and App. Fig. 5). However, it is important to highlight that this study only analysed the effect of LAI and crop height. These parameters affect the interception loss of precipitation and irrigation in the canopy and the height adjustment of the K_c respectively (Kayatz et al., 2019a). Information such as rooting depth or a more locally representative K_c values were not changed since they were not available and are also rarely avaiable in a farm setting. Satti et al. (2004) compared different ET_0 approaches to determine *IWR* in the USA and showed that the K_c is more relevant compared to the chosen ET_0 method. Opposing findings have also been published by Multsch et al. (2015) for Australia, showing that the importance of K_c may be location-, climate-, and crop-specific.

4.3. Assessment of plant water stress and irrigation water requirements for field management

Although ET_a at a daily level may be helpful to inform irrigation management at the farm level, the aim of this work was also to understand, through model cross-comparison, how uncertainty in the input data propagates into uncertainty of model outcomes for *IWR* as well as the accuracy of K_s.

Both model set-ups showed good agreement predicting water stress periods throughout the growing season albeit with a slight overestimation when using global data. *IWR* showed a considerable offset (see Fig. 4). Therefore, CFTWglobal may support decision-making by providing periods of water stress, but lacks the accuracy to provide *IWR*.

Again, the highest contribution factor was for precipitation data in particular for the sites US-Ne1, US-Ne2, US-Ne3, CH-Oe2 and DE-Kli (see Fig. 5). Similar to ET_a, the dominance of precipitation is not observed consistently. ET_0 has a higher contribution factor towards the offset for *IWR* for most seasons at IT-Bci and FR-Gri. Enhancing the accuracy of soil information only dominated at BE-Lon. For the same sites, the dominant contribution factors for the difference in K_s*accuracy* are more diverse, as soil or ET_0 are the major contribution factors for increasing the alignment of both model outputs.

Together with the findings for ET_a this shows that even though model performance is most consistently improved by using local precipitation data, this is also highly site-specific. Furthermore, full testing of CFTW for accuracy of K_s and *IWR* for global datasets would require soil moisture measurements, which are not consistently available in the FLUXNET2015 dataset and are therefore beyond the scope of this study.

Wisser et al. (2008) and Uniyal et al. (2019) have previously shown how differences in input data have a substantial impact on *IWR* at catchment level and global scale. Estimates of global irrigation water requirements may differ by 30% depending on input data (Wisser et al., 2008). However, both of these studies focus on regional or global assessments and thus depend on gridded meteorological data. Field-scale assessments require higher accuracy in order to provide useful insights but are also able to offer field-level information.

When applying different irrigation management to both model variants, *IWR* and duration of water stress were highly correlated for both model inputs for most growing seasons (see App. Fig. 6 and App. Fig. 7). Clear disagreement was only present in a few growing seasons as periods of water stress did not generally overlap. Similar to the assessment of the actual management, the results showed considerable differences for absolute *IWR* values. This is consistent with findings from Kayatz et al. (2019a).

Decision-making based on CFTWglobal may allow relative comparisons of different management scenarios for periods of water stress and *IWR* but does not provide the accuracy for absolute values for the latter.

4.4. Decision-making under uncertainty

Due to their inherent heterogeneity and dynamic nature, crop production systems always exhibit substantial uncertainty concerning key variables driving evapotranspiration. Nevertheless, decisions regarding water management have to be made, whether for short or long-term planning. Important questions are then: How much time, effort, and cost should be made to reduce uncertainty? What are the implications of uncertainty and what compromises need to be accepted? The decision maker needs to recognise the caveats of the predictions and have a sufficient understanding of potential improvements that would reduce prediction uncertainties. Especially when individual farms and their production are at stake.

The results presented in this study show that CFTW with global input data enables management decisions by providing the dynamics of ET_a and indicating periods of water stress. Furthermore, the model set-up allows for a relative comparison of water management interventions.

However, uncertainty for water use, *IWR* and crop water stress can be greatly reduced in most cases by collecting local information for precipitation and thus aligns with the results of previous studies for crop modelling (Dias and Sentelhas, 2021; Menezes et al., 2022; Rasera et al., 2023). The possibility of filling this data gap is highly location-specific and may be much easier when a dense weather station network is available. Implementing measurements may be an alternative option but measurement uncertainties would need to be considered (e.g. Habib et al., 2001; Ouyang et al., 2021).

Therefore, the utility of decision support tools and models such as CFTW depends on the risk the user is able to accommodate. Risks need to be balanced against the practicalities of using the model, including those of obtaining the driving data. In a greenhouse setting, Mondaca-Duarte et al. (2020) showed that irrigation strategies under zero-tolerance for uncertainty in evapotranspiration and soil information may hinder any water savings, while a degree of risk tolerance may encourage the uptake of lower irrigation applications.

Furthermore, it is essential which evaluation criteria are applied to evaluate a decision support tool. Wallach et al. (2012) conducted a Bayesian analysis of modelled crop yield uncertainty and emphasized that it is important to be clear about the evaluation criteria. While the corn crop model used in their study did not perform well for yearly yield assessments, it delivered acceptable results for yields averaged over a number of years. Our study focussed on daily or seasonal model outputs for water management. Given the consistent overestimation of *IWR* and underestimation of ET_a a multiyear evaluation would most likely result in similar findings in contrast to Wallach et al. (2012).

Evaluation criteria may depend on the situation and purpose of the modelling results and therefore acceptability of risk may vary. If, for example, water and costs are not a limiting factor the user may be willing to err on the side of over irrigating rather than risk limitation of crop growth due to water limitation.

5. Conclusions

Assessing the agro-hydrological model CFTW using global and local datasets for the accuracy of ET_a, crop water stress, and *IWR* and, thereby, the ability to support decisions for water management showed:

i) Global data significantly increases the *bias* for ET_a, but shows only a limited impact on estimating the daily dynamic of ET_a.
ii) Closing this gap in model performance CFTW would require, firstly, more accurate information for precipitation, and then ET_0. Soil data and especially crop data only contributed to an improved model performance for a few of the growing seasons and sites analyzed in this study. However, the results show some heterogeneity between sites and seasons, therefore requiring further analysis of the uncertainty of global input datasets.
iii) Predictions for crop water stress under current management agreed well for most growing seasons for local and global input but tend to slightly overestimate periods of water stress. *IWR* was also highly correlated for both model variants but showed a high offset between both model outputs.
iv) Alternative management scenarios showed a high correlation for periods of water stress and *IWR* but disagreed in absolute terms.

Overall, the present study shows how decision support tools using global datasets may help to assess different scenarios and identify relative management improvement, but lack the accuracy to guide daily on-field irrigation management. The latter requires robust information about absolute irrigation requirements and timing. Our findings may help to improve decision support tools for crop water management and increase the accuracy of crop water footprints.

CRediT authorship contribution statement

Benjamin Kayatz: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gabriele Baroni:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Conceptualization. **Dirk Freese:** Supervision, Funding acquisition. **Martin Wattenbach:** Supervision, Funding acquisition. **Jon Hillier:** Writing – original draft, Supervision, Methodology, Conceptualization. **Stefan Lüdtke:** Software, Methodology, Data curation.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Benjamin Kayatz reports financial support was provided by European Institute of Innovation & Technology. Benjamin Kayatz reports a relationship with Cool Farm Alliance that includes: consulting or advisory. Jon Hillier reports a relationship with Cool Farm Alliance that includes: board membership and consulting or advisory.

Data availability

Data will be made available on request.

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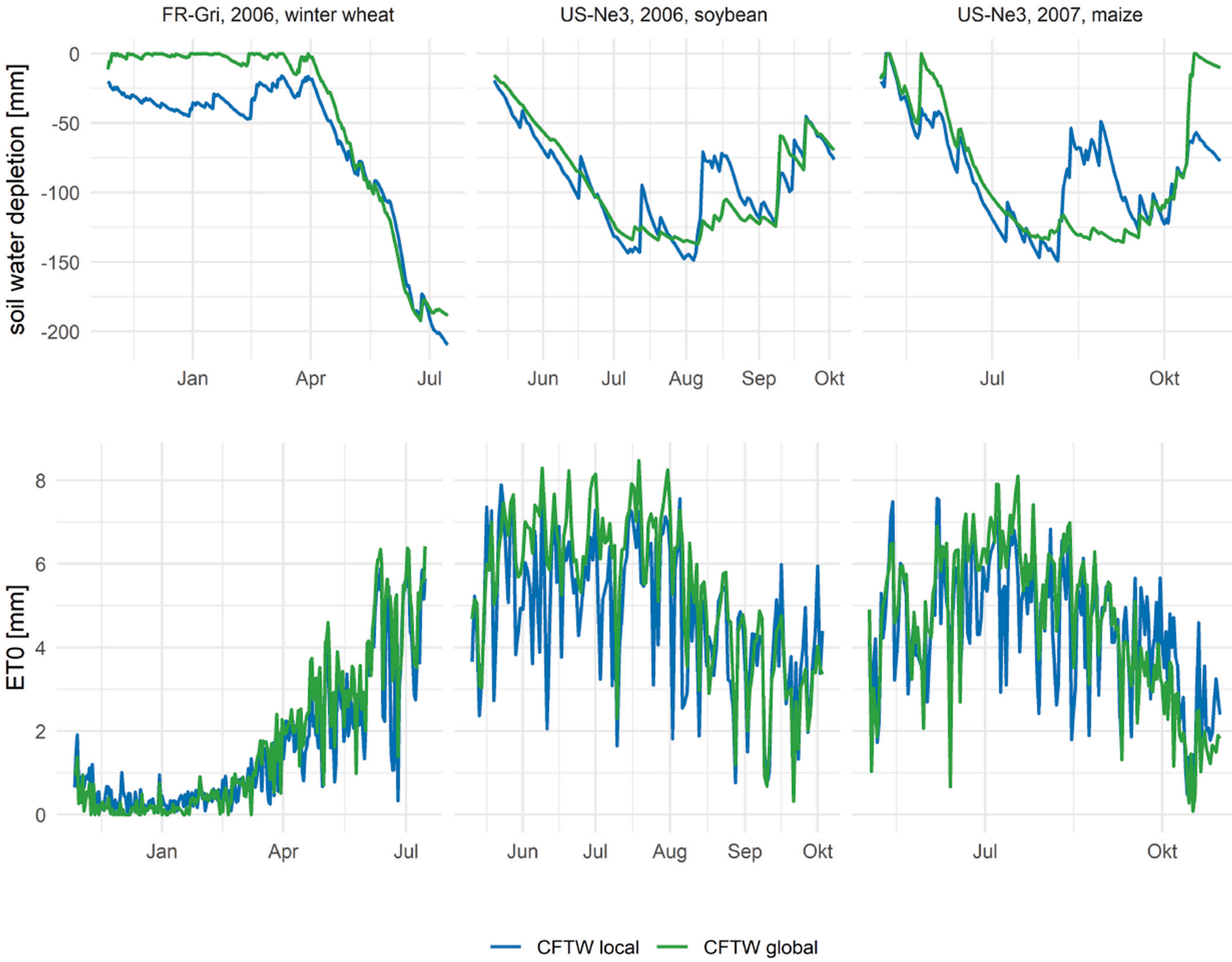
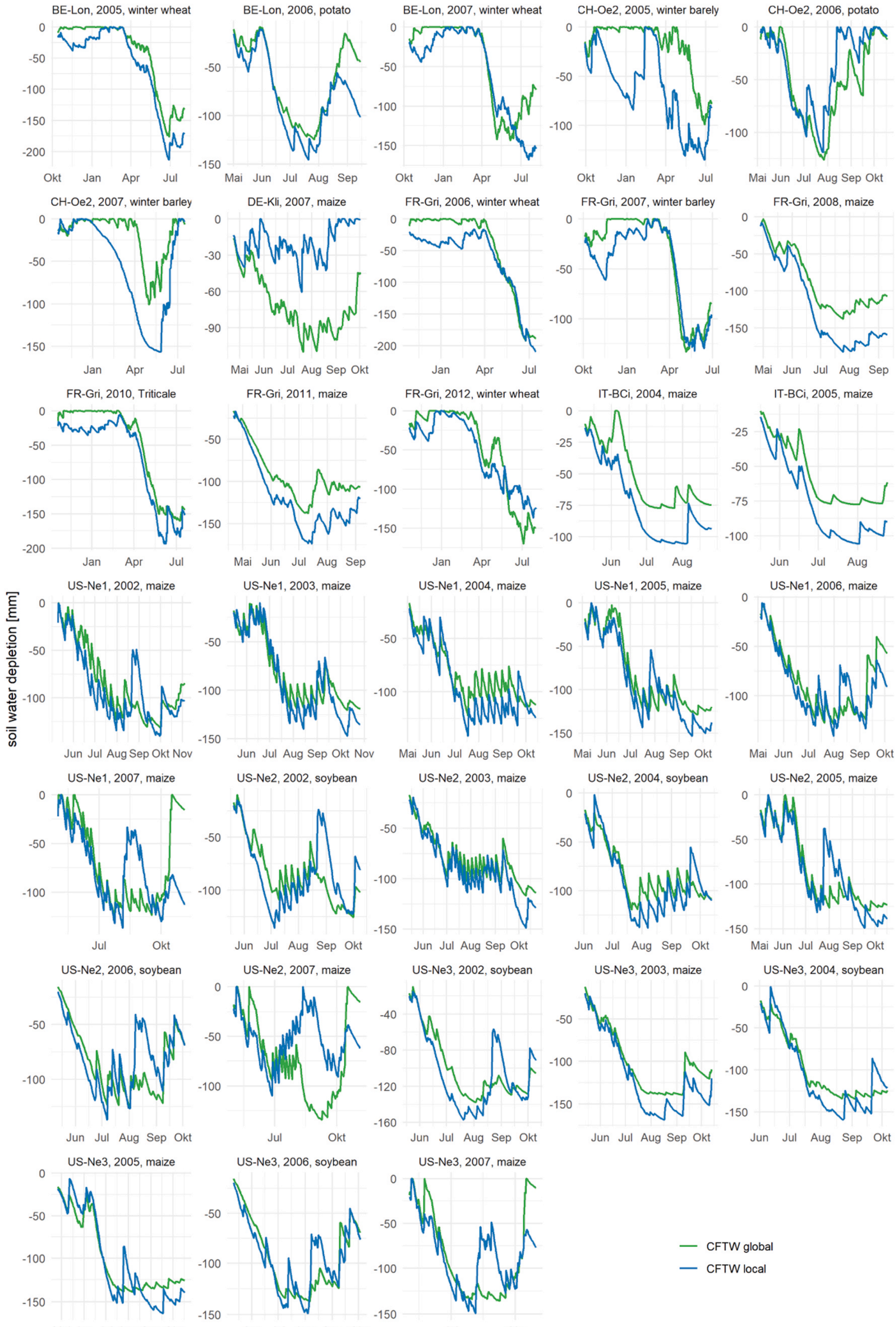
Appendix

App. Table 1
bias, *RMSE*, and Correlation of all daily weather variables comparing global ERA Interim data to local observations. The median, mean, and standard deviation (sd) describe the statistics across all 33 growing seasons.

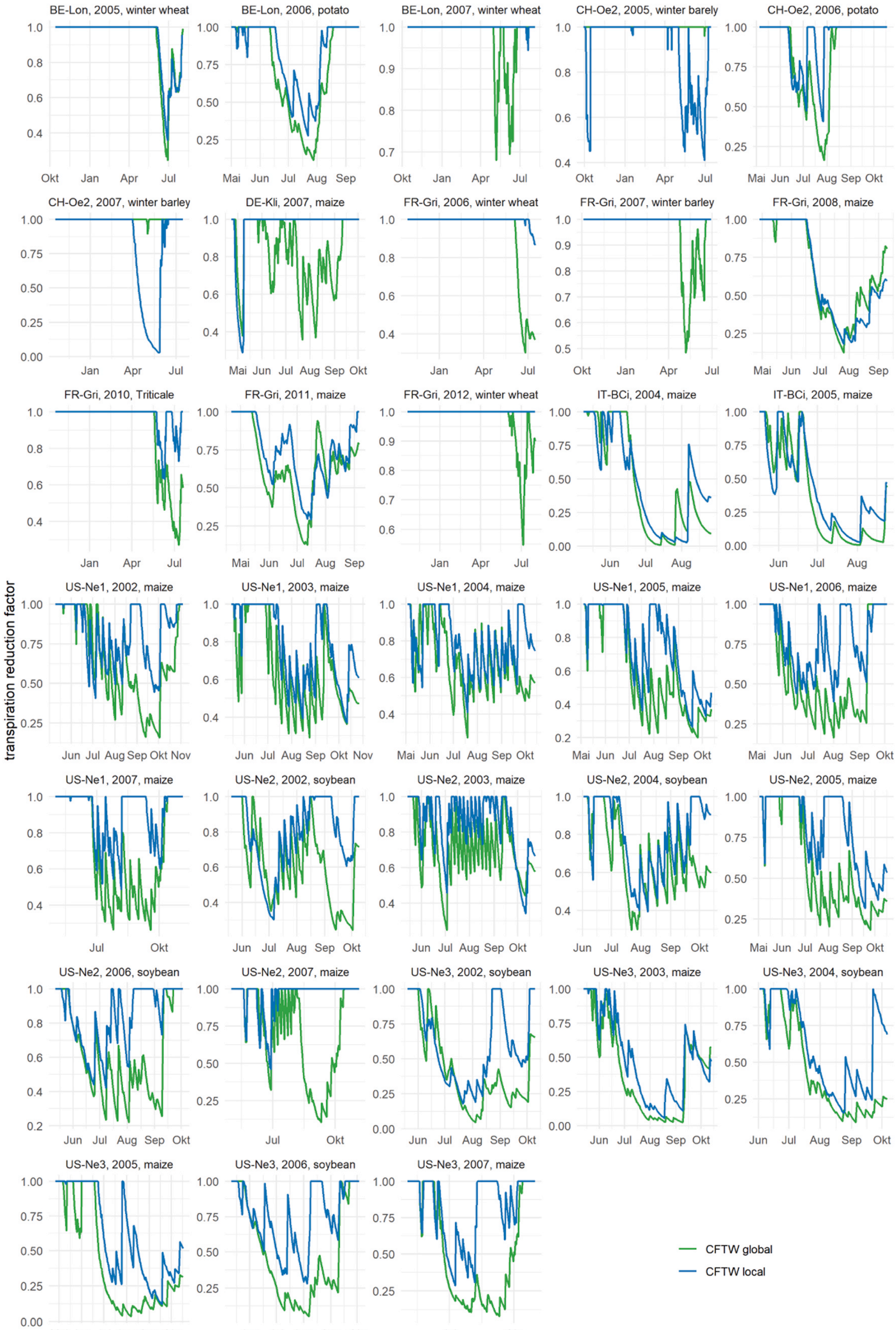
	Bias %			RMSE			Correlation		
	mean	median	sd	mean	median	sd	mean	median	sd
tmax	0.21	1.80	5.99	2.22	2.08	0.96	0.92	0.95	0.09
tmin	7.53	10.60	11.62	2.29	2.29	0.74	0.94	0.96	0.06
precip	-16.94	-29.00	30.69	5.51	5.64	2.15	0.55	0.54	0.11
tdew	-8.00	-8.20	9.83	2.71	2.56	0.83	0.87	0.90	0.07
P	-0.63	-0.60	0.84	0.74	0.64	0.88	0.90	0.99	0.22
tmean	2.78	5.00	7.40	1.83	1.88	0.70	0.95	0.97	0.05
rhmin	-7.92	-9.00	8.47	11.40	11.60	2.57	0.75	0.78	0.12
Rn	6.82	6.50	12.64	2.72	2.64	0.71	0.83	0.84	0.10
ET0	5.44	6.50	9.61	0.94	0.98	0.23	0.83	0.83	0.09



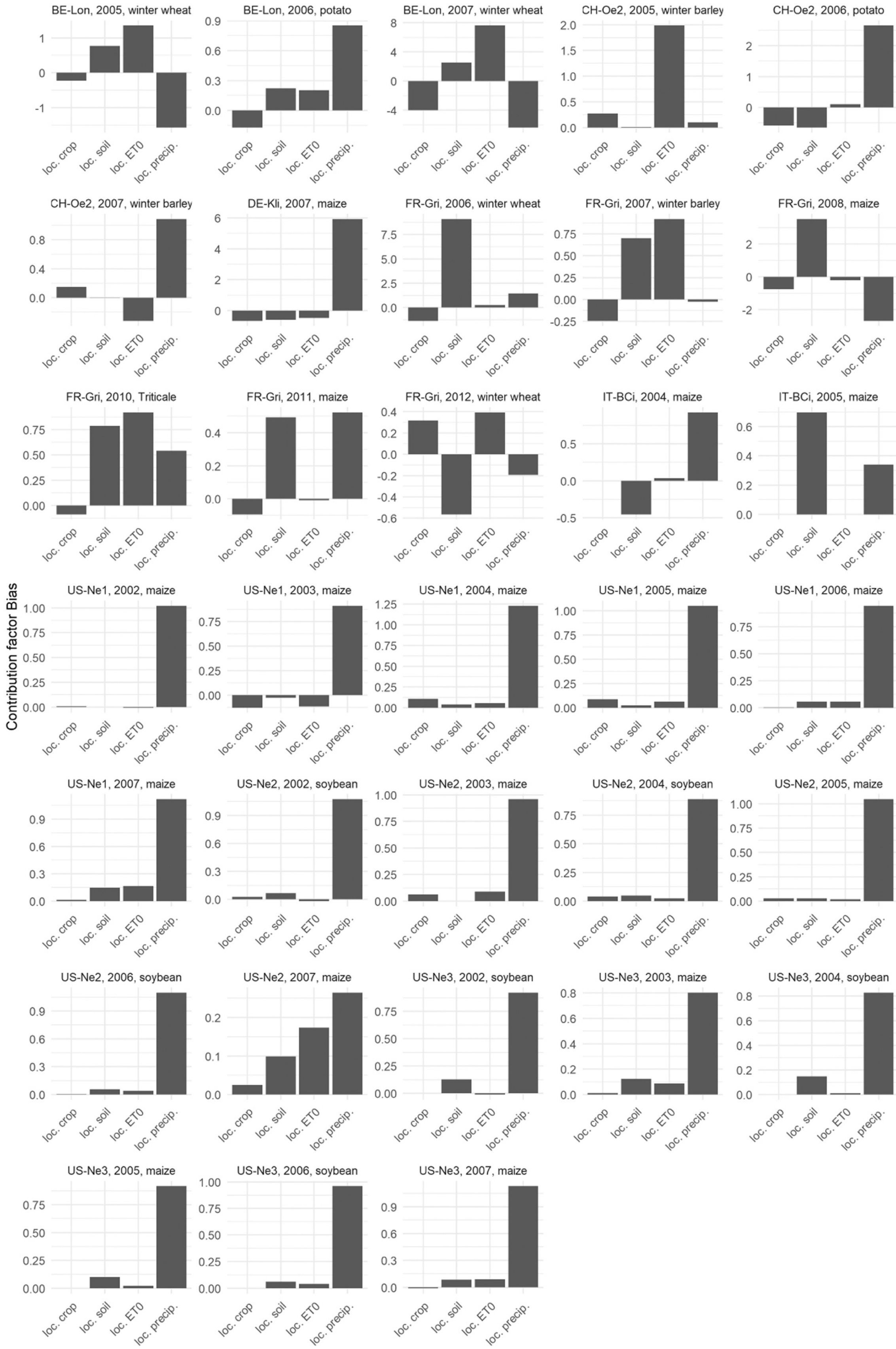
App. Fig. 1. Daily soil water depletion and ET_0 simulated with CFTW using global and local input for FR-Gri in 2006 and US-Ne3 in 2006 and 2007.



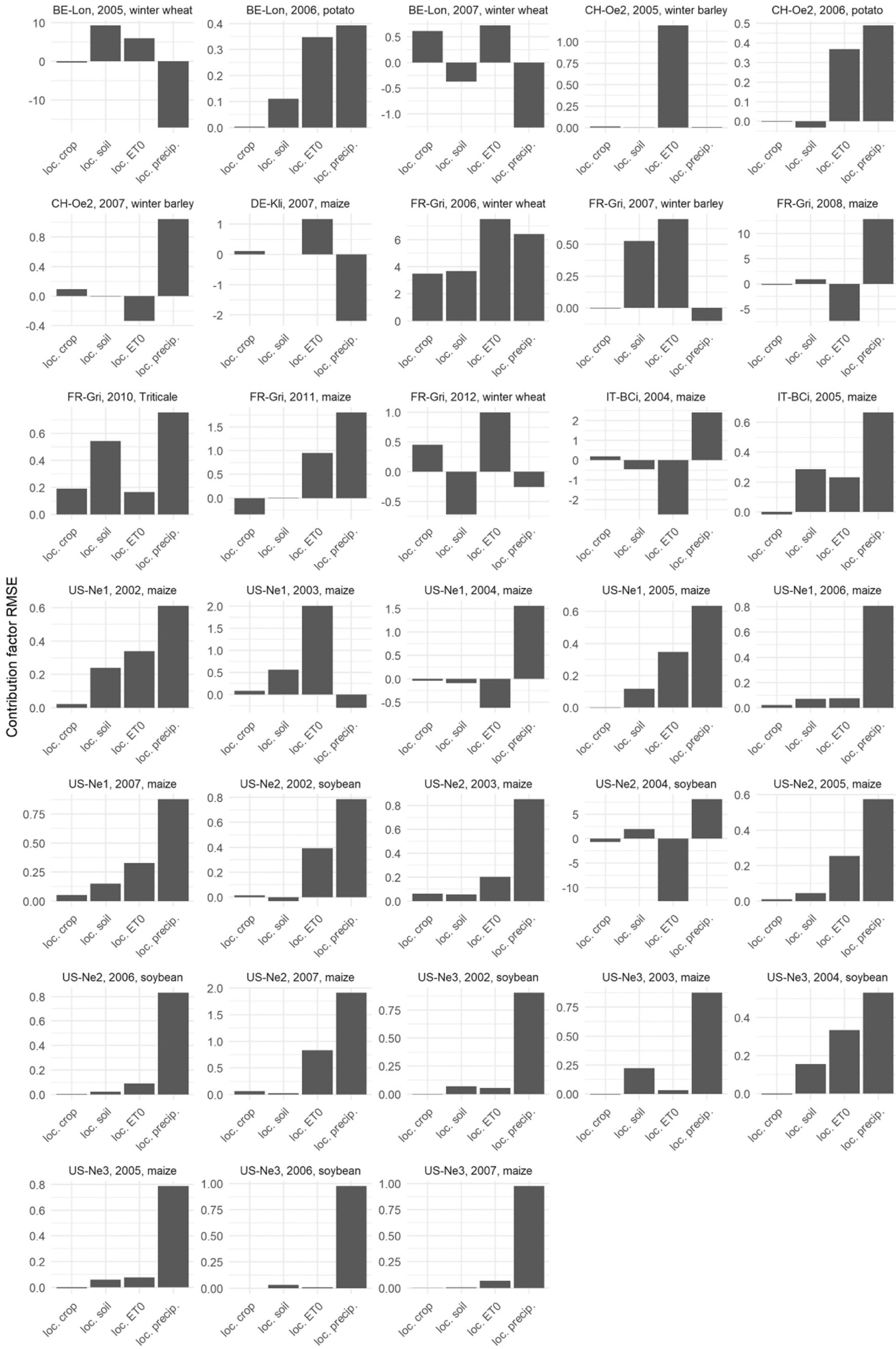
App. Fig. 2. Modelled daily soil water depletion using CFTW with global and local input data.



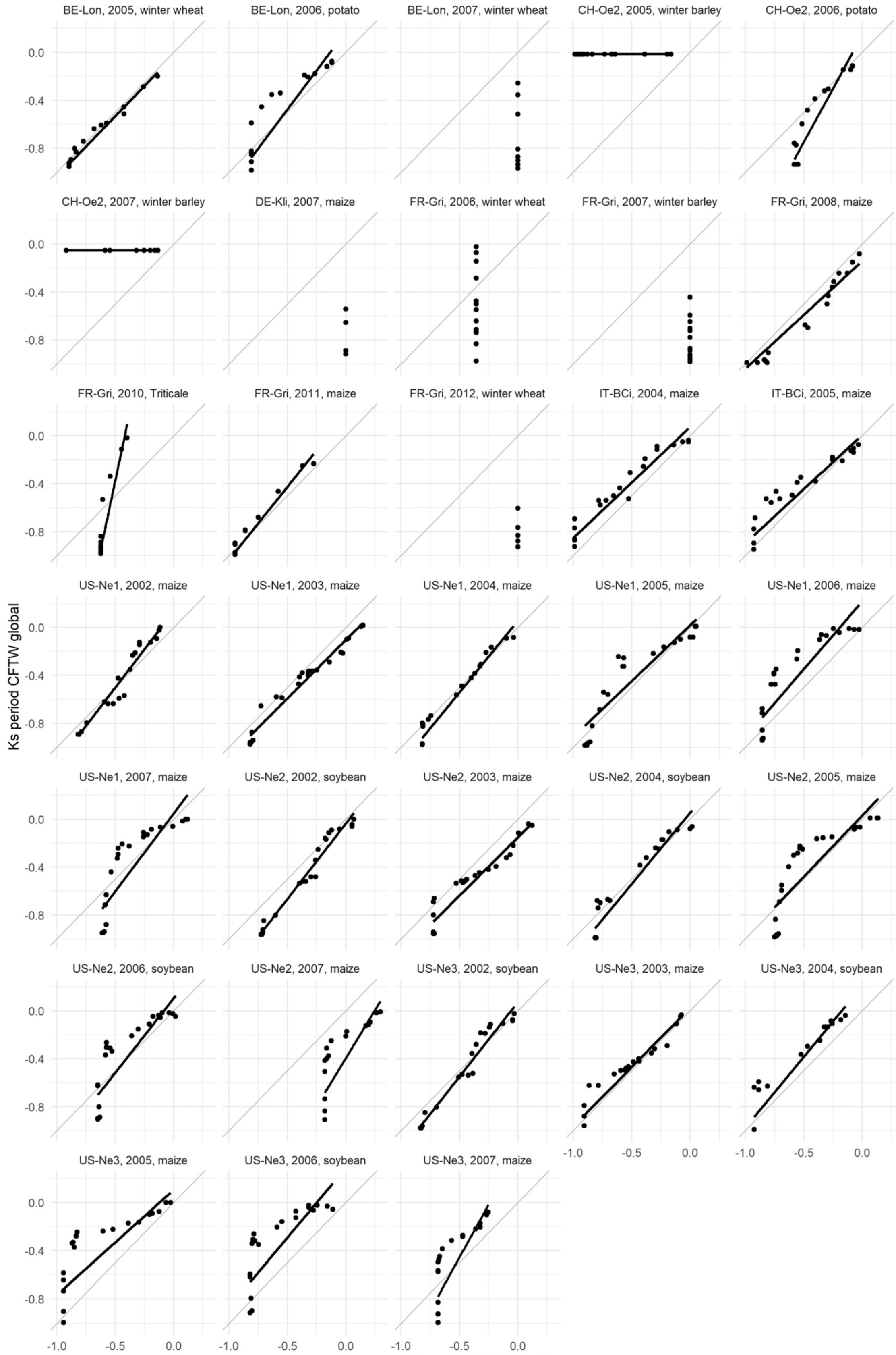
App. Fig. 3. Modelled transpiration reduction factor expressing crop water stress using CFTW with global and local input data.



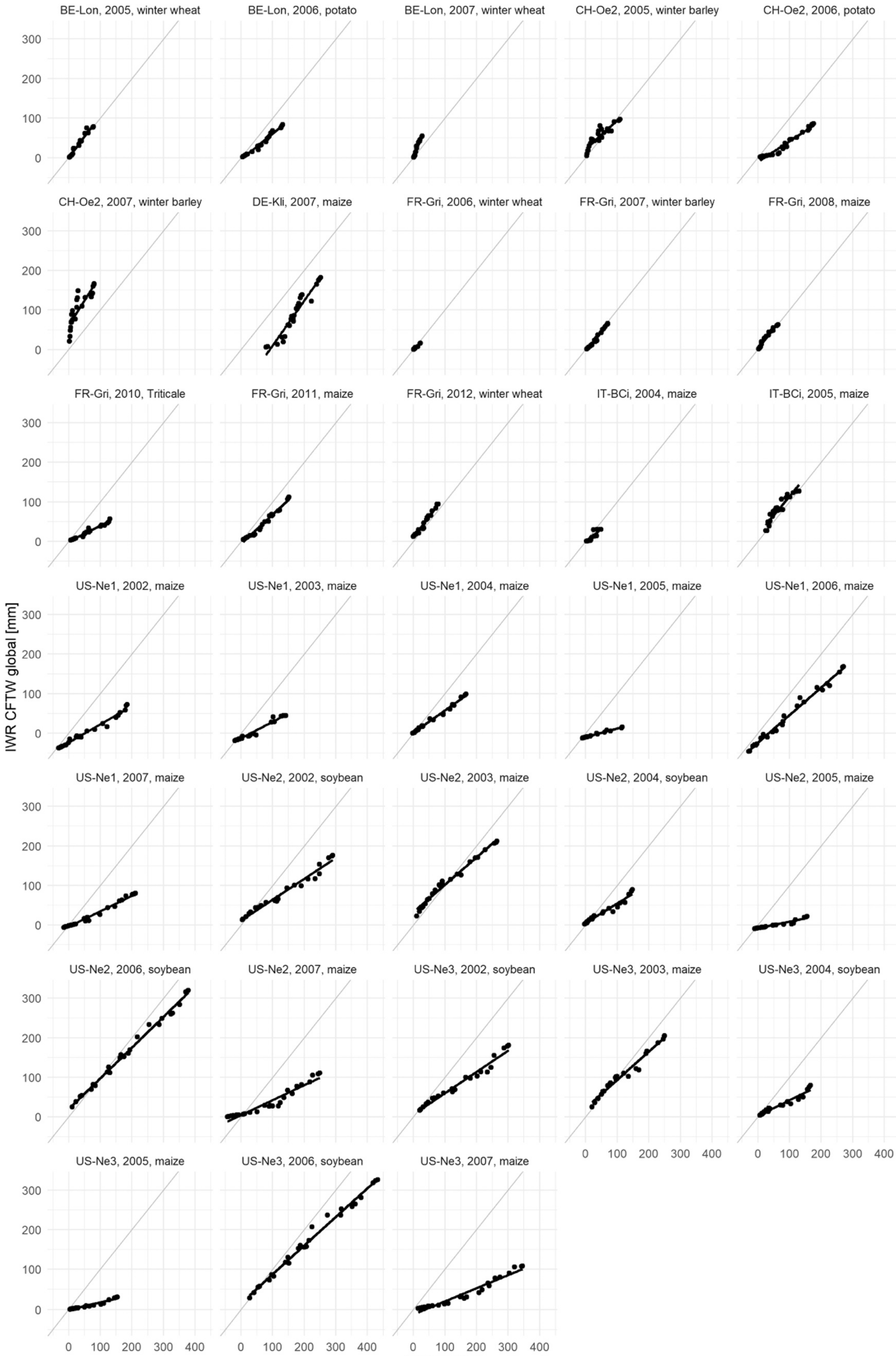
App. Fig. 4. The barplot shows the site-specific contribution factors to improved model performance for the *bias* for actual evapotranspiration *ETa*.



App. Fig. 5. The barplot shows the site-specific contribution factors to improved model performance for the *RMSE* for actual evapotranspiration *ETa*.



App. Fig. 6. Comparison of CFTWglobal vs. CFTWlocal for periods of water stress during the irrigation periods applied for the different management scenarios. The values display the difference between no irrigation management and the irrigation scenarios. A negative value therefore indicates a reduction of the period exposed to water stress. Each point represents one management intervention defined by irrigation rate and irrigation interval.



App. Fig. 7. Comparison of CFTWglobal vs. CFTWlocal for *IWR* during the irrigation periods applied for the different management scenarios. The values display the difference between no irrigation management and the irrigation scenarios. Each point represents one management intervention defined by irrigation rate and irrigation interval.

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