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Optimization of a coupled hydrology–crop growth model through the assimilation of observed soil moisture and leaf area index values using an ensemble Kalman filter

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[1] It is well known that the presence and development stage of vegetation largely influences the soil moisture content. In its turn, soil moisture availability is of major importance for the development of vegetation. The objective of this paper is to assess to what extent the results of a fully coupled hydrology–crop growth model can be optimized through the assimilation of observed leaf area index (LAI) or soil moisture values. For this purpose the crop growth module of the World Food Studies (WOFOST) model has been coupled to a fully process based water and energy balance model (TOPMODEL-Based Land-Atmosphere Transfer Scheme (TOPLATS)). LAI and soil moisture observations from 18 fields in the loamy region in the central part of Belgium have been used to thoroughly validate the coupled model. An observing system simulation experiment (OSSE) has been performed in order to assess whether soil moisture and LAI observations with realistic uncertainties are useful for data assimilation purposes. Under realistic conditions (biweekly observations with a noise level of 5 volumetric percent for soil moisture and 0.5 for LAI) an improvement in the model results can be expected. The results show that the modeled LAI values are not sensitive to the assimilation of soil moisture values before the initiation of crop growth. Also, the modeled soil moisture profile does not necessarily improve through the assimilation of LAI values during the growing season. In order to improve both the vegetation and soil moisture state of the model, observations of both variables need to be assimilated.

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1. Introduction

[2] Water stored in the near-surface unsaturated soil zone is generally referred to as soil moisture. In several research domains soil moisture is an important variable. From a hydrologic point of view, soil moisture determines the partitioning of the precipitation into runoff, evaporation, and infiltration, and the partitioning of the net radiation into latent, sensible, and ground heat fluxes [*Pauwels et al.*, 2002]. In numerical weather prediction and climate studies the predicted precipitation is highly sensitive to the soil moisture conditions [*Betts et al.*, 1996]. In agriculture, numerous studies have shown the importance of the soil moisture content on the development of agricultural crops [*Shepherd et al.*, 2002; *Anwar et al.*, 2003; *Patil and Sheelavantar*, 2004]. On the other hand, vegetation has shown to have a strong effect on the soil moisture content [*Fu et al.*, 2003], demonstrating the need for a good representation of the land cover properties in hydrologic models for an accurate estimation of the soil moisture content.

[3] In most hydrologic models, vegetation properties such as the leaf area index (LAI) and the rooting depth, are obtained off-line, and are considered as vegetation parameters. These can then be kept constant throughout a model simulation, or can be regularly updated, using a look-up table. The disadvantage of this approach is that these parameters will always be kept constant throughout a certain period, while in reality they are continuously evolving. Such simplification will thus lead to errors in the model results. In order to overcome this problem, the hydrologic model should be enhanced with a module able to simulate vegetation development. The coupling of hydrologic and crop growth models is also encouraged by the conclusions from *Eitzinger et al.* [2004], who stated that crop growth models which accurately model soil water flow processes should be preferred to other models, and that even those crop growth models can be improved by a proper modeling of the evapotranspiration. Since all these processes are represented in hydrologic models, the coupling of hydro-

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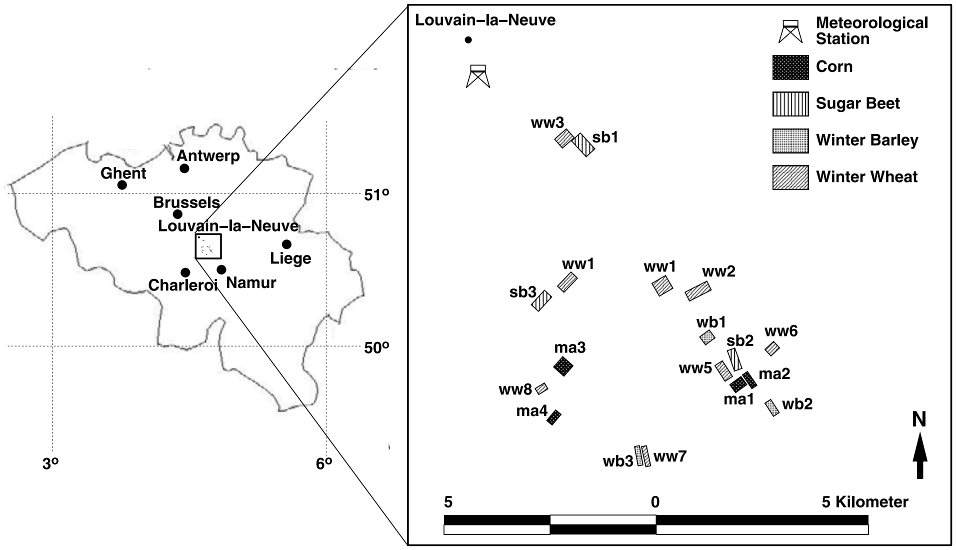

Figure 1. Location of the study site and the measured fields.

logic and crop growth models can be expected to be beneficial for both hydrology and agronomy. Dynamic vegetation effects have already been incorporated into hydrologic models using relatively simple models, for example, in the ISBA-A-g$_s$ model [*Calvet et al.*, 1998; *Calvet and Soussana*, 2001] or in the Common Land Model [*Dai et al.*, 2003]. Efforts have already been made to couple crop growth and hydrologic models [*Boegh et al.*, 2004], but at this point, no fully coupled hydrologic–crop growth models are available that are adequate for ensemble-based data assimilation purposes.

[4] The errors in the land cover parameters are not the only cause for errors in hydrologic model results. Other sources of errors are found in the meteorological forcings, soil parameters, topographic data, and errors or oversimplifications in the model physics. For this reason, *Kostov and Jackson* [1993] suggested that the ideal approach to estimate soil moisture is the combination of hydrologic models with observed soil moisture, thus minimizing the errors associated with both methods. This methodology is commonly referred to as data assimilation.

[5] With respect to hydrology, a wide variety of studies have put data assimilation into practice. The most frequently used methods to update the soil moisture state of land surface models are direct insertion [*Walker et al.*, 2001a; *Heathman et al.*, 2003], statistical correction [*Houser et al.*, 1998; *Pauwels et al.*, 2002], Newtonian nudging [*Houser et al.*, 1998; *Pauwels et al.*, 2001; *Paniconi et al.*, 2002], optimal interpolation [*Seuffert et al.*, 2004], Kalman filtering [*Hoeben and Troch*, 2000; *Walker and Houser*, 2001; *Walker et al.*, 2001b, 2001a; *Reichle et al.*, 2002a, 2002b; *Margulis et al.*, 2002; *Walker et al.*, 2002; *Crow and Wood*, 2003; *Crow*, 2003; *Reichle and Koster*, 2003; *Walker and Houser*, 2004; *Pauwels and De Lannoy*, 2006], Kalman smoothing [*Dunne and Entekhabi*, 2005, 2006], and variational data assimilation [*Reichle et al.*, 2001a, 2001b; *Caparrini et al.*, 2003, 2004; *Margulis and Entekhabi*, 2003; *Crow and Kustas*, 2005].

[6] Currently, remotely sensed vegetation parameters are used more and more frequently as inputs for hydrologic models. These remotely sensed parameters are prone to errors, so if they have to be used in a hydrologic model, some correction needs to be made. On the other hand, if the evolution of these parameters can be also be described by the hydrologic model, a weighted average between the remote sensing data and the modeled parameters can be made. The question of the required observational frequency and accuracy thus arises. The objective of this study is to assess to what extent the results of a fully coupled hydrology–crop growth model can be optimized through the assimilation of observed leaf area index (LAI) and soil moisture values under realistic error levels and accuracies. The paper will focus on the resulting LAI time series and soil moisture profiles and time series, but the modeled evapotranspiration will also be analyzed. The crop growth module of the World Food Studies (WOFOST) [*Van Diepen et al.*, 1989] model is first coupled to the TOPMODEL [*Beven and Kirkby*, 1979] based Land-Atmosphere Transfer Scheme (TOPLATS [*Famiglietti and Wood*, 1994]). The coupled model is then thoroughly validated using LAI and soil moisture observations from 18 agricultural fields. An observing system simulation experiment (OSSE) is performed, for the assessment of the accuracy requirements of LAI and soil moisture observations in order to be useful for data assimilation purposes. An ensemble Kalman filter (EnKF) is used as data assimilation algorithm.

[7] The paper is organized as follows. First, an overview of the study site and the data sets used in this study is given. The hydrologic and crop growth models, and their coupling, are then described, after which the coupled model is validated using observed soil moisture and LAI values. Then the data assimilation algorithm is explained. After this, the results of the data assimilation study are described. Finally, the conclusions that can be drawn from this work are summarized.

2. Site and Data Description

[8] The data used for this study were all collected in the Loamy region in the central part of Belgium. Figure 1 shows an overview of the study site. The site is an intensive

agriculture area with a uniform soil texture and an altitude ranging from 100 to 200 m asl. Eighteen agricultural fields were intensively monitored throughout the study period, which lasted from January through July 2003. These fields were covered with four crop types: corn (four fields, crop code ma), sugar beet (three fields, crop code sb), winter barley (three fields, crop code wb), and winter wheat (eight fields, crop code ww).

[9] The soil of the Loamy region is a Pleistocene loam deposit with a very stable textural composition. Its thickness varies between one to tens of meters. The predominant soil type in this region is Gray Brown Podzolic Soil with favorable drainage condition. Only for a few fields (ma1, ma2, ma3, and ww6, see Figure 1), the drainage conditions are not good and some gleyic properties (properties associated with prolonged wetness) are present. However, during the study period such a prolonged wetness was not observed.

[10] Soil moisture values at 5 cm depth were measured using the gravimetric method and then converted into volumetric soil moisture using field averaged values for the bulk density. For each field a minimum of eight locations, and three repetitions per location, were sampled. LAI values were measured using a LiCor LAI 2000 instrument (LI-COR, Cambridge, UK) on three locations per field, for each location 10 measurements were taken in two perpendicular directions. The uncertainty (standard deviation of the observation error) associated with the measurements was approximately 0.04 volumetric for the soil moisture and 0.3 for the LAI values. These uncertainties have been calculated as the standard deviation of the measurements inside each field.

[11] Meteorologic data were recorded by the meteorologic station of the Institut d'Astronomie et de Géophysique Georges Lemaître at Louvain-la-Neuve (latitude 50°39′55″, longitude 4°37′30″m, altitude 148 m asl). Available data were air temperature and humidity, precipitation, wind speed and direction, atmospheric pressure, and solar radiation. Longwave radiation (also needed by the model in addition to solar radiation) was calculated using the air temperature and humidity following the approach of *Brutsaert* [1975].

3. Model Description

3.1. Hydrologic Model

[12] The hydrologic model used in this study, the TOPMODEL-Based Land-Atmosphere Transfer Scheme (TOPLATS), has as its foundation the concept that shallow groundwater gradients set up spatial patterns of soil moisture that influence infiltration and runoff during storm events, and evaporation and drainage between these events. The assumption is made that these gradients can be estimated from local topography (through a soil topographic index [*Sivapalan et al.*, 1987]). From this foundation, the model was expanded to include infiltration and resistance-based evaporation processes, a surface vegetation layer and a surface energy balance equation with an improved ground heat flux parameterization, and the effect of atmospheric stability on energy fluxes [*Famiglietti and Wood*, 1994; *Peters-Lidard et al.*, 1997]. The model was originally developed to simulate the surface water and energy balance for warm seasons [*Famiglietti and Wood*, 1994; *Peters-Lidard et al.*, 1997]. More recently, winter processes (frozen ground and a snowpack), an improved water and energy balance scheme for open water bodies, and a two-layer vegetation parameterization were added [*Pauwels and Wood*, 1999a]. For a detailed model description, we refer to *Famiglietti and Wood* [1994], *Peters-Lidard et al.* [1997], and *Pauwels and Wood* [1999a]. Application to the Zwalm catchment [*Pauwels et al.*, 2001, 2002; *Pauwels and De Lannoy*, 2006], the Upper Kuparuk River Basin in Alaska [*Dery et al.*, 2004], and the Red-Arkansas River Basin [*Crow et al.*, 2001; *Crow and Wood*, 2002] and to field experiments such as FIFE [*Peters-Lidard et al.*, 1997], BOREAS [*Pauwels and Wood*, 1999b, 2000], SGP97 [*Crow and Wood*, 2003], SGP99 [*Gao et al.*, 2005], and SMEX02 [*Crow et al.*, 2005] have shown that the model can adequately simulate surface energy fluxes, soil temperature, and soil moisture.

3.2. Crop Growth Model

[13] WOFOST simulates crop production potentials as dictated by environmental conditions (soils, climate), crop characteristics, and crop management (irrigation, fertilizer application). The overall goal of the model is to simulate the plant development stage and the crop growth. In the original version, WOFOST uses the Simple and Universal Crop growth Simulator (SUCROS) approach for potential production conditions, and uses the Penman equation, plus a crop factor, for water-limited production. A soil water balance was calculated using a tipping bucket approach with three compartments, i.e., a root zone, a transmission zone, and a groundwater zone. For a detailed model description we refer to *van Ittersum et al.* [2004].

3.3. Coupling of the Models

[14] In the coupled version, the original Penman approach for water-limited evapotranspiration has been replaced by the full energy and water balance formulation from TOPLATS, and the soil water balance has been replaced by the TOPLATS method. The calculated vegetation parameters, more specifically rooting depth and LAI, are then used as input for TOPLATS.

[15] The coupling has been performed as follows. While WOFOST has been designed to operate at a daily time step, TOPLATS uses an hourly time step. Thus WOFOST is called every 24 time steps in TOPLATS. Before calling WOFOST, TOPLATS calculates the daily average evapotranspiration, soil moisture, solar radiation, precipitation, water table level, and the daily maximum and minimum temperature. These variables are then used as inputs for WOFOST. Every 24 time steps WOFOST calculates the rooting depth and the LAI, which are then used as inputs for the next 24 simulations of TOPLATS. This way, both models are fully coupled in a computationally efficient manner.

4. Model Validation

[16] The coupled model was validated using observed soil moisture and LAI values from the 18 different fields described in section 2. The model was applied at each field separately using the observed meteorological data described in section 2. The soil parameters were assigned based on the

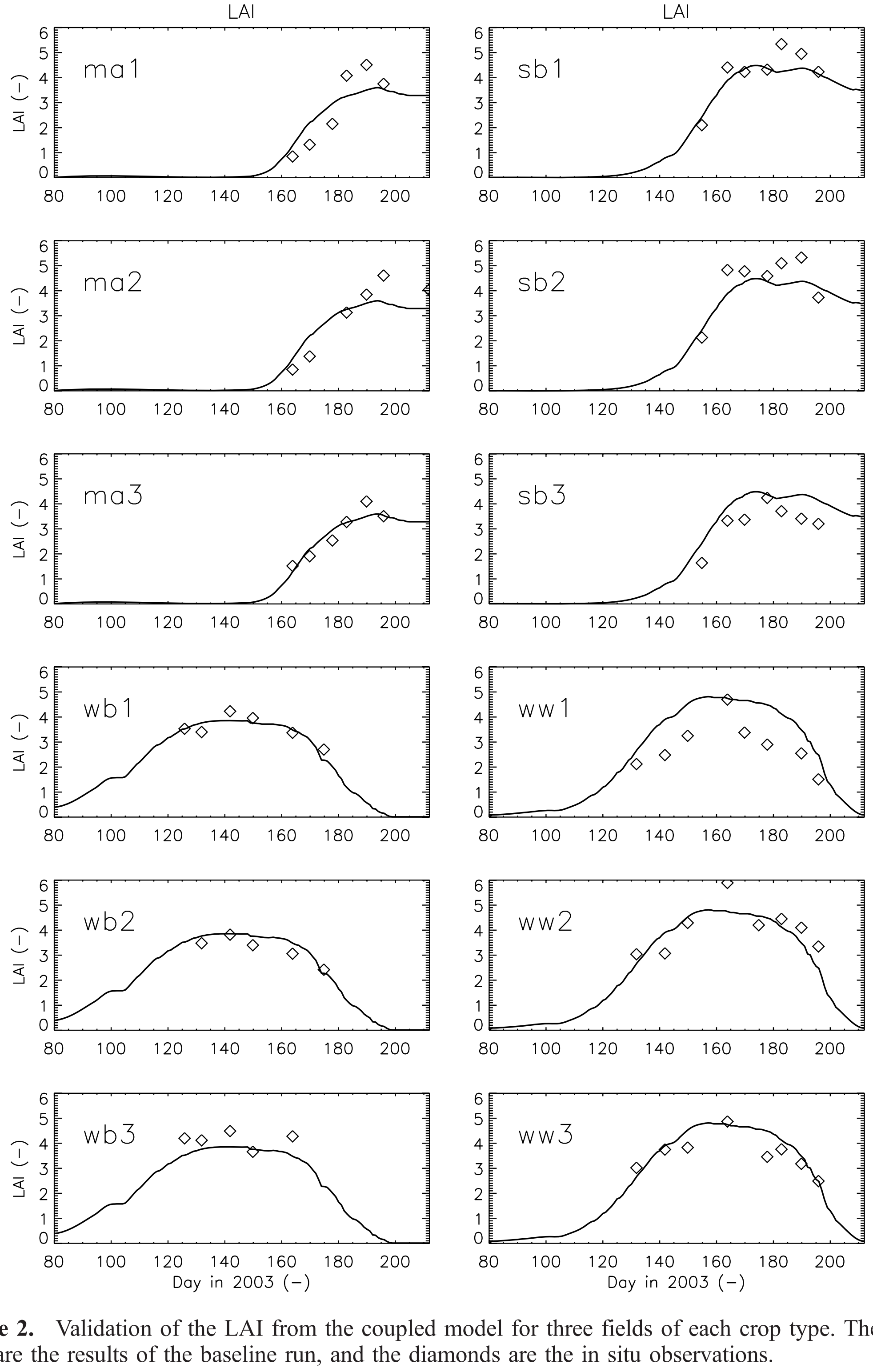

Figure 2. Validation of the LAI from the coupled model for three fields of each crop type. The solid lines are the results of the baseline run, and the diamonds are the in situ observations.

soil texture, following *Rawls et al.* [1982]. The land cover parameters were determined based on the vegetation type, following *Peters-Lidard et al.* [1997]. The parameters for the crop growth module were taken from the sample input files [*Supit and van der Goot*, 2003]. The depths of the soil layers were taken to be 5, 10, and 20 cm, for the upper, second, and third layer, respectively. The fourth layer extends from the bottom of the third layer to the groundwater table. The initial seed weight, and the sowing dates were determined from field observations. A LAI value of 0 and a rooting depth of 0 m were used as initial conditions. For the remainder of the simulations, these values were calculated by the crop growth module of the model. Simulations were performed at an hourly time step from January through July 2003. The soil, vegetation, and crop growth parameters were kept uniform for each vegetation type.

[17] Figure 2 shows the validation for the LAI of the coupled model for three fields of each crop type. The

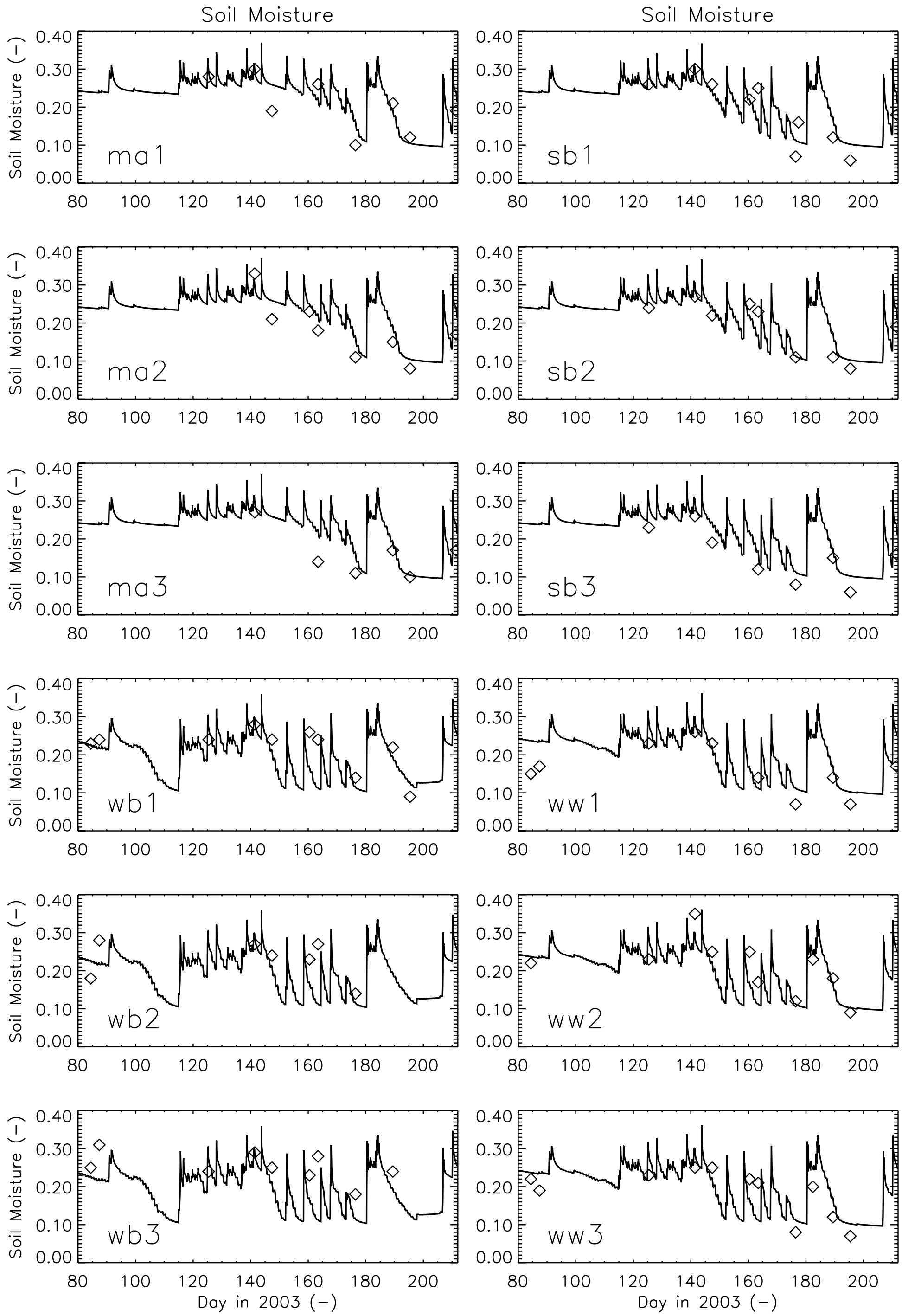

Figure 3. Validation of the soil moisture from the coupled model for three fields of each crop type. The solid lines are the results of the baseline run, and the diamonds are the in situ observations.

temporal evolution of the LAI observations is adequately matched (meaning that the maxima correspond and that there is no time shift) by the simulations. Figure 3 shows the validation for the soil moisture of the coupled model for the same fields as Figure 2. With some exceptions, the temporal evolution of the soil moisture is adequately matched. Table 1 shows the root-mean-square error (RMSE) between the observations and the simulations for the model validation. This RMSE is calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(s_i - o_i)^2} \tag{1}$$

Table 1. RMSE Between the in Situ Observations and the Simulations for the Model Validation

	Soil Moisture		LAI	
Field	RMSE	Number of Observations	RMSE	Number of Observations
ma1	0.0407	8	0.79	6
ma2	0.0431	8	0.72	5
ma3	0.0491	6	0.34	6
ma4	0.0375	6	0.74	6
sb1	0.0455	10	0.53	7
sb2	0.0411	9	0.64	7
sb3	0.0473	8	0.80	7
wb1	0.0524	11	0.30	6
wb2	0.0685	8	0.27	5
wb3	0.0708	10	0.57	5
ww1	0.0516	11	1.09	8
ww2	0.0421	11	0.76	8
ww3	0.0473	12	0.49	8
ww4	0.0510	10	0.56	8
ww5	0.0542	10	0.46	7
ww6	0.0677	10	0.59	7
ww7	0.0641	10	0.52	7
ww8	0.0646	10	0.56	6

n is the number of observations, s_i are the model simulations, and o_i are the observations. The relatively low values for both RMSE values indicate that the model can simulate the soil water content and the LAI with an acceptable accuracy (meaning that the RMSE is of the same order of accuracy as for remotely sensed data sets, for which values are listed in section 7.2).

[18] The main objective of the paper was to assess up to what level the results of the coupled hydrology–crop growth model can be improved by the assimilation of external data. Therefore a data assimilation study is performed, in order to assess the accuracy and frequency requirements of these external data sets.

5. Assimilation Method

[19] In order to meet the objective of this study, the soil moisture and LAI state modeled by the coupled hydrology–crop growth model have to be updated, using observations of either both or only one of these variables, depending on the availability of the observations. For this purpose a flexible assimilation technique is needed. The ensemble Kalman filter (EnKF) assimilation method was chosen for this study. In this section only a brief description of the EnKF will be given. For a more detailed description we refer to *Reichle et al.* [2002b].

[20] In the EnKF, an ensemble of state vectors is propagated forward in time. Each state vector $\hat{\mathbf{x}}_k^i$, with i the ensemble member number and k the time step, consists of the modeled state variables. Each time an observation becomes available, the state vector of each ensemble member is updated by taking a weighted average between the observvxations and the model simulations:

$$\hat{\mathbf{x}}_k^{i+} = \hat{\mathbf{x}}_k^{i-} + \mathbf{K}_k\left(\mathbf{y}_k - \mathbf{H}_k\hat{\mathbf{x}}_k^{i-} + \mathbf{v}_k^i\right) \quad (2)$$

$\mathbf{y}_k$ is the vector with the observations from time step k. $\hat{\mathbf{x}}_k^{i+}$ is the a posteriori state vector for ensemble member i, i.e., after the assimilation of the observations, while $\hat{\mathbf{x}}_k^{i-}$ is the a priori state vector, i.e., before the assimilation. $\mathbf{H}_k$ is the observations transition matrix, and describes the relationship between the state vector and the vector with observations. $\mathbf{v}_k^i$ is a random realization of the measurement error [*Burgers et al.*, 1998]. $\mathbf{K}_k$ is the Kalman gain factor, and is calculated as follows:

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^{\mathrm{T}}\left[\mathbf{H}_k\mathbf{P}_k^-\mathbf{H}_k^{\mathrm{T}} + \mathbf{R}_k\right]^{-1} \quad (3)$$

$\mathbf{R}_k$ is the measurement noise covariance matrix, of which the diagonal elements are the standard deviation of the measurement noise for each observed variable, and the off-diagonal elements are zero. The superscript T indicates the transpose operator. $\mathbf{P}_k^-$ is the a priori error covariance, and is calculated as follows:

$$\mathbf{P}_k^- = \frac{1}{N-1}\mathbf{D}_k\mathbf{D}_k^{\mathrm{T}} \quad (4)$$

with N the ensemble size (the number of parallel model trajectories), and $\mathbf{D}$ is the matrix with the deviations from the mean state for each ensemble:

$$\mathbf{D}_k = \left[\hat{\mathbf{x}}_k^{1-} - \bar{\hat{\mathbf{x}}}_k^- \ldots \hat{\mathbf{x}}_k^{N-} - \bar{\hat{\mathbf{x}}}_k^-\right], \bar{\hat{\mathbf{x}}}_k^- = \frac{1}{N}\sum_{i=1}^{N}\hat{\mathbf{x}}_k^{i-} \quad (5)$$

For this study, the state vector consists of the modeled soil moisture at four different depths, and the modeled LAI:

$$\hat{\mathbf{x}}^i = \left[\theta_{k,1}^i\theta_{k,2}^i\theta_{k,3}^i\theta_{k,4}^i\mathrm{LAI}_k^i\right]^{\mathrm{T}} \quad (6)$$

$\theta_{k,j}^i$ is the volumetric soil moisture content at time step k for layer j and ensemble member i. LAI_k^i is the modeled LAI value for time step k and ensemble member i. If both LAI and soil moisture observations at 5 cm are available, $\mathbf{y}_k$ and $\mathbf{H}_k$ can be written as follows:

$$\mathbf{y}_k = \begin{bmatrix}\theta_k^o \\ \mathrm{LAI}_k^o\end{bmatrix}, \mathbf{H}_k = \begin{bmatrix}1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1\end{bmatrix} \quad (7)$$

θ_k^o and LAI_k^o are the observed upper layer soil moisture value and LAI for time step k, respectively. If only soil moisture observations are available, the first row of $\mathbf{y}_k$ and $\mathbf{H}_k$ is retained. If only LAI observations are available, only the second row is retained.

6. Synthetic Experiment

6.1. Experiment Design

[21] The objective of the data assimilation study is to assess to what extent the results of the coupled model can be optimized through the assimilation of LAI and soil moisture observations. In other words, the required accuracy and assimilation frequency of these observations has to be determined. The most convenient manner to do this is to perform and OSSE. Basically, instead of in situ observed data, synthetically generated data are used, with varying assumed accuracies. The experiment has been set up as follows.

[22] As a first step, the results from the model applications from section 4 are treated as the synthetic truth. An a

priori defined observation error is added to the synthetically true LAI and upper layer soil moisture, and the resulting values are treated as synthetic observations. Then, the most important crop (the sowing date and the initial seed weight) and soil parameters (the hydraulic conductivity, the parameter which describes the exponential decay of the hydraulic conductivity with depth, and the saturated base flow) have been perturbed, which leads to errors in the model results. These parameters were identified through a sensitivity analysis. This ensemble model run is referred to as the baseline run. At regular temporal intervals, the synthetic observations are assimilated into the coupled model. These model runs are referred to as the assimilation runs. The impact of different temporal intervals and observation accuracies on the modeled evolution of the LAI and soil moisture is then assessed. It should be noted that for all the synthetic experiments the RMSE values are calculated across the entire time series at hourly intervals, which is possible because the synthetic truth is known at each hourly time step.

[23] In order to mimic the possibility to invert radar backscatter observations under bare soil or small vegetation, and not under more developed vegetation, synthetically observed soil moisture values were assumed to be available when the synthetically observed LAI was lower than 0.1. Above this threshold, only synthetic observations of the LAI were assumed to be available. Synthetic observations of the LAI and soil moisture were thus assumed to be not available simultaneously.

[24] The experiment has been performed on one field for each crop type, more specifically on fields ma1, sb1, ww1, and wb1.

6.2. Ensemble Generation

[25] An important issue in data assimilation using the EnKF is the generation of the ensemble of model trajectories (the ensemble members). In this study, the ensemble members are generated by disturbing the most important soil and vegetation parameters, and the meteorological forcings. Following *Reichle et al.* [2002b], the meteorological forcings are disturbed by adding a random number with zero mean and a specified standard deviation to the input values. This standard deviation is 5 K for the air and dew point temperatures, 1 m s^{-1} for the wind speed, 50 W m^{-1} for the shortwave radiation, 25 W m^{-1} for the longwave radiation, 1 kPa for the atmospheric pressure, and 50% of the magnitude for the precipitation. Care was taken that the perturbation did not yield negative radiation, wind speed, atmospheric pressure, and precipitation, and that the perturbation did not yield relative humidities above 100%.

[26] The land cover parameters were disturbed by adding a zero mean Gaussianly distributed random number to the most important parameters. As stated in the previous section, a sensitivity analysis led to the conclusion that the sowing date, the initial seed weight, and the temperature sums required to finish the different development stages, are the most important vegetation parameters. The standard deviation of the random number was set to 50% of the parameter value.

[27] The soil parameters were also disturbed by adding a mean zero random number to the soil hydraulic conductivity, the parameter which describes the exponential decay of the hydraulic conductivity with depth, and the saturated base flow. For these parameters, the standard deviation of the random number was set to 25% of the parameter value.

7. Results

7.1. Impact of the Number of Ensemble Members

[28] In data assimilation studies with the ensemble Kalman filter, the number of ensemble members is an important parameter. In order to test the sensitivity of the results of the data assimilation to the ensemble size, the results of the data assimilation runs were compared for an ensemble size of 16, 32, and 64 members. A first set of model applications assimilated perfect observations, a second set used an error level of 0.25 for the LAI and 0.025 for the soil moisture, and a third set an error level of 0.5 and 0.05 for these observations. Observations were assimilated with a weekly interval. Figure 4 shows the results of these modeled LAI values for the four crop types. From these plots it can be concluded that the modeled LAI values are not sensitive to the ensemble size if the ensemble size is larger than 32.

[29] Table 2 shows the impact of the ensemble size on the modeled soil moisture values, for the simulations using an observation error of 0.05 for the soil moisture. These statistics are calculated over all time steps for the entire period in which soil moisture data are assimilated. Again, the ensemble size does not have a strong impact on the model results, neither with respect to the resulting RMSE nor to the bias, if the ensemble size is larger than 32. We may thus conclude that with an ensemble size of 32 members equally good results are obtained as with 64 members. For the remainder of this study, an ensemble size of 32 members is used.

7.2. Impact of the Observation Error

[30] An important aspect in data assimilation is the quality of the observations. More specifically, the smaller the degree of uncertainty of the observations, the more the model results will be relaxed toward the observations. The objective of this section is to assess whether observed data under realistic conditions (high degree of error) are still useful for data assimilation purposes. For this purpose the measurement noise of the synthetic observations has been set to a number of predetermined values, and the impact on the model results has been quantified. For the LAI values, the measurement noise has been set to 0 (perfect observations), 0.1, 0.25, 0.5, and 1. The latter values are typical values for remotely sensed LAI observations [*Fang et al.*, 2003; *Meroni et al.*, 2004; *Casa and Jones*, 2005]. For soil moisture, this measurement noise has been set to 0 (perfect observations), 0.01, 0.025, 0.05, and 0.1. The latter value is a value that can be assumed to be typical for radar remotely sensed soil moisture observations if the uncertainty in the soil roughness is large (N. E. C. Verhoest et al., Soil moisture retrieval from ERS SAR backscattering under soil roughness uncertainty using a possibilistic approach, submitted to *Water Resources Research*, 2006). The synthetically observed values are assimilated with a weekly time step. Before the onset of the growing season soil moisture values are assimilated, after which LAI data are assimilated.

[31] Figure 5 shows the results of the assimilation run for the modeled LAI values for all four crop types. As can be expected, the correspondence between the simulations and

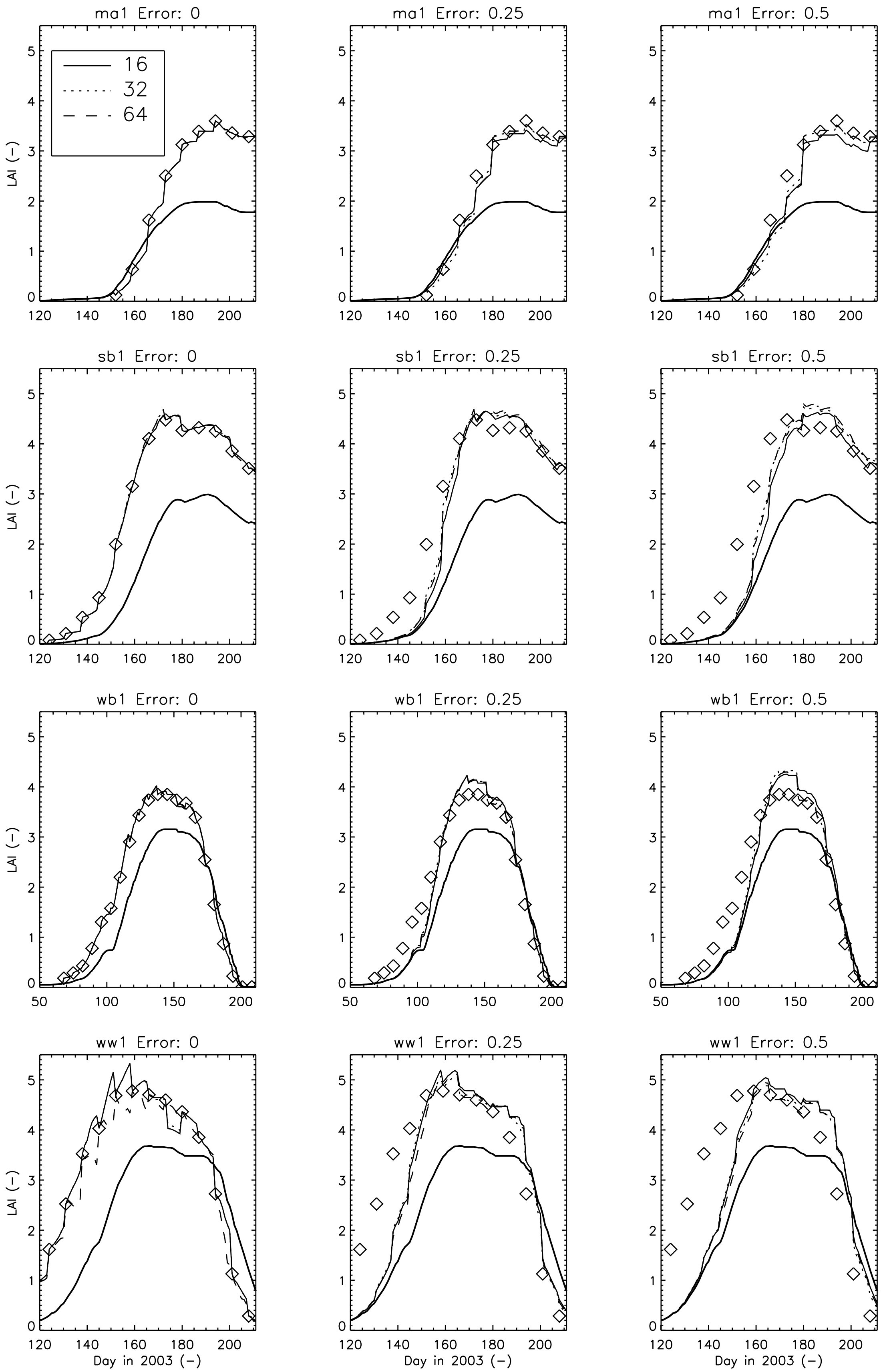

Figure 4. Impact of the ensemble size on the simulated LAI values for the four crop types. The thick solid line is the baseline run using 32 ensembles, which is almost identical to the baseline run using 64 ensembles. The diamonds indicate the synthetic truth.

Table 2. Impact of the Ensemble Size on the Modeled Soil Moisture for All Soil Layers for the Period in Which Soil Moisture Data Are Assimilated[a]

Field	Layer	$\bar{X}$	Baseline Run		32 Members		64 Members	
			$\bar{Y}$	RMSE	$\bar{Y}$	RMSE	$\bar{Y}$	RMSE
ma1	1	0.257	0.228	0.0298	0.231	0.0271	0.232	0.0271
ma1	2	0.260	0.230	0.0302	0.233	0.0274	0.234	0.0268
ma1	3	0.279	0.260	0.0196	0.265	0.0142	0.267	0.0133
ma1	4	0.372	0.365	0.0109	0.369	0.0088	0.371	0.0087
sb1	1	0.255	0.228	0.0285	0.229	0.0267	0.230	0.0267
sb1	2	0.258	0.229	0.0289	0.231	0.0270	0.231	0.0269
sb1	3	0.277	0.259	0.0185	0.263	0.0150	0.263	0.0147
sb1	4	0.369	0.365	0.0099	0.367	0.0097	0.368	0.0100
ww1	1	0.259	0.230	0.0292	0.232	0.0272	0.233	0.0272
ww1	2	0.261	0.232	0.0295	0.234	0.0274	0.235	0.0271
ww1	3	0.280	0.262	0.0179	0.267	0.0137	0.267	0.0130
ww1	4	0.367	0.366	0.0078	0.369	0.0080	0.370	0.0083
wb1	1	0.262	0.234	0.0292	0.235	0.0276	0.235	0.0276
wb1	2	0.264	0.235	0.0294	0.237	0.0277	0.237	0.0275
wb1	3	0.282	0.267	0.0165	0.270	0.0128	0.271	0.0124
wb1	4	0.364	0.368	0.0056	0.371	0.0084	0.372	0.0094

[a]$\bar{X}$ (dimensionless) is the average of the synthetic truth, $\bar{Y}$ (dimensionless) is the average of the assimilation run, and RMSE (dimensionless) is the root-mean-square error between the results of the assimilation run and the synthetic truth. The baseline run has been calculated using 32 ensembles. These statistics are calculated across all time steps.

the synthetic truth improves as the degree of error of these synthetic observations decreases. For all crop types there is a strong improvement in the model results, even if the standard deviation of the LAI observation error is 1. From the results in Figure 5 we can thus conclude that even under realistic LAI observation errors the coupled model benefits from the assimilation of LAI observations. This implies that the model errors caused by erroneous initial seed weights and sowing dates (which cannot be determined through remote sensing) can be corrected through the assimilation of remotely sensed LAI values.

[32] Figure 6 shows the results of the assimilation run for the modeled soil moisture content in all four soil layers, for the four crop types. These RMSEs are calculated on an hourly basis, during the entire period in which soil moisture data are assimilated. As can be expected, the RMSE between the synthetic truth and the model simulations for the upper soil layer increases as the observation error increases. The slope of this increase of the RMSE with the observation error becomes relatively close to zero for an observation error above 0.05. This can also been seen to a lesser extent in the results from *Walker and Houser* [2004], with the difference that in Figure 6 the results of the assimilation runs are never more erroneous than the baseline run, while in the work by *Walker and Houser* [2004] this occurs for increasing soil moisture observation errors. This can be explained by the use of the ensemble Kalman filter in this paper, which is likely to yield a better estimate of the model error covariance than the extended Kalman filter. The bias in the model results (defined as the model result minus the truth) is also strongly reduced by the assimilation of perfect observations. For increasing observation errors this improvement is reduced.

[33] The improvement in the upper layer soil moisture content is also propagated toward the lower soil layers. The potential to improve entire soil moisture profiles through the assimilation of observations of the upper part of the profile has been demonstrated in previous studies [e.g., *Hoeben and Troch*, 2000]. For both the second and third soil layer both the RMSE and the bias are reduced by the assimilation. As can be expected, the improvement in the model results is best for perfect observations, and decreases with increasing observation errors.

[34] For the three topsoil layers it can thus be stated that the effect of assimilating more accurate observations will only lead to better results if the accuracy of the observations is below 0.05. For observation errors above 0.05 no improvement in the model results can be expected by the use of more accurate data.

[35] The results for the bottom soil layer, however, behave differently. The soil moisture content for this layer has been overcorrected by the assimilation, as can be seen from Figure 6 (bottom right). The increase in the upper layer soil moisture content is propagated toward this layer, which results in an increase in its moisture content. For the corn and sugar beet fields, the assimilation of perfect observations changes the underestimation from the baseline run into an overestimation. For the winter wheat field, the almost zero bias is increased. For the winter barley field, the initial overestimation is increased. For the two latter fields, this increase in bias leads to the increase in RMSE if perfect observations are assimilated. This increase in RMSE decreases with increasing observation errors, and becomes negligible for error levels of 0.05. For all other error levels the results for the assimilation runs are comparable to the results from the baseline run.

[36] Table 3 shows that this improvement in the soil moisture content and the modeled LAI leads to an improvement in the modeled evapotranspiration. For the corn field, the slight (approximately 15 mm per year) underestimation by the baseline run is removed if perfect observations are assimilated, and reduced by more than 50% if the most erroneous observations are assimilated. Similar results are obtained for the winter wheat field. For the other two crop types, the underestimation of the evapotranspiration by the baseline run is higher (approximately 70 mm per year for the sugar beet field and 50 mm per year for the winter barley), and the improvement caused by the assimilation of the most erroneous observations is relatively lower.

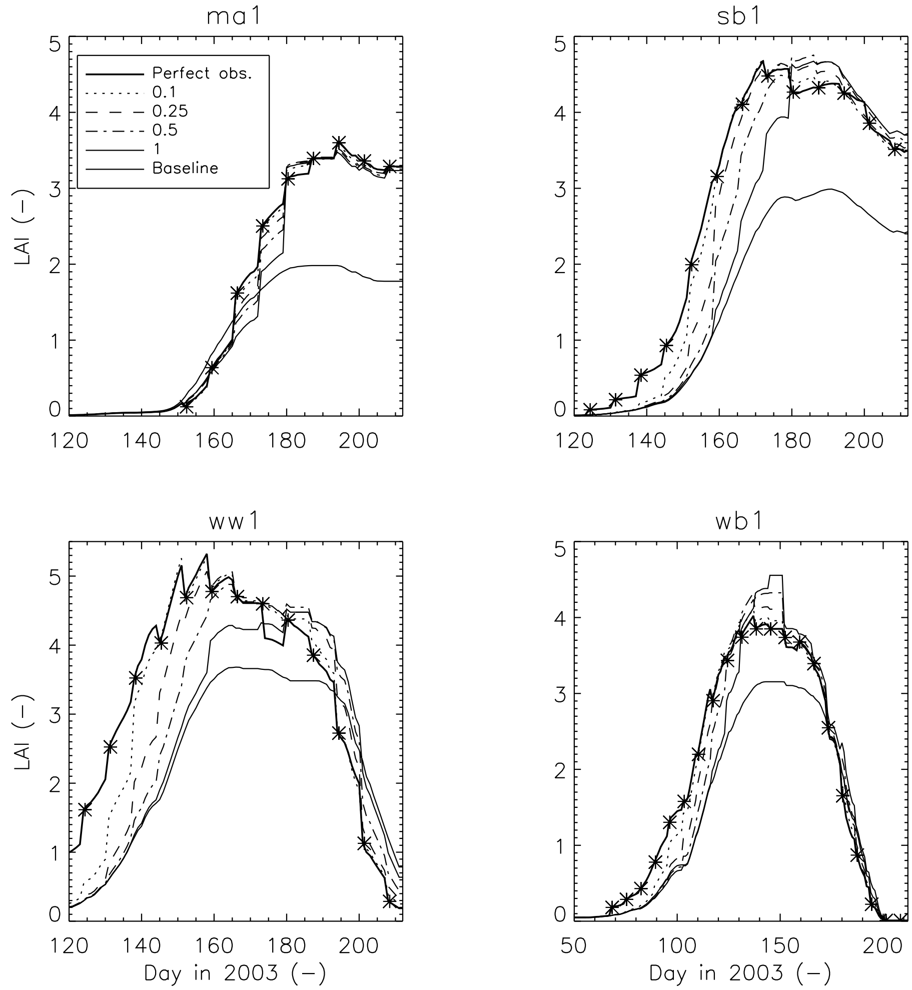

Figure 5. Impact of the LAI observation error on the simulated LAI values for the four crop types. The numbers in the legend are the errors associated with the LAI observations. The asterisks indicate the synthetic truth.

[37] From this section we can conclude that, even under realistic error levels for both the LAI and soil moisture observations, a general improvement in the model results can be expected from the assimilation of observed LAI or soil moisture values. However, for soil moisture and LAI observation errors above 0.05 and 0.5, respectively, improving the accuracy of the assimilated data will not lead to a strong improvement in the accuracy of the model results.

7.3. Impact of the Observation Frequency

[38] Another important issue in data assimilation is the frequency with which observations are available. In section 7.2 observations were assumed to be available with a weekly temporal interval. In this section, the impact of an observation interval of two and four weeks is assessed. An observation error of 0.5 for the LAI and 0.05 for the soil moisture was used for this purpose, in order to assess the impact of the observation frequency under realistic conditions.

[39] Figure 7 shows the impact of the observational frequency on the modeled LAI values for all four crop types. For sugar beet, winter wheat, and winter barley, the temporal evolution in the modeled LAI is approximately similar if the assimilation frequency is two or four weeks. The magnitude of the LAI is slightly better if the observation frequency is two weeks or less. For corn, the LAI is underestimated during the four weeks between the end of June and the beginning of July. This is caused by the correction of the overestimation around day 165. However, this underestimation is strongly reduced around day 190.

[40] For the modeled soil moisture values, similar results were obtained. Table 4 shows the comparison between the biases and the RMSEs between the model simulation and the synthetic truth for the three observation frequencies, for all soil layers. These statistics were calculated taking into account the synthetic truth at every time step, not only at the time steps at which synthetic observations were assimilated. Table 4 and Figure 7 together lead to the conclusion that the model results can benefit from the assimilation of LAI or soil moisture values with a temporal interval of even one month. However, it is better to assimilate the observations with a temporal resolution of no more than two weeks, if the temporal evolution of the LAI should be predicted accurately, and if the modeled soil moisture should be significantly improved.

7.4. Assimilation of Soil Moisture Only

[41] As soil moisture is an important variable in the crop growth process, it was investigated whether an improve-

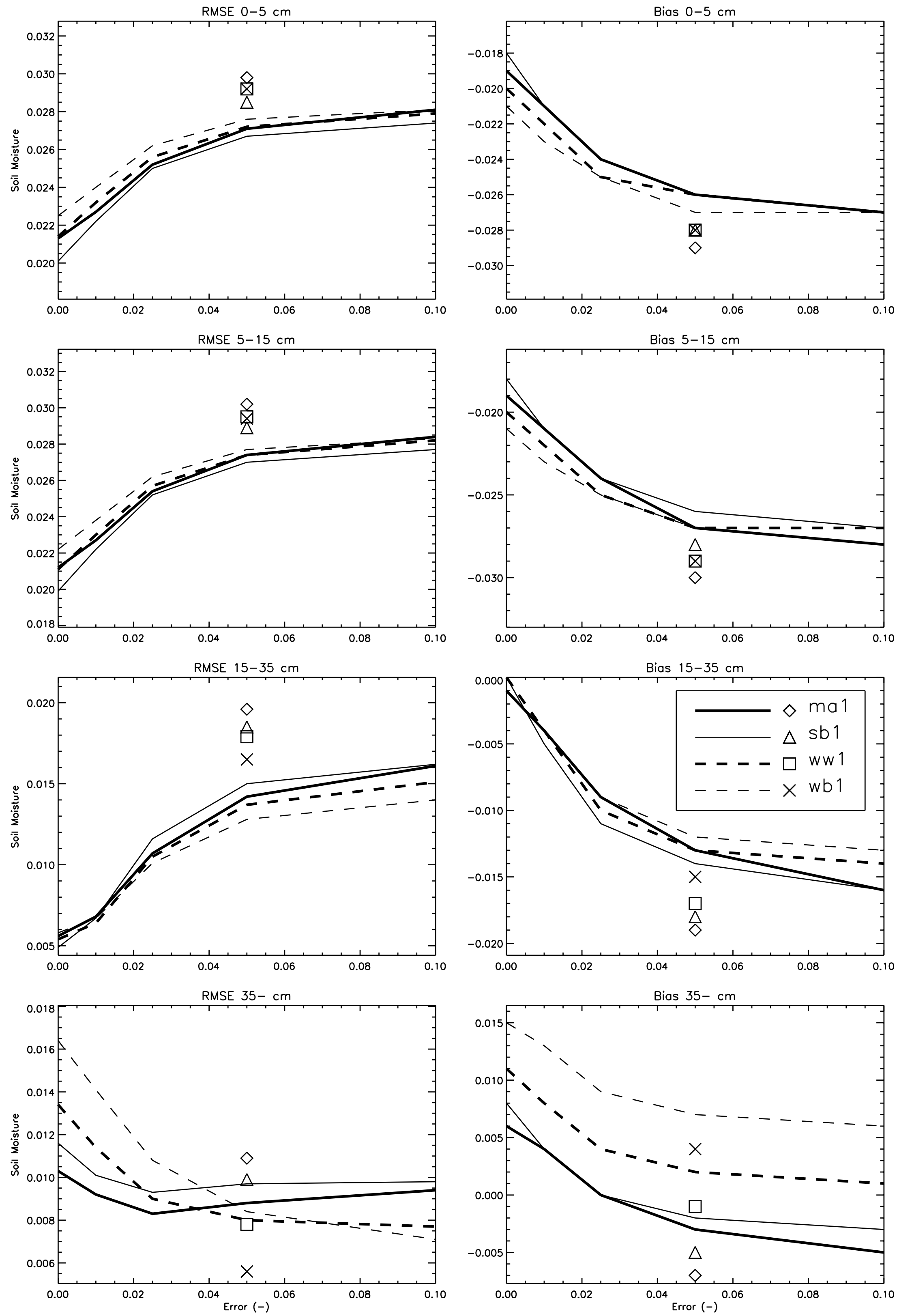

Figure 6. Impact of the soil moisture observation error on the accuracy of the model results. The lines represent the results of the assimilation runs, and the symbols represent the results of the baseline run. (left) RMSE between the model results and the synthetic truth. (right) Bias in the model results.

Table 3. Impact of the Data Assimilation on the Modeled Evapotranspiration[a]

			Assimilation of Soil Moisture and LAI Errors					Assimilation of LAI Only Errors				
Field	Synthetic Truth	Baseline Run	Perfect	θ = 0.01, LAI = 0.1	θ = 0.025, LAI = 0.25	θ = 0.05, LAI = 0.5	θ = 0.1, LAI = 1	Perfect	0.1	0.25	0.5	1
ma1	240.2	225.3	240.3	239.0	239.5	237.7	234.7	241.7	241.5	239.3	237.0	235.4
sb1	327.6	261.8	322.8	307.1	296.6	288.5	280.5	323.1	304.6	293.4	284.0	273.4
wb1	387.3	339.7	385.5	354.7	349.5	347.5	345.3	386.5	353.6	348.8	347.3	345.9
ww1	365.3	344.1	365.6	356.7	352.6	351.0	351.3	366.8	360.5	354.8	350.1	344.5

[a]Units are mm yr^{-1}.

ment in the modeled soil moisture before the onset of the crop growth can lead to an improvement in the modeled LAI values. Thus the synthetic soil moisture observations were assimilated at exactly the same dates as in section 7.2, but no LAI values were used when the synthetic soil moisture data were no longer available. In order to assess the impact of the observation error, both perfect observations and observations with an uncertainty of 0.05 soil moisture were assimilated into the coupled model.

[42] Figure 8 shows the results of this assimilation study. For the ma1 field the modeled LAI magnitudes are slightly worsened by the assimilation, while for the wb1 field they are slightly improved. For the other two fields, the modeled LAI is insensitive to the assimilation of the soil moisture values before the growing season. In all four cases, however, the temporal evolution of the modeled LAI is unaltered.

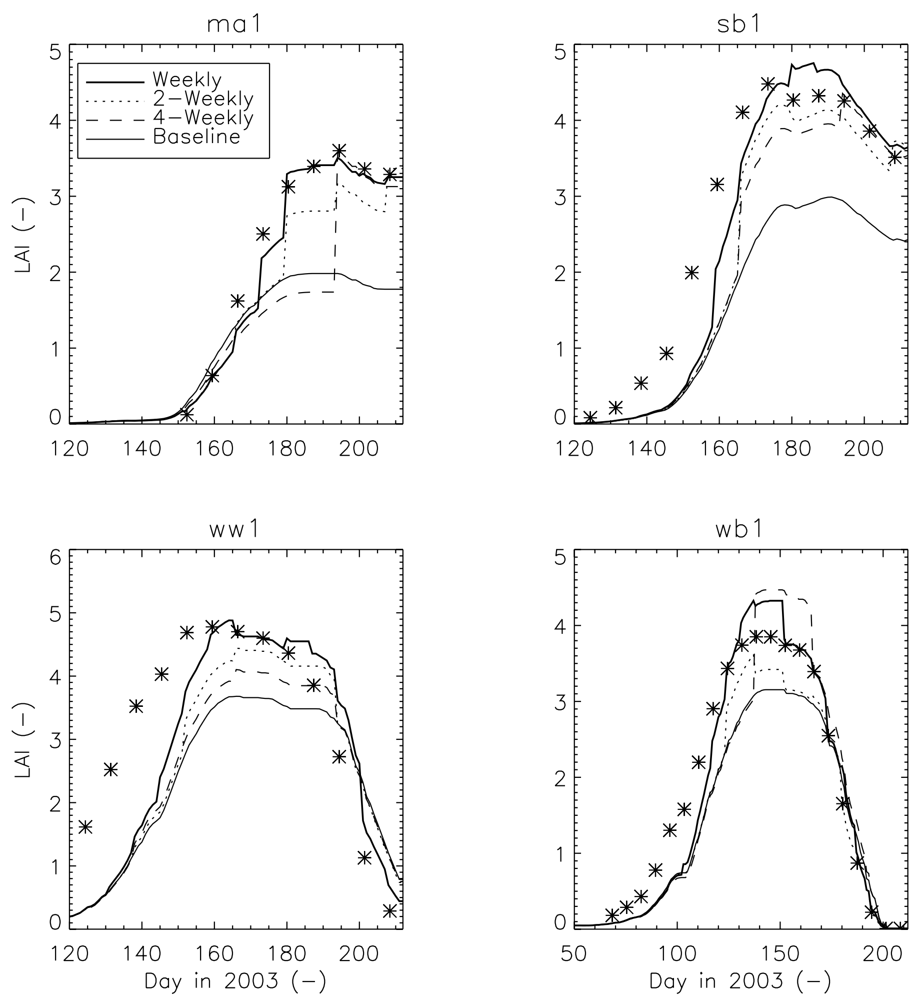

Figure 7. Impact of the assimilation frequency on the simulated LAI values for the four crop types. The asterisks indicate the synthetic truth.

Table 4. Impact of the Assimilation Frequency on the Modeled Soil Moisture for All Soil Layers[a]

			Baseline Run		Weekly Interval		2-Week Interval		4-Week Interval	
Field	Layer	$\bar{X}$	$\bar{Y}$	RMSE	$\bar{Y}$	RMSE	$\bar{Y}$	RMSE	$\bar{Y}$	RMSE
ma1	1	0.257	0.228	0.0298	0.231	0.0271	0.230	0.0283	0.229	0.0295
ma1	2	0.260	0.230	0.0302	0.233	0.0274	0.232	0.0287	0.230	0.0300
ma1	3	0.279	0.260	0.0196	0.265	0.0142	0.263	0.0166	0.260	0.0190
ma1	4	0.372	0.365	0.0109	0.369	0.0088	0.367	0.0086	0.366	0.0106
sb1	1	0.255	0.228	0.0285	0.229	0.0267	0.229	0.0270	0.228	0.0284
sb1	2	0.258	0.229	0.0289	0.231	0.0270	0.231	0.0273	0.229	0.0289
sb1	3	0.277	0.259	0.0185	0.263	0.0150	0.262	0.0155	0.259	0.0183
sb1	4	0.369	0.365	0.0099	0.367	0.0097	0.367	0.0076	0.365	0.0102
ww1	1	0.259	0.230	0.0292	0.232	0.0272	0.231	0.0281	0.230	0.0291
ww1	2	0.261	0.232	0.0295	0.234	0.0274	0.233	0.0284	0.232	0.0294
ww1	3	0.280	0.262	0.0179	0.267	0.0137	0.265	0.0157	0.263	0.0176
ww1	4	0.367	0.366	0.0078	0.369	0.0080	0.368	0.0064	0.367	0.0083
wb1	1	0.262	0.234	0.0292	0.235	0.0276	0.234	0.0287	0.234	0.0289
wb1	2	0.264	0.235	0.0294	0.237	0.0277	0.236	0.0290	0.236	0.0291
wb1	3	0.282	0.267	0.0165	0.270	0.0128	0.268	0.0155	0.268	0.0157
wb1	4	0.364	0.368	0.0056	0.371	0.0084	0.369	0.0060	0.369	0.0062

[a]$\bar{X}$ (dimensionless) is the average of the synthetic truth, $\bar{Y}$ (dimensionless) is the average of the assimilation run, and RMSE (dimensionless) is the root-mean-square error between the results of the assimilation run and the synthetic truth.

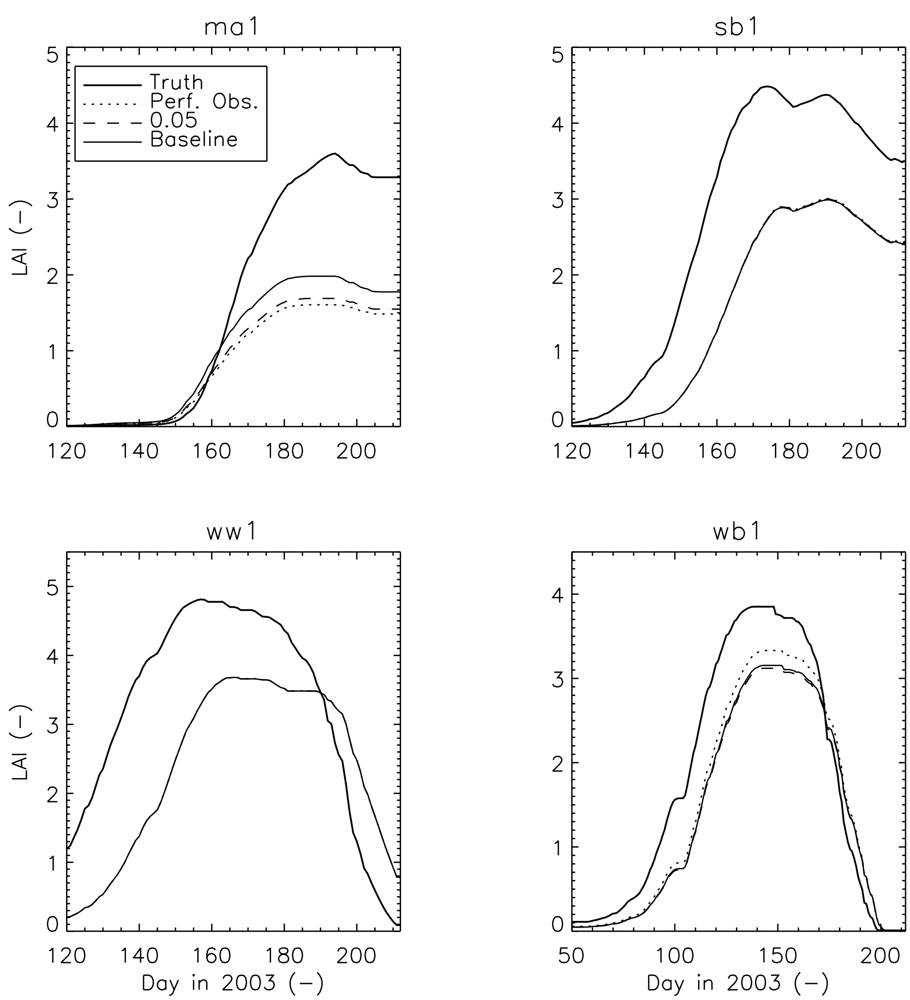

Figure 8. Impact of the assimilation of observed soil moisture values before the initiation of crop growth on the modeled LAI.

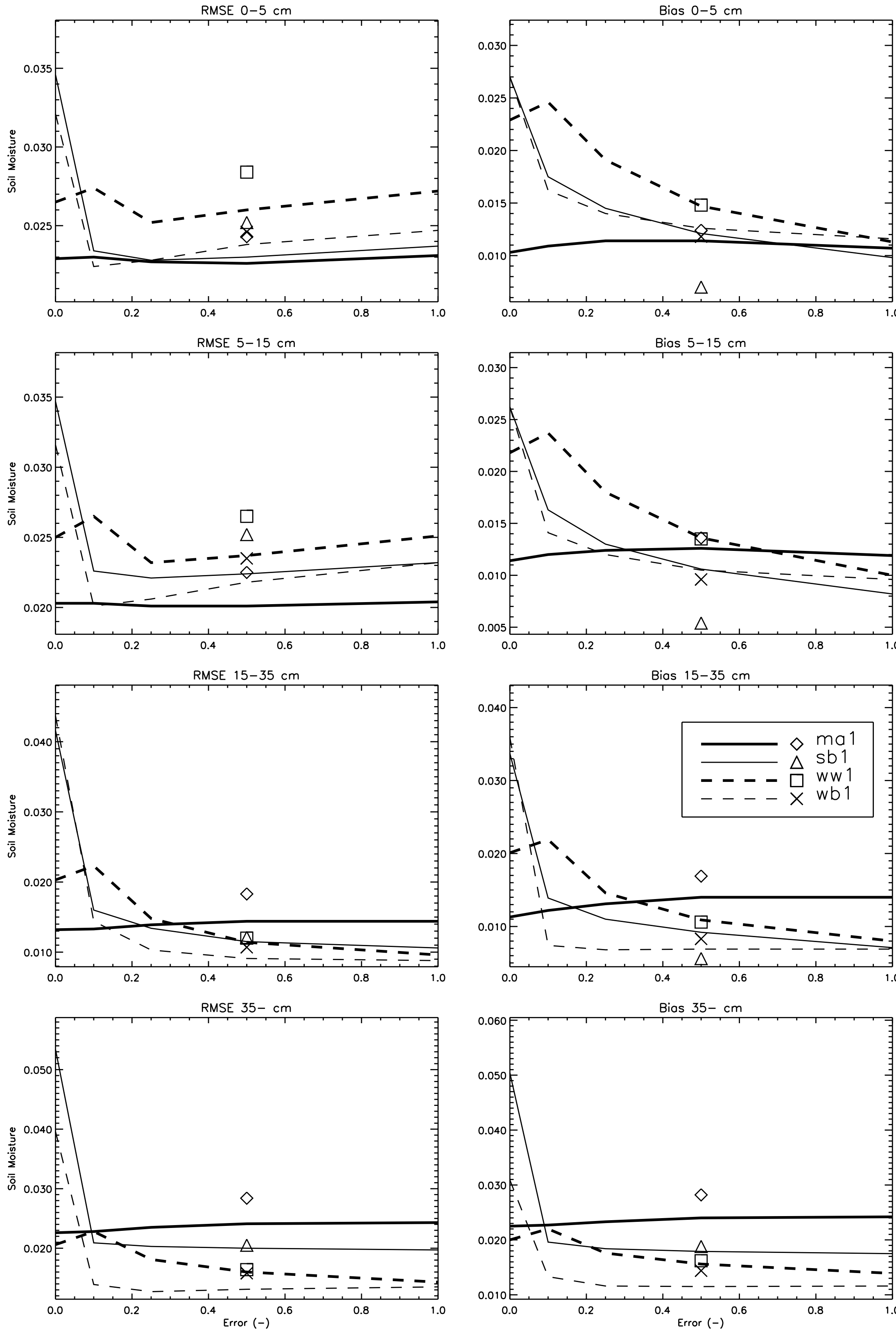

Figure 9. Impact of the assimilation of observed LAI values during the growing season on the modeled soil moisture profile for the four vegetation types. The lines represent the results of the assimilation runs, and the symbols represent the results of the baseline run. (left) RMSE between the model results and the synthetic truth. (right) Bias in the model results.

Table 5. Values of the Kalman Gain for the Soil Moisture State in Case LAI Values Are Assimilated

Time Step (Day of Year)	Upper Layer				Bottom Layer			
	ma1	sb1	wb1	ww1	ma1	sb1	wb1	ww1
117	0.000	0.038	0.000	0.034	0.000	0.072	0.000	0.097
124	0.000	−0.012	0.000	−0.012	0.000	0.012	0.000	0.022
131	0.000	−0.007	0.000	−0.008	0.000	0.004	0.000	0.010
138	0.000	0.002	0.000	0.002	0.000	0.010	0.000	0.017
145	0.000	0.001	0.000	0.001	0.000	0.016	0.000	0.022
152	0.000	−0.014	0.000	−0.011	0.000	0.008	0.000	0.008
159	0.000	−0.005	0.000	−0.005	0.006	0.003	0.012	0.004
166	−0.010	−0.011	−0.010	−0.010	0.000	0.002	0.004	0.003
173	−0.015	−0.011	−0.014	−0.009	−0.002	0.001	0.001	0.002
180	−0.027	−0.001	−0.025	−0.001	−0.003	−0.001	0.000	0.002
187	−0.005	−0.002	−0.005	−0.002	−0.003	−0.001	−0.002	0.002
194	−0.024	−0.003	−0.022	−0.004	−0.003	−0.003	−0.001	0.001
201	−0.022	−0.001	−0.022	−0.002	−0.008	−0.007	−0.001	0.001
208	−0.009	−0.004	−0.009	−0.003	−0.013	−0.012	−0.001	0.001

[43] The conclusion from these model applications is that, in order to improve the LAI estimates by the model, it is not sufficient to assimilate the soil moisture values before the growing season. During the growing season, LAI observations need to be assimilated also.

7.5. Impact of the Assimilation of LAI Values on the Modeled Soil Moisture Profile

[44] The objective of this section is to assess whether it is possible to improve the modeled soil moisture profile through the assimilation of LAI observations during the growing season. Observations with an error level of 0, 0.1, 0.25, 0.5, and 1, with a weekly interval, were assimilated into the model. No soil moisture values were assimilated in the period preceding the growing season. Figure 9 shows the results of this assimilation study for the four fields. These RMSE and bias values are calculated using the data from all time steps during which LAI values were assimilated.

[45] From Figure 9 it can be concluded that assimilating LAI values does not necessarily improve the modeled soil moisture profile. For the ma1 field, a decrease in the RMSE between the true and modeled soil moisture values has been obtained for all observation errors. An improvement in the modeled bias has also been obtained. For the ww1 field, the RMSE for the two top layers improves through the assimilation, but not for the bottom layers when the observation error is below 0.5. In all cases the bias only improves if the observational error is high. For the sb1 and wb1 fields, the assimilation procedure reduces the RMSE for the top two layers, except for when perfect observations are used, in which case the RMSE strongly increases. For the two bottom layers, an improvement in the RMSE is obtained only under high observational errors. Again, for perfect observations the RMSE strongly increases. For these two fields, the bias only improves if the observation error is high.

[46] The correction of the modeled LAI does have a beneficial impact on the modeled evapotranspiration, as can be seen in Figure 4. If the observation error is above 0.5, however, this improvement becomes negligible.

[47] The explanation for this discrepancy is the fact that LAI values are not directly related to the soil moisture content, as opposed to for example radar backscatter values or brightness temperatures. However, the data assimilation algorithm updates the soil moisture profile depending on the difference between the observed and the modeled LAI. These differences can be quite large (see, for example, Figure 7). An excessive update of the soil moisture content in all soil layers can thus occur, even if the value of the Kalman gain for the soil layers is relatively low, as can be seen in Table 5. From this section we can thus conclude that assimilating LAI values during the growing season will not necessarily lead to a better estimate of the soil moisture content.

8. Conclusions

[48] The objective of this study was to assess to what extent the results of a fully coupled hydrology–crop growth model can be optimized through the assimilation of observed LAI or soil moisture values. A crop growth model (WOFOST) has been coupled to a hydrologic model (TOPLATS) for this purpose. Through an observed system simulation experiment (OSSE), it has been found that the assimilation of observed soil moisture values throughout the period preceding the crop growth has a negligible impact on the modeled LAI values. It is thus better to assimilate LAI observations during the growing season in order to improve the modeled LAI. On the other hand, the assimilation of LAI observations does not necessarily lead to a better estimation of the soil moisture profile. If both the vegetation and soil moisture state of a model need to be improved, observations of both variables need to be assimilated. Further, the results indicate that even under realistic degrees of error in the observations (an error of 0.1 for the soil moisture and 1 for the LAI observations) the model results benefit from the assimilation of soil moisture and LAI data. However, the mismatch between the true and the modeled soil moisture only decreases significantly if the observation error is below 0.05. It is found that the model results improve if observations are assimilated with a monthly interval, but that an assimilation frequency of no more than 2 weeks should be used, if the temporal evolution of the LAI should be predicted accurately, and if the modeled soil moisture should be significantly improved. The better match in the modeled LAI and soil moisture values has been found to lead to an improvement in the modeled evapotranspira-

tion. The overall conclusion from this work is therefore that there is real potential to improve the results of coupled hydrologic/crop growth models through the assimilation of remotely sensed LAI and soil moisture data under realistic conditions, but that observations of both variables need to be assimilated.

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