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Alternative methods to predict actual evapotranspiration illustrate the importance of accounting for phenology – Part 2: The event driven phenology model

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Abstract

Evapotranspiration (*ET*) flux constitutes a major component of both the water and energy balances at the land surface. Among the many factors that control evapotranspiration, phenology poses a major source of uncertainty in attempts to predict *ET*. Contemporary approaches to *ET* modeling and monitoring frequently summarize the complexity of the seasonal development of vegetation cover into static phenological trajectories (or climatologies) that lack sensitivity to changing environmental conditions. The Event Driven Phenology Model (EDPM) offers an alternative, interactive approach to representing phenology. This study presents the results of an experiment designed to illustrate the differences in *ET* arising from various techniques used to mimic phenology in models of land surface processes. The experiment compares and contrasts two realizations of static phenologies derived from long-term satellite observations of the Normalized Difference Vegetation Index (NDVI) against canopy trajectories produced by the interactive EDPM trained on flux tower observations. The assessment was carried out through validation of predicted *ET* against records collected by flux tower instruments. The VegET model (Senay, 2008) was used as a framework to estimate daily actual evapotranspiration and supplied with seasonal canopy trajectories produced by the EDPM and traditional techniques. The interactive approach presented the following advantages over phenology modeled with static climatologies: (a) lower prediction bias in crops; (b) smaller root mean square error in daily *ET* – 0.5 mm per day on average; (c) stable level of errors throughout the season similar among different land cover types and locations; and (d) better estimation of season duration and total seasonal *ET*.

1 Introduction

Water flux from the land surface to the atmosphere from evaporation and transpiration is a key variable that describes the surface climate and links it to the functioning of

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ecosystems. ET is characterized by the volume of liquid water transformed into water vapor and by the energy (latent heat, LE) spent to effect this phase transition. On a global level, ET accounts for approximately 62×10^{12} m^3 of water per year (Peixoto and Oort, 1992), but this volume is distributed unevenly in space and time. Over vegetated surfaces the number of factors like the precipitation regime, fraction vegetation cover, and changing canopy structure interact to greatly complicate the ET estimation. The UN Food and Agriculture Organization (FAO) recommended using the Penman-Monteith model (Monteith, 1965) to estimate "reference" evapotranspiration (ET_0) on croplands (Allen et al., 1998). The concept of ET_0 has been used extensively in agriculture since it can mimic the ET dynamics over cereal crops with fully developed canopies. Actual evapotranspiration (ET_a), however, poses a great challenge for monitoring and even a greater one for prediction due to the high variability in environmental conditions observed across the land surface (Kalma et al., 2008).

Researchers have developed numerous approaches to retrieve ET_a. For flux tower data, the eddy covariance method relates rapid fluctuations in water vapor density to ET_a (Suyker and Verma, 2009). Yet, point-based estimates do not capture the spatiotemporal variability of evapotranspiration, even in feasibly dense networks (Kalma et al., 2008). Remote sensing provides means to achieve a better estimation of actual ET in the spatially explicit manner. Monitoring of ET_a is based on retrievals of land surface temperature, which closely follows the sensible heat flux at the land surface. The ET_a is then derived from the energy balance equations (Kustas and Anderson, 2009). Also, using surface energy balance (Bastiaanssen et al., 1998; Allen et al., 2005, 2007; Su et al., 2005; Senay et al., 2007; Mu et al., 2007) or water balance (Verdin et al., 2002; Senay and Verdin, 2003), ET_a models have had varying degrees of success in addressing spatiotemporal variation. However, these approaches were designed for monitoring purposes, only to be used in retrospective data analysis and hence offer little for prediction.

The principal challenge in remote estimation of ET_a is to capture canopy dynamics (Cleugh et al., 2007; Mu et al., 2007; Godfrey et al., 2007; Senay, 2008; Weiß and

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Menzel, 2008). This factor is determined by the phenological development in specific vegetation types (Suyker and Verma, 2009) and therefore cannot be well represented by a model constant. Varying in space and in time, canopy factor often correlates with weather variables, posing a challenge for modelers to separate their influences on canopy resistance to transpiration. The various trajectories of canopy dynamics composed possibly of multiple species within a limited area constitute a complex object of land surface phenology (LSP). Land surface phenology studies the spatiotemporal development of the vegetated land surface using remote sensing (de Beurs and Henebry, 2004), and sometimes called "remote sensing phenology" (Morisette et al., 2009). Several pioneering studies in land surface phenology (de Beurs and Henebry, 2004; Reed, 2006; Zhang et al., 2007; Stöckli et al., 2008; Xiao et al., 2009) point to the need to move beyond the conventional representation of LSPs as static trajectories of vegetation cover properties with negligible response to changing weather conditions.

Traditionally, hydrological models have used just one coefficient to represent canopy factor where the value of the coefficient stayed the same for the whole season (e.g., Manabe 1969; Weiß and Menzel, 2008). More recent land surface models (LSM) with hydrology modules typically use static climatologies (seasonal trajectories averaged over multiple years) of canopy parameters (Mitchell et al., 2004; Montaldo et al., 2005; Lawrence and Chase, 2007; Senay, 2008) for the estimation of ET_a and other land surface fluxes. This approach is employed in a number of models, including MOSAIC (Koster and Suarez, 1996), SAC (Koren et al., 2004), Noah LSM (Ek et al., 2003), MIROC (Hasumi and Emori, 2004), and many other LSMs. In smaller scale studies the progression sometimes simply runs as a curve fitted into prior observations (Montaldo et al., 2005) to represent phenology as a function of time. Despite their robustness, the static climatologies and time functions also introduce errors by ignoring interannual phenological variability and transients due to abrupt weather events (Milly et al., 2008; Wegehenkel, 2009).

An interactive approach to phenology modeling was first introduced in applied plant growth models (Pitman, 2003). Relying on proxy variables such as thermal time, duration of daylight, or accumulated precipitation, interactive phenology modules determine the start, end, and duration of the growing season using empirical thresholds (Dickinson et al., 1998; Foley et al., 2000; Reed et al., 2003). In some vegetation models, developers went beyond just dates and linked seasonal dynamics of leaf area index (LAI) to thermal time based on plant thermal response functions (Neitsch et al., 2002; Bondeau et al., 2007; Rötzer et al., 2010). In other works researchers started using multiple factors simultaneously to derive phenological trajectories (Jolly et al., 2005; Setiyono et al., 2007; Stöckli et al., 2008). Finally, the interactive approach has been extended to include the concept of event drivers with the first successful trials reported in the companion paper (Kovalskyy and Henebry, 2011). This concept stands apart from all traditional models that have climatic variables such as air temperature, insolation, precipitation, and others acting as constant forcing factors. The event driven concept transforms the continuous dynamics of weather and other factors into discrete triggers of change in the manner that takes into account the ecological particularities of modeled vegetation types. Hence, daily insolation, daily thermal time, precipitation, freezing temperatures, and heat stress can each contribute to building phenological trajectories by triggering corresponding vegetation responses collected from prior observations. The EDPM can simulate daily canopy dynamics from the actual weather data and, thus, it has the potential to replace the static climatologies used in LSMs.

In this paper we compare and contrast both static and interactive approaches to the modeling of land surface phenologies. The LSPs representing both approaches are evaluated via parameterizing simplified model of actual evapotranspiration – VegET – that is currently used operationally in the Famine Early Warning System (FEWS NET). We use the original implementation of the VegET model parameterized with static NDVI climatologies as a starting point. We then replace the static parameterization with (1) contemporaneous NDVI time series to server as a reference and, alternatively, (2) vegetation index (VI) trajectories produced by the interactive EDPM. Within this experiment, VegET with alternative phenological parameterizations produced daily ET_a values during the growing season for maize, soybean, and grassland canopies. We compare each modeled ET_a outcome with ET measured at corresponding flux towers, reporting the differences between estimates and observations. Specifically, the study aims to answer the following questions: (1) Does the interactive phenology differ from the static phenology? (2) If so, then by how much? (3) Is the difference statistically significant? (4) If so, then when and where are results from the interactive phenology significantly different from the static phenology? Analytical procedures used to answer these questions are described in detail in Sect. 2.6 that provides the roadmap for the analyses we used.

2 Methods and materials

2.1 Evapotranspiration model

VegET is a recent development in ET modeling; it uses water balance principles and remote sensing data to drive the evapotranspiration process (Senay, 2008). The model is simple and flexible enough to provide framework for our analysis. VegET uses the standard Penman-Monteith equation to address the influence of all climatic factors within a single time step in one location for one vegetation type. Transition to a different set of vegetation and soil conditions is effected through two coefficients capturing canopy dynamics and ground water regime:

$$ET_a = K_s \cdot K_{cp} \cdot ET_0 \tag{1}$$

where K_s is a soil moisture stress coefficient computed from daily water balance (Eq. 2) and K_{cp} is a plant coefficient driven by phenology and distinct from K_c, the traditional stage standardized crop coefficient recommended by the FAO.

$$\text{if } (\mathrm{SW}_i < \mathrm{MAD}), \text{ then } (K_s = \mathrm{SW}_i/\mathrm{MAD}), \text{ else } (K_s = 1) \tag{2}$$

where SW_i is soil water content at the current step, MAD is the Maximum Allowable Depletion level. The rationale for using K_{cp} instead of K_c comes from multiple observations of linear relationships between K_c and VIs (e.g., Hunsaker et al., 2003; Tasumi et

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al., 2005). In evaluating VegET performance, Senay (2008) used very simple transformations from NDVI to K_{cp} based on the thresholds and observed variability of the NDVI derived from AVHRR data. Despite the coarse resolution of the sensor (1 km pixels), results using K_{cp} showed improvement in sensitivity to canopy dynamics compared to K_c and remarkable performance in capturing the actual *ET* (Senay, 2008): Pearson correlation coefficients of 0.87 and 0.88 for flux towers in South Dakota and Arizona, respectively.

2.2 Representation of phenologies

In his original paper, Senay (2008) derived K_{cp} from long term averages of NDVI from AVHRR. Smoothed with the temporal three-point moving average filter, the resulting curve is an NDVI climatology that is presumed to produce minimal errors over the long term. A set of empirically derived thresholds was used to mark the beginning and end of the growing seasons. We saw several limitations to this approach. First, the NDVI is not consistent across AVHRR, MODIS, and other synoptic sensors due to differences in sensor spectral bandwidth and band placement (van Leeuwen et al., 2006; Kovalskyy et al., 2011b). These sensor differences may cause discrepancies in derived K_{cp}, but the significance of these has yet to be determined. Therefore, it was important for this study to assess the sensitivity of the model to the NDVI derived from AVHRR versus MODIS sensors. Second, the VegET relies on expert knowledge about the seasonal NDVI dynamics and on published maximum and minimum values of K_{cp} for a given vegetation type. This approach worked empirically, but for a potential improvement it is possible to invert Eq. (1) and estimate K_{cp} from properly equipped weather stations or flux towers. Therefore, we examined closely the relationship between the vegetation index and the phenologically forced coefficient.

Implementing a better solution for these problems, we turned to the interactive modeling of LSPs. We use our newly-developed Event Driven Phenology Model (EDPM; Kovalskyy and Henebry, 2011) as an interactive alternative to the long-term averages used previously with VegET (Senay, 2008; Senay et al., 2009). The EDPM is data

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driven, but instead of a historical record of satellite observations, it incorporates flux tower observations with sequence modeling to simulate daily dynamics of a modeled variable (e.g., a vegetation index), depending on the phase of canopy development. The EDPM treats daily forcings as transient "events" that can potentially modify trajectories of canopy development. From collections of such events the model builds the phenological trajectories at daily steps. The EDPM has been successfully tested on flux-tower derived normalized difference vegetation index (TNDVI; Wittich and Kraft, 2008). To generate an LSP, the model represented the TNDVI value in the next step as conditioned on the current value, with ongoing events potentially modifying the current TNDVI value with change slope E as follows:

$$\mathrm{TNDVI}_{t+1} = E_t \cdot \mathrm{TNDVI}_t \tag{3}$$

where TNDVI is the vegetation index value, E is the step-change coefficient (or slope produced by events), and t is the time step index. Detailed description of how the EDPM works is given in the companion paper (Kovalskyy and Henebry, 2011).

In this experiment, the EDPM used six kinds of forcings that can manifest as events during the growing season: (1) rain, (2) heat stress, (3) frost, (4) insufficient insolation, (5) adequate insolation, and (6) growing degree days. The impacts of these events depend on the vegetation type and ongoing phenophase. The internal phenological phase control module is responsible for autonomous estimation of key growing season dates. Meanwhile, external dates for each phenophase transition can be supplied to the model to reassure the accuracy of phenological timing. In this experiment, this last feature of the EDPM was used together with other functionalities to evaluate the impact of errors in phenological timing on the accuracy of ET_a estimates by the VegET.

2.3 Study sites

The study sites included rain-fed maize and soybean fields and grasslands located within the "corn belt" and "soy belt" of the central United States. Climatic particularities and the geographic settings of the belts produce strong ET gradients. The northern tier

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has only 600 mm *ET* annually; whereas, at the southern end, the annual *ET* can reach 1000 mm. Maize and soybean are the two most prevalent crops across the region. For that reason, we chose two sites from the AmeriFlux network to represent croplands at the extremes of the region: Bondville, Illinois, to the east and Mead, Nebraska, to the west. A similar strategy was used for grasslands: the Fermi site in Illinois represented humid grassland and the Brookings site in South Dakota represented a subhumid grassland. (We did not include in this study a site representing the arid end of the grassland spectrum.) We presumed that the responses of the grasses at each location were sufficiently similar – all "spring-green" – so as not to require different types of phenological patterns.

2.4 Data sources

The experiment devised for this study required microclimatological records from flux tower sites as well as satellite observed canopy states for the locations. Level 2 flux tower data were downloaded from http://ameriflux.ornl.gov/; specifically, the energy fluxes, microclimate records, and soil moisture for rain-fed agricultural sites and grassland sites. After checking the data quality (by examining the consistency of records), we selected twelve growing seasons for the experiment (Table 1).

Remotely sensed observations from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) and from NOAA's Advanced Very High Resolution Radiometer (AVHRR) were obtained from the following two sources: (1) MODIS NBAR collection 5 product (2000–2009) at ftp://e4ftl01u.ecs.nasa.gov/MOTA/MCD43C4.005/; and (2) AVHRR 7-day NDVI composites by USGS (1989–2007) at http://edcsns17.cr.usgs.gov/EarthExplorer/.

2.5 Data preparation

Estimation of the daily actual evapotranspiration with VegET model required us to calculate the reference evapotranspiration and the soil water stress. However, before the calculations were made, we had to reprocess the hourly records of each variable into daily totals and averages depending on the nature of weather factor or surface attribute. The reference evapotranspiration was calculated using the Penman-Monteith equation (Monteith, 1965). We used the AmeriFlux site descriptions to obtain values for soil permanent wilting point and water holding capacity at each site. Finally, we used descriptions of crops (Nielsen, 2002; Setiyono et al., 2007) and grasses (Henebry, 2003, 2010) to obtain rooting depth profiles and critical soil water depletion levels. Based on these data we calculated the SW within the root layer. Daily dynamics of soil water stress coefficient K_s were derived from SW records via Eq. (2) and stored along with daily ET_0 as common inputs for calculations of multiple estimates of actual evapotranspiration.

Next step was the calculation of K_{cp} trajectories from satellite data. Climatologies from MODIS NDVI and AVHRR NDVI time series were transformed into the K_{cp} coefficient for VegET model as specified in Senay (2008) to represent static LSP modeling approach. The same transformation method was used on the contemporaneous MODIS NDVI time series representing observations of the canopy condition during the modeled growing seasons. The 8 day composite values of contemporaneous NDVI were linearly connected to make up daily time series. These contemporaneous time series served as a benchmark for the VegET model performance since with K_{cp} derived from contemporaneous observations the ET_a estimation becomes retrospective. Such parameter coefficients should, in theory, produce better model outcomes despite gaps due to cloud cover. Comparing other predicted ET_a against retrospective estimates should give an idea of how closely the two approaches to phenological predictions match with the best performance of the VegET model.

Representing the interactive LSP modeling approach, the EDPM produced the phenological forcings by simulating seasonal trajectories of TNDVI (see Kovalskyy and Henebry, 2011). Transformation to K_{cp} was affected through the linear relationships between the observed TNDVI and K_{cp} obtained from inverting ET_a and soil moisture data from flux towers (Fig. 1a and b), yielding slopes of 1.22 for maize-soy cropland and

1.38 for mesic grassland. Both relationships retained substantial noise (RMSE of 0.23 and 0.34, respectively). However, the residuals at grassland sites were found to correlate well with vapor pressure deficit. Therefore, we used the polynomial fit (Fig. 1c) to model the residuals. When included into the TNDVI – K_{cp} transformation process, the modeled residuals helped to reduce dramatically the spread of errors around the linear fit (RMSE = 0.26; Fig. 1d). Therefore, modeled residuals were used to transform the EDPM derived TNDVI into the K_{cp} at the Fermi and Brookings sites resulting in specific pattern of K_{cp} parameters for grassland in Fig. 2.

The initial testing of the EDPM showed that the phenological control module requires adequate training as its procedures are parameterized from observed distributions of phenological timing (Kovalskyy and Henebry, 2011). Since this module controls transitions of phenophases, it makes the choices of canopy behavior patterns used to build the TNDVI curve. We decided to deploy the EDPM in two simulation regimes: (1) using automated phenological transition point (PTP) estimation; and (2) using prescribed PTPs extracted from observed TNDVI dynamics following the approach of Viña et al. (2004). We used this flexibility of the EDPM to assess its potential under conditions of a better estimation of PTPs during the growing seasons listed in Table 1. The arising differences in performance between these two regimes should reveal discrepancies created by poorly defined distributions of phenological transitions due to insufficient training of the EDPM.

Figure 2 shows all combinations of VegET parameterization by vegetation factor K_{cp}.

The parameter sets shown in Fig. 2 were organized as input feeds to the VegET to produce five alternative sets of evapotranspiration estimates: (1) *ET-EA* where the *ET* was obtained with the VegET parameterized by K_{cp} from the EDPM in automatic PTP estimation regime (EDPM-A); (2) *ET-EP* where the *ET* was obtained with the VegET parameterized by K_{cp} from the EDPM in prescribed PTP regime (EDPM-P); (3) *ET-CA* where the *ET* was derived with the VegET driven by K_{cp} based on AVHRR climatologies; (4) *ET-CM* where the *ET* was derived with the VegET driven by K_{cp} based on MODIS climatologies; and (5) *ET-OB* where the *ET* was derived with the VegET driven

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by K_{cp} produced from retrospective MODIS NDVI time series contemporary with the modeled seasons. In addition, we introduced a sixth alternative: the reference evapotranspiration ET_0 (*ET-PM*).

A total of six distinct sets of *ET* estimates were compared (1) against flux tower observations, and (2) across the different LSP modeling approaches. When making the comparisons, we were aware of variable footprint dynamics in eddy covariance records, footprint size differences between spaceborne sensors and flux tower instrumentation, geo-location issues related to remotely sensed products, spectral differences of the AVHRR and MODIS instruments, and many other sources of noise and uncertainty. All these issues can create deviations in the flux tower records as well as in the remotely sensed data; consequently, these deviations can also appear in model output because they were embedded into the data used for model inputs. Yet here, we follow in the steps of many others (Nagler et al., 2005; Cleugh et al., 2007; Mu et al., 2007; Senay, 2007, 2008; Zhang et al., 2009) who have used best available remotely sensed data with high quality ground observations to calibrate, refine, and validate their models. Thereby, this experiment gives a picture of the relative differences between six realizations of phenological forcings on VegET predictions.

2.6 Roadmap for analysis

We selected four procedures to evaluate the predictive performance of the alternative parameterizations of VegET: (1) residual analysis; (2) Kolmogorov-Smirnov test (K-S test) ; (3) assessment of overall accuracy of different ET_a estimates; (4) a non-parametric evaluation of temporal aspect in VegET's performance; and (5) a graphical assessment of modeled values that characterized the overall seasonal performances of the VegET by parameterization types. With each procedure we aimed to capture particular aspects of model performance as follows: (1) presence of bias in estimates of daily evapotranspiration; (2) any substantial difference in distribution of errors as a function of parameterization type; (3) ability of the models to maintain similar levels of accuracy across vegetation types and locations; (4) ability of the different phenological

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parameterizations to bring VegET predictions closer to observations during three main phases of growing season; and (5) consequences of assumptions and errors in phenological forcings projected on total seasonal *ET*.

To analyze the differences in performance between the six alternative parameterizations of the VegET, we first focus on analyzing the distributions of residuals (DOR). Here, the shape and location of the distribution relative to zero deviation describes the precision and accuracy of model output. Out of the six sets of results, the parameterization that produces an average difference from observations closest to zero is preferred. Also, analysis of residuals allows using the mean root square error (RMSE) as a metric of error spread. Lower RMSE means that the parameters from a particular source produce outcomes with higher accuracy. A better performing phenology representation yields a narrow symmetrical residual distribution centered on zero. We used Student's t-test to evaluate whether each residual distribution was significantly different from zero. However, since the t-test here could not take into account differences in variance, we needed to complement this analysis with the Kolmogorov-Smirnov two-sample test to refine distinctions amongst phenological parameterizations in the predictions made by the VegET. Given the number of the alternative ET_a estimates, we had fifteen pairs for comparison and so, to reduce the risk of a Type I error, we used the Dunn-Sídak procedure to adjust the critical p-value in multiple comparisons (de Beurs and Henebry, 2005).

To assess differential performance across three broad phenophases (green-up, reproduction, and senescence), we used a simple nonparametric score *F* to show the chances of one model to produce a better estimate than another. The procedure assigned scores to *ET* estimates based on residuals: given a pair of *ET* estimates and a specific observation, the estimate with smaller residual would earn the score of 1 and the one with larger difference with observation would receive the score of 0. The total score, whether for a specific phenophase or the whole season, was calculated as follows:

$$F = \frac{\sum_{i=1}^{n} f_i}{n} \quad (4)$$

where n is the number of considered pairs of absolute deviations and f is the score (1 or 0 depending on whether the deviation is less than the reference deviation). A similar scoring approach is used in internal workings of K-S test (Press et al., 1986). This technique also aimed to highlight the temporal consistency in accuracy of different ET_a estimates.

Finally, we needed a measure of VegET performance that could summarize pros and cons of the different parameterizations. We were specifically interested in the ability of the alternative parameterizations to estimate (1) the total seasonal evapotranspiration and (2) the duration of season in days. The use of K_{cp} time series derived from either MODIS or AVHRR climatologies implies fixed growing season trajectories and dates for all sites/locations, regardless of vegetation type. Unlike climatologies, the EDPM can simulate seasonal trajectories of K_{cp} for individual crops and grassland also producing phenological transition dates such as start and end of season. We analyzed the differences between estimated and observed lengths of seasons as well as total seasonal ET to identify the better performer. However, the number of seasons considered for each crop (3 crops) or location (4 locations) was too few to draw statistically reliable inferences separately for each group out of the total 12 seasons. Therefore, we have included figures for each crop type and each parameterization source to illustrate how both the modeled total seasonal ET and the modeled growing season length differed from observations.

All four aspects of model performance were independently analyzed in the context of vegetation type and locations. Geographic differences in evapotranspiration regimes and the magnitude of daily ET_a values between locations gave us another reason not to compare the distribution of estimates, but to examine the residuals instead. Vegetation type is another crucial factor potentially affecting parameterizations of VegET

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since crops and grassland differ dramatically in terms of phenology (Henebry, 2010). Therefore, we present differences in model performance stratified by location and by vegetation type.

3 Results

3.1 Detecting bias in the outcomes

We calculated the differences from the observations (estimated ET_a – observed ET_a) for estimated ET_a derived with the six parameterizations. Figure 3 displays the histograms of the DORs for each version of estimated ET_a structured by vegetation type (A) and by location (B). Central tendencies of obtained DORs are shown as the dotted lines in Fig. 3. The top two rows show results from EDPM forcings, which exhibit low bias in each realization having dotted lines close to 0. In contrast, the DORs for crops produced by static forcings (rows 3 and 4) clearly show overestimation bias. Slightly better alignments can be observed in row 5, which show DORs produced by retrospective MODIS NDVI parameterization of VegET. The grassland DORs exhibit low bias for both climatologies, but also low accuracy resulting from high variability. The DORs from the Penman-Monteith equation appear to be biased positively in each subset, whether structured by vegetation type or location.

In support of this visual assessment of the DORs, the statistical analyses confirm significant biases in the estimates of *ET* produced by the six realizations of VegET (Table 2a and b). Only the residuals from *ET* estimates derived with the EDPM (prescribed PTPs) managed to keep the p-value slightly greater than 0.01 in the bias test for the two crops (Table 2a and b). Both tables show that all sets of ET_a estimates had some bias in every vegetation type, but the t-scores were consistently lower in residuals coming from the EDPM (Table 2a). At the same time, the DORs from the EDPM (prescribed PTPs) showed insignificant bias at Bondville, Mead, and Brookings sites (Table 2b). *ET* estimates from climatologies and retrospective MODIS derived

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K_{cp} show larger means of residuals and higher t-scores than those produced by the EDPM (Table 2a). In Table 2b the situation repeats, with only the South Dakota grassland site showing insignificant bias in satellite-derived parameterizations. As expected, potential evapotranspiration values (*ET-PM*) showed an overestimation of actual *ET* in every subset of residuals.

Estimates of actual evapotranspiration obtained with the use of the EDPM (automatic PTPs) forcings produced DORs with significant biases in every subset except for the site in Brookings, South Dakota. This pattern indicates that the automatic estimation of phenological transition points can become a substantial source of model error. Yet, the biases from the EDPM forcings seen in this experiment were smaller than those produced by climatologies of canopy parameters (AVHRR and MODIS). Also in most cases, the EDPM outcomes had smaller bias than the VegET parameterized with contemporaneous observations of MODIS NDVI expected to be a reference of a better VegET performance.

3.2 Contrasting the distributions of residuals from the six sets of ET_a estimates

The distinctions between biases were captured by the Kolmogorov-Smirnov tests that looked at the divergences between the entire DORs, not just the means. With Dunn-Sidak procedure, we adjusted the critical level of p-value to 0.0007, thereby keeping the overall probability of Type I error below 0.01. Detected differences were organized into diagrams (Fig. 4) showing exhaustive pairwise comparisons of residuals structured by vegetation type and locations. Both automatic and prescribed PTPs in the EDPM gave K_{cp} parameters that performed similarly in grassland and maize, but not in soybeans (Fig. 4). Also, the EDPM parameters with prescribed PTPs produced the DOR different from the one produced by automatic PTPs in Bondville, Illinois, where the sites had both soybean and maize crops. Yet, in 5 out of 7 comparisons the Kolmogorov-Smirnov tests could not distinguish between DORs coming from the two regimes of the EDPM.

Across the vegetation types (top row of Fig. 4) the EDPM parameterizations stood apart from every other phenological parameterization. Similar situation appeared where residuals were stratified by location, except for the Brookings site. At that location the use of EDPM yielded a DOR that could not be distinguished from DORs coming from other parameterizations. The situation at Brookings was unique since the VegET produced no substantial bias regardless of phenological parameterization (Table 2b). Only the Penman-Monteith model substantially overestimated ET_a at Brookings tower (Fig. 4).

The performance of VegET parameterized with the long time averaged MODIS and AVHRR NDVI transformed into K_{cp} turned out to be indistinguishable between the two instruments in all seven comparisons. Only in maize (Fig. 4) were the DORs of climatologies different from the DOR of retrospective MODIS derived K_{cp} parameters. At the same time, the Kolmogorov-Smirnov test failed to distinguish between the DORs from reference ET and the DORs from ET estimates produced with AVHRR and MODIS climatologies in the soybean crop and at Mead, Nebraska. Phenological parameters from contemporaneous MODIS NDVI were found different from Penman-Monteith model in every test combination except for soybean. In total the VegET with different parameterizations went through 35 comparisons with Penman-Monteith model and produced different DORs in 30 cases. These results together with the smaller biases make the VegET stand far apart from ET_0 but closer to the observed ET_a values. Consequently, this distinction serves as an evidence of the crucial role of canopy conditions and phenology in seasonal variation of actual evapotranspiration.

3.3 Comparing overall accuracy of different realizations of VegET

In this section the Fig. 5 shows the root mean squared errors as measures of model accuracy structured by vegetation type and location. RMSEs of the EDPM parameterized VegET (top two bars) were smaller than the RMSEs of potential ET coming from the Penman-Monteith equation (bottom bar). The difference between these RMSEs reached the maximum of 2 mm per day (at Fermi, IL, Fig. 5), but in other cases it dropped as low as 0.2 mm per day (in soybean, Fig. 5). A similar situation was observed for ET_a estimates derived with use of climatologies. The differences with RMSE

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of ET_0, however, were not as drastic. Sometimes the RMSEs from MODIS climatologies were comparable to those from the Penman-Monteith equation (in soybean and at Mead, NE, Fig. 5). Contemporaneous MODIS observations of canopy conditions produced ET_a with smaller RMSEs than either climatologies or the Penman-Monteith equation.

Figure 5 also reveals advantages (smaller RMSEs) of the EDPM forcings over K_{cp} trajectories derived from long term averages of AVHRR and MODIS based NDVI. The contrasts were not as noticeable as with the reference ET, and the differences disappeared for the EDPM with automatic PTPs at Bondville, IL. Yet, with prescribed PTPs the EDPM had an advantage over climatologies in every arrangement with differences varying from 0.3 to 1 mm of ET per day. Figure 5 shows minor dissimilarities between the RMSEs from two realizations of the EDPM parameters. Despite the uncertainty in estimation of phenological timing, the EDPM with automatic PTPs managed to predict canopy conditions for VegET almost as well as it was done by contemporaneous MODIS NDVI observations. The RMSE differences between the EDPM and retrospective MODIS NDVI forcings were negligible within the two crops and grew only up to 0.4 mm per day for the grassland in Fermi, Illinois.

Another important issue depicted in Fig. 5 is the variability of RMSE within one source of canopy parameterization. Without accounting for phenology and soil moisture conditions, the Penman-Monteith equation produces ET estimates with RMSE varying from 1.5 to 3.2 mm per day depending on vegetation type and locations. The forcing from retrospective MODIS NDVI manages to hold the RMSE within 1.2–1.6 level in all cases except for Fermi. ET estimates from climatologies had their RMSEs varying parallel to each other and inflating greatly in the grassland (Fermi, IL). EDPM forcings produced ET_a with the most stable RMSE varying from 1.1 to 1.6 mm per day for the results produced with automatic PTPs. Comparable or greater error levels were reached by Nagler et al. (2005), Cleugh et al. (2007), Mu et al. (2007), Kang et al. (2009), Zhang et al. (2009). The EDPM also managed to produce RMSE of 1.1 to 1.2 mm per day for ET estimates derived from prescribed PTPs. The last point suggests that a more stable agreement with observations in the EDPM is achieved with a better capturing of phenophase transitions. At the same time, the variability of errors in VegET outcomes from the EDPM forcings (as seen in Fig. 5) is superior to forcings from climatologies and even to K_{cp} trajectories derived from contemporaneous NDVI.

3.4 Temporal aspects of VegET performance

The temporal aspect of the VegET performance with different parameterization remained hidden until this point. To disclose this detail we calculated F scores (Eq. 4) showing the probability that one coupling scheme was closer to observation than another. Here the main intent was to identify segments of the season when one of the coupling schemes performed better (or worse). The first baseline for comparison was the ET_0 against all other coupling schemes that actually accounted for phenology. The expectation was to see the coupling schemes working most effectively during the green-up and brown-down phases when the phenological factor has a greater dynamic range than during the relatively stable reproductive phase. The upper rows in Fig. 6a and b clearly show that VegET performance with phenological factor derived from climatologies drops during the reproductive phase when compared to the reference ET.

In contrast with the expectation, Fig. 6 shows that both versions of the EPDM-driven VegET largely outperformed the Penman-Monteith equation during all three phenophases. The use of predefined PTPs for the derivation of K_{cp} via EDPM produced higher F-scores even during reproductive phase in most cases. Sometimes, however, the automatic estimation of PTPs was reaching similar performance level showing the same chances (F-scores) in outperforming the Penman-Monteith model. The VegET outcomes for crops derived with the use of climatologies received high scores in the top rows of Fig. 6a and b only during the greenup and senescence. The ET_a produced with contemporaneous MODIS NDVI followed this same pattern with F-scores going slightly higher than those of climatologies. Matching the expectations, the climatologies and the contemporaneous MODIS NDVI parameters did not give an advantage to the VegET during reproductive phase in crops. In grassland (combined)

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and at the two grassland sites, inspection of the top rows of Fig. 6 does not reveal a clear "winner". Nevertheless, every coupling scheme provided better performance for this vegetation type than the "raw" Penman-Monteith model.

The bottom rows of Fig. 6a and b show the chances of EDPM forcings to be more effective than the K_{cp} parameters from other sources: AVHRR climatology, MODIS climatology and MODIS contemporaneous NDVI. The graphs reveal that EDPM produced parameters yielded higher F-scores than climatologies coming from AVHRR for maize during green-up and the reproductive phases. The chances that the EDPM was performing better were also high during the reproductive phase in soybeans. For the senescence, both sets of K_{cp} parameters coming from MODIS produced ET_a with somewhat better F-scores than the EDPM (automatic PTPs) forcings, but with prescribed PTPs, the event driven model managed to keep up even at that stage. For crops and for agricultural sites, the F-scores of the EDPM coupled VegET followed very close patterns during growing seasons: high scores when tested against AVHRR climatologies and somewhat lower scores against phenological parameters from MODIS. For grassland, however, the EDPM forcings produced a very stable (>0.5) level of F-score when tested against all other sources of VegET parameterization. The only noticeable difference within grassland sites arose for the scores of the EDPM over contemporaneous MODIS NDVI derived forcings.

3.5 Assessment of impact from errors in daily estimates on total seasonal ET

Turning from the details and looking at the big picture, it was necessary to demonstrate the implication of the choices made for parameterization of the VegET in its ability to estimate total seasonal ET. Figures 7 and 8 can provide an idea about the consequences of biases in forcings as well as choices made for determining phenological parameters of growing seasons. Considering only the observed timing of a growing season, it became apparent that the overestimation of daily ET_a by VegET climatologies results in additional 100 mm of ET per season on average for crops and somewhat less for grassland. Having observed ranges of seasonal ET between 400 and 700 an

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error of this magnitude can be considered quite substantial. The EDPM with automatic PTP estimation provided parameters with considerably smaller biases resulting in only an additional 50 mm of ET per season for crops or 50 mm less for grassland. Using predefined phenological dates, the EDPM forcings lowered those errors by 50 %.

Figure 8 shows that in addition to the overestimation of daily ET_a, climatologies added extra days to the duration of a season. The extra time was more apparent in crops adding more than 80 days to the growing period of the year. The automatic phenological control module of the EDPM overestimated season durations in crops by less than 20 days on average. For grassland the EDPM underestimated the length of growing cycle by around 30 days. This last issue, however, was better handled by climatologies where they overestimate the length of growing period for grassland by 20 days. Finally, Fig. 8 shows that the differences in observed and estimated lengths of growing season in retrospective MODIS NDVI were not as big as in climatologies but not as small as those of the EDPM.

4 Discussion

4.1 Phenology factor in evapotranspiration process

This modeling experiment highlighted not only the role of phenology in the evapotranspiration, but also showed the particular significance of phenological factor in time, space, and vegetation type. Clearly, the overall impact from phenology in ET over vegetation will always be relative to the dynamic range of changes caused by other factors. The best instance is presented by grassland sites where the dynamic range of physiological changes in the canopy is often overshadowed by the response of grasses to water stress. Consistent F-scores in Fig. 6 for grassland during all three phenophases tell that VegET gives advantage over the P-M model mostly through its ability to incorporate the water stress. For crops, however, the phenological factor becomes the dominant source of advantage pushing the F-scores up during green-up and senescence.

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Therefore, in the systems where other factors have minor influences, phenology becomes the key driving force for evapotranspiration, second only to the weather. The particularities of phenological development and the interaction of phenology with the climate are also important as plant communities shape their growing cycles dynamically in response to current weather conditions. Capturing those particularities by the EDPM provided an advantage and a better idea about evapotranspiration not only on a daily basis but also when giving a seasonal summary.

4.2 Performance of VegET in point based estimation of actual evapotranspiration

The representation of phenology factor turned out to be the key issue of the VegET performance in capturing the temporal dynamics of ET_a. In fact, it is fair to say here that the VegET output was at least as good as its phenological parameters. Relying on contemporaneous 8-day observations of canopy conditions from MODIS the model estimated ET with accuracy that surpassed Penman-Monteith equation by at least 0.5 mm per day. This translates into five tons of water per hectare per day, which can be crucial for farmers trying to estimate plant water demand for irrigation. Of course, the satellite observations arrive only after the fact and for forecasting one must use long term averages of the phenological factor or some other prognostic phenology model. The results of this experiment suggested that, in the case of climatologies, there was a loss of accuracy. However, the use of the event driven phenology model as a source of K_{cp} parameter helped the VegET to give prognoses of ET_a values that were at least as accurate as those produced using 8-day MODIS NDVI observations. The EDPM achieved this level of performance by capturing fine temporal details of canopy component K_{cp}. Most of these details were averaged and smoothed out in climatologies. The retrospective time series of MODIS NDVI appear to do a better job than climatologies, but the temporal details were lost due to the 8-day compositing period and process (Roy et al., 2006).

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Looking at all the aspects of VegET performance in this experiment, we ranked the parameterization sources in a quantitative manner giving 1, 2, or 3 points to the source that performed best, second best, and third for each of the several evaluation criteria. Lower scores indicated better performance.

a. For the smallest average bias, the EDPM ranked first, with retrospective MODIS NDVI second, and climatologies third. The order was also supported by the Student t-test that distinguished the EDPM with prescribed PTPs as the only parameterization source that had insignificant bias in crops and most locations. Yet, the Kolmogorov-Smirnov tests suggested that the residuals from the two EDPM realizations were not so different. Also in the analysis of DORs, the contemporaneous MODIS NDVI parameters stood in between the EDPM forcings (lowest biases) and the climatologies (highest biases).

b. Accuracy assessment with RMSE and F-scores resulted in the EDPM with prescribed PTPs taking first place, with the contemporaneous MODIS NDVI and the EDPM with automatic PTPs placing second and third, respectively. The F-scores also confirmed that ET_a estimates from the VegET coupled with the EDPM working on predefined phenophases had more chances to be closer to observed evapotranspiration than any other realization of the VegET. The retrospective MODIS NDVI placed second in F-scores but the EDPM with automatic PTPs was not too far behind with slightly smaller RMSE.

c. Producing estimates of total seasonal ET and growing season duration, the EDPM outperformed contemporaneous MODIS NDVI and it was a clear winner for crops. However, the advantage (smaller differences in total seasonal ET_a) of the interactive model was not as obvious for grassland. The K_{cp} parameters from climatologies placed third with similar differences with observed seasonal ET and durations of growing period.

Overall, this investigation demonstrated that, when parameterized by climatologies, the VegET lost sensitivity to ongoing shifts in phenological timing and to finer temporal fluctuations of canopy characteristics, especially in crops. Relying on empirical thresholds for determining the start and end of the growing season binds the original methodology to the settings of the original experiment. Transfer of the same threshold to different locations was often problematic for spectral indices such as the NDVI (Verstraete et al., 1996). Therefore, perhaps, even the retrospective MODIS NDVI could not capture the growing season duration using the original constraints proposed for the VegET (Senay, 2008). Relying on a different mechanism and incorporating multiple factors for capturing phenological parameters, the EDPM gave a more realistic response to the changing weather conditions and thereby yielded substantially smaller errors for crops as well as for grassland. Therefore, the overall ranking makes the EDPM-produced K_{cp} the best choice for VegET parameterization out of the six evaluated in this investigation.

4.3 Addressing issues in the EDPM functioning encountered during the experiments

Several caveats should be disclosed here for the future use of the EDPM in the described coupling scheme. Compare to climatologies, EDPM predictions require additional input data and computational effort. The forecast made by the EDPM will depend on the reliability of weather scenarios supplied to the model, but so will the Penman-Monteith estimates of evapotranspiration. For other coupling schemes that do not use weather data already, deployment of the EDPM may be redundant unless the higher level of accuracy is an absolute requirement. Long term averages may deliver sufficient results for places with stable species composition and little to no interannual variation in the course of the growing season. Meanwhile, the EDPM can provide a better phenological parameterization to models of land surface processes, but one must consider that not every factor influencing phenology has yet been brought into the modeling framework. Furthermore, the EDPM was trained to simulate phenologies for only three vegetation types. The automatic estimation of growing season parameters (dates) still constitutes a considerable source of error. The novelty of the event driven approach to phenology may well present an obstacle for wider applications of the model.

The EDPM has made its first steps in simulation experiments, revealing some problems related to the unsettled methodological issues discussed in the companion paper (Kovalskyy and Henebry, 2011) and to limitation in data resources for training and testing. These problems can be and will be resolved as more flux tower data flow to the archives of AmeriFlux and other microclimatological data networks. However, we do not propose here that all of the problems in *ET* forecasting can be solved with good phenological forcing, since it has only a relative impact on *ET*. Training the model on new data and refining the patterns of vegetation responses to different event types has the potential to improve accuracy of outcomes produced by the EDPM. Though, the consistency and quality of microclimate records – training materials – can pose an obstacle for addressing model performance issues. New types of events should be included in the framework to drive the curves of canopy dynamics of current and new vegetation types. The work should continue on enhancing the precision of automatic estimation of the phenological transition dates.

4.4 Assessing the application potential for the event driven phenology model

Despite known issues, the EDPM and VegET coupling scheme showed potential to be used in modeling of evapotranspiration over vegetated areas. The biases and error measures of the produced estimates were comparable to those encountered in other investigations (Nagler et al., 2005; Kang et al., 2009; Zhang et al., 2009). Stability of error levels across vegetation types and locations seen in this experiment makes this scheme attractive for spatially explicit estimation of actual *ET*. Narrow focus of the EDPM on vegetation types allows using maps of vegetation species and mix LSPs within areal units (here pixels, but potentially as polygons). The interactive approach of the EDPM is anticipated to produce more precise trajectories of canopy characteristics, capturing more finely resolved *ET* changes on daily and growing season bases. The inherent limitation for the VegET and EDPM scheme in capturing spatial details would be the relatively coarse spatial resolution of input weather data. However, using the built-in data assimilation scheme (see Kovalskyy and Henebry, 2011), the EDPM is expected to bring in the moderate spatial resolution MODIS NDVI observations to enhance the resolution of VegET model outcomes. Although the current small number of supported vegetation types limits the domain of application to croplands and grasslands of the central part of the United States, extension to other vegetation types should be possible, given the availability of appropriate quality flux tower data. The results of spatially explicit trials of the EDPM plus VegET scheme are to be reported in the forthcoming paper (Kovalskyy et al., 2011a).

5 Conclusions

This investigation has shown how multiple aspects of phenology affect evapotranspiration during the growing season. It provided statistical and graphical evidence that accounting for phenology improves the accuracy of ET_a estimation by the VegET and gives it an advantage over the Penman-Monteith model for all three vegetation types. The level of improvement, however, varies across sources of phenological parameters. We also found that when using climatologies the VegET overestimated total seasonal ET in two aspects. First, climatologies forced the model into overestimation of daily ET_a during the actual growing season and therefore increase total seasonal ET. Second, climatologies overestimated durations of seasons, adding to the gap between estimates and observations of total ET flux during that period. With the standard deviation of more than 5 weeks within crops, it resulted in an additional 100 to 200 mm of ET per season, which can account for about 25 % of seasonal ET in drier western sites. Therefore, we conclude that when used with climatologies, the VegET showed only a modest sensitivity to variation in growing season weather, yet it can offer a benefit if no better alternative is available.

Parameterization of the VegET with the EDPM-simulated K_{cp} proved to be more advantageous in capturing the impact of phenology on ET than the one provided by the climatologies. In both regimes the EDPM produced daily ET_a with smaller RMSE. It is possible, though, that some of the differences between the climatologies and the event driven model for grassland were due to the way of derivation of the canopy coefficient. Yet, the residuals produced by the EDPM were closer to zero for agricultural sites and differed substantially with distribution of residuals coming from VegET with AVHRR or MODIS forcings. Even with automatic estimation of PTPs, the EDPM did a better job improving the accuracy of VegET results to the level achieved by parameters from contemporaneous MODIS NDVI. In the automatic regime the overestimation of total seasonal evapotranspiration did not go beyond 15 %, even for the maize, while the automatic PTP estimation system still has potential for improvement. Hence, we conclude that the EDPM is a better option for phenological parameterization of land surface models than long-term averages of canopy properties.

Finally, this study has opened the door and established a precedent of the EDPM deployment in a coupling scheme to estimate a land surface flux that depends on vegetation dynamics. Even just for *ET* estimation/monitoring over vegetated surfaces, there is an array of models listed by Allen et al. (2007), Kalma et al. (2008), Kustas and Anderson (2009) that might be able to adopt the EDPM for parameterization of their regional applications. At this point, the encouraging results of the EDPM indicate a promising new approach to overcoming the challenge of addressing phenological factors in models of land surface processes.

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Table 1. Arrangement of vegetation types, locations, and years.

Vegetation cover type	Location (latitude, longitude)	Year of the growing season
Maize	Mead, NE (41.01, −96.29)	2002
	Bondville, IL (40.01, −88.29)	2005
	Mead, NE	2006
	Bondville, IL	2007
Soybeans	Bondville, IL	2004
	Mead, NE	2005
	Bondville, IL	2006
	Mead, NE	2007
Grassland	Brookings, SD (44.3453, −96.8362)	2005
	Fermi, IL (41.84, −88.241)	2006
	Fermi, IL	2007
	Brookings, SD	2008

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Table 2a. Presence of bias in VegET outcomes from different phenological parameterization sources: distributions are presented by vegetation types.

Test parameters	*ET-EA*	*ET-EP*	*ET-CA*	*ET-CM*	*ET-OB*	*ET-PM*
Maize						
Mean of residuals	0.52	0.22	1.19	1.18	0.93	1.73
Standard deviation	1.34	1.15	1.19	1.26	1.11	1.35
t-score	5.73	2.85	14.70	13. 80	12. 50	18.80
p-value	<0.01	0.01	<0.01	<0.01	<0.01	<0.01
Soy						
Mean of residuals	0.40	−0.20	1.08	1.08	0.96	1.21
Standard deviation	1.21	1.10	0.97	1.01	0.94	0.94
t-score	4.97	2.71	16.60	16.00	15.10	19.2
p-value	<0.01	0.01	<0.01	<0.01	<0.01	<0.01
Grassland						
Mean of residuals	−0.26	−0.22	0.31	0.55	0.49	1.78
Standard deviation	1.12	1.14	1.73	1.80	1.56	2.04
t-score	4.15	3.56	3.21	5.54	5.60	15.70
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

ET-EA is the *ET* obtained through VegET parameterized by K_{cp} from EDPM in automatic phenological transition point (PTP) estimation regime; *ET-EP* is the *ET* obtained with use of VegET parameterized by K_{cp} from EDPM in prescribed PTP regime; *ET-CA* is the *ET* derived via VegET driven by K_{cp} from AVHRR based climatologies; *ET-CM* is the *ET* derived via VegET driven by K_{cp} from MODIS based long term averages; *ET-OB* is the *ET* derived via VegET driven by K_{cp} transformed from retrospective MODIS time series; *ET-PM* is the results from the Penman-Monteith equation (ET_0).

Table 2b. Presence of bias in VegET outcomes from different phenological parameterization sources: distributions are structured by locations.

Test parameters	*ET-EA*	*ET-EP*	*ET-CA*	*ET-CM*	*ET-OB*	*ET-PM*
Bondville						
Mean of residuals	0.69	0.11	1.15	1.03	0.98	1.77
Standard deviation	1.47	1.24	1.29	1.23	1.21	1.33
t-score	6.62	1.30	12.50	11.80	11.40	18.90
p-value	<0.01	0.19	<0.01	<0.01	<0.01	<0.01
Mead						
Mean of residuals	0.27	−0.08	1.12	1.22	0.91	1.22
Standard deviation	1.06	1.05	0.87	1.06	0.84	1.02
t-score	4.00	1.16	19.70	17.80	16.90	18.60
p-value	<0.01	0.25	<0.01	<0.01	<0.01	<0.01
Fermi						
Mean of residuals	−0.34	−0.36	0.69	0.98	0.77	2.14
Standard deviation	1.14	1.13	1.91	1.96	1.81	2.43
t-score	3.90	4.09	4.65	6.44	5.52	11.40
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Brookings						
Mean of residuals	−0.17	−0.09	−0.10	0.10	0.18	1.40
Standard deviation	1.09	1.13	1.41	1.48	1.18	1.42
t-score	1.92	0.96	0.84	0.87	1.95	12.40
p-value	0.06	0.34	0.40	0.38	0.05	<0.01

ET-EA is the *ET* obtained through VegET parameterized by K_{cp} from EDPM in automatic phenological transition point (PTP) estimation regime; *ET-EP* is the *ET* obtained with use of VegET parameterized by K_{cp} from EDPM in prescribed PTP regime; *ET-CA* is the *ET* derived via VegET driven by K_{cp} from AVHRR based climatologies; *ET-CM* is the *ET* derived via VegET driven by K_{cp} from MODIS based long term averages; *ET-OB* is the *ET* derived via VegET driven by K_{cp} transformed from retrospective MODIS time series; *ET-PM* is the results from the Penman-Monteith equation (ET_0).

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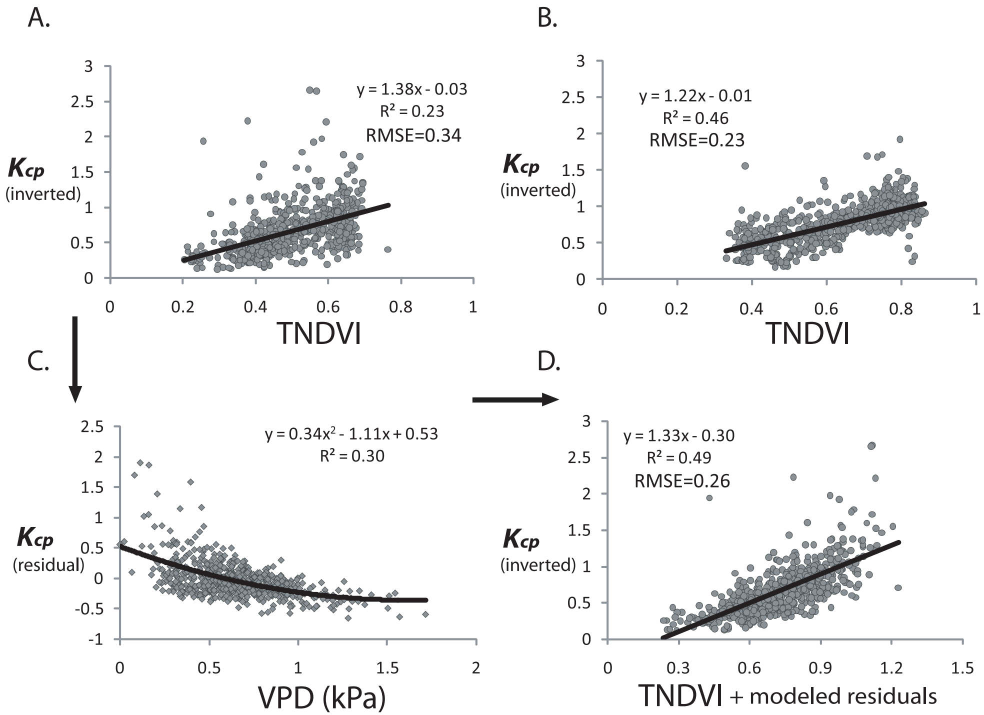

Fig. 1. Derivation of the phenological factor in evapotranspiration (K_{cp}) from TNDVI. **(A)** K_{cp} – TNDVI relationship in grassland. **(B)** K_{cp} – TNDVI relationship in cropland. **(C)** Modeling K_{cp} residuals in grassland. **(D)** Relationship between observed and TNDVI in grassland with modeled residuals added.

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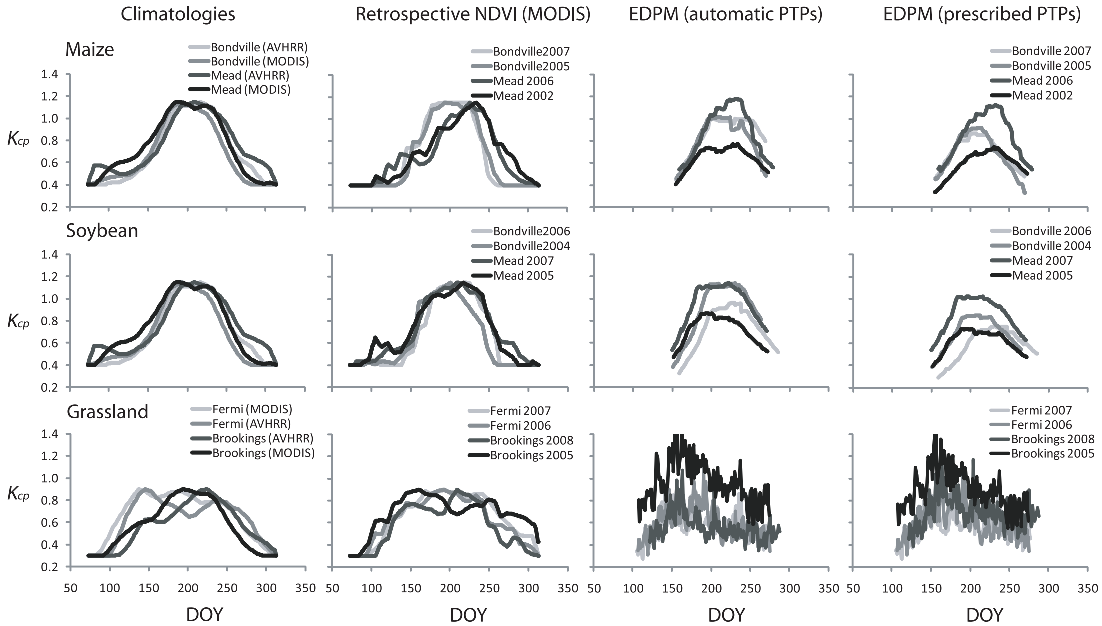

Fig. 2. Phenological parameterizations for the VegET.

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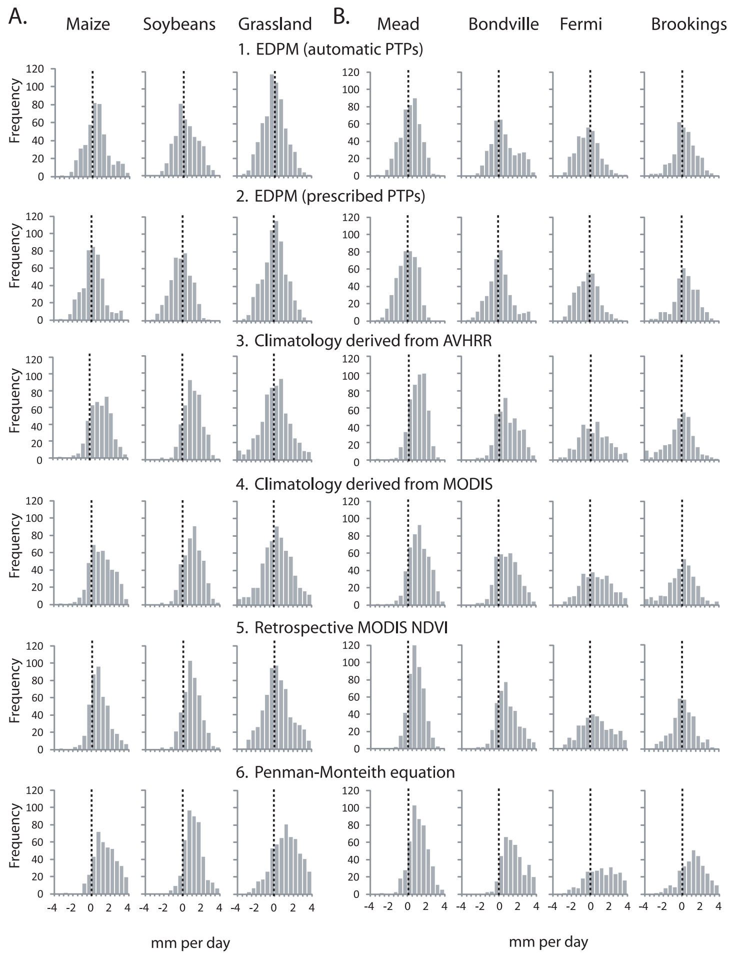

Fig. 3. Histograms of differences of daily ET_a estimates from flux tower observations structured by vegetation/crop type **(A)** and by location **(B)**.

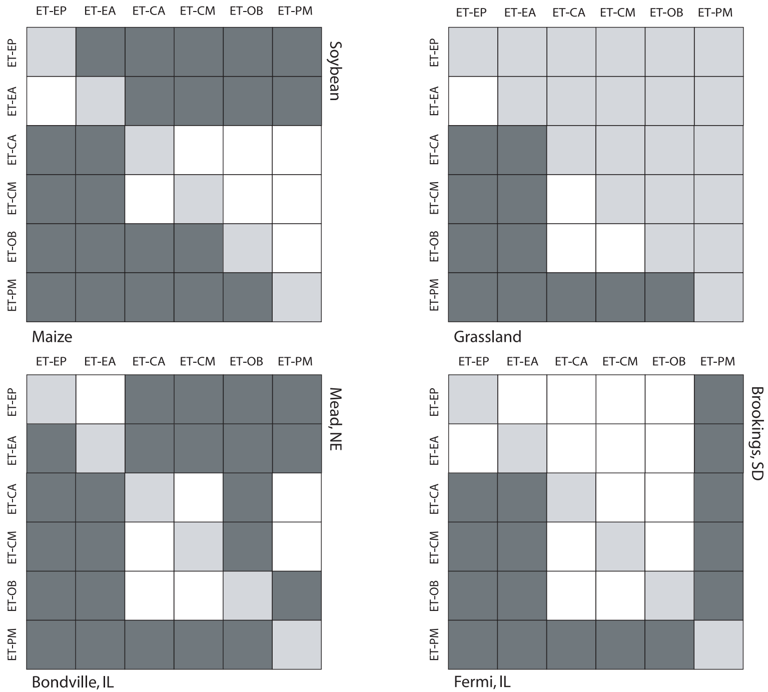

Fig. 4. Diagram of differences between DORs revealed by Kolmogorov-Smirnov tests. In the top row DORs grouped by vegetation type; bottom row – by location. Dark grey color indicates significant difference with p-value <0.01 between compared distributions; white is no significant difference between DORs; light grey is no comparison made. *ET-EA* is the *ET* obtained through VegET parameterized by K_{cp} from EDPM in automatic phenological transition point (PTP) estimation regime; *ET-EP* is the *ET* obtained with use of VegET parameterized by K_{cp} from EDPM in prescribed PTP regime; *ET-CA* is the *ET* derived via VegET driven by K_{cp} from AVHRR based climatologies; *ET-CM* is the *ET* derived via VegET driven by K_{cp} from MODIS based long term averages; *ET-OB* is the *ET* derived via VegET driven by K_{cp} transformed from retrospective MODIS time series; *ET-PM* = ET_0 is the Penman-Monteith equation.

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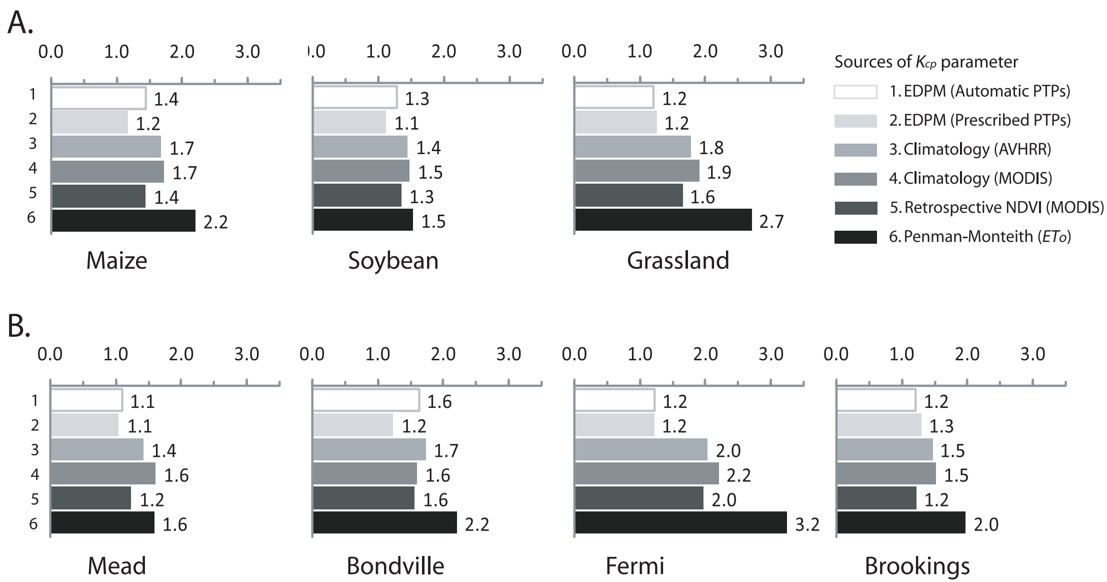

Fig. 5. Root Mean Squared Errors produced by different evapotranspiration estimates: arranged **(A)** by vegetation/crop type and **(B)** by location.

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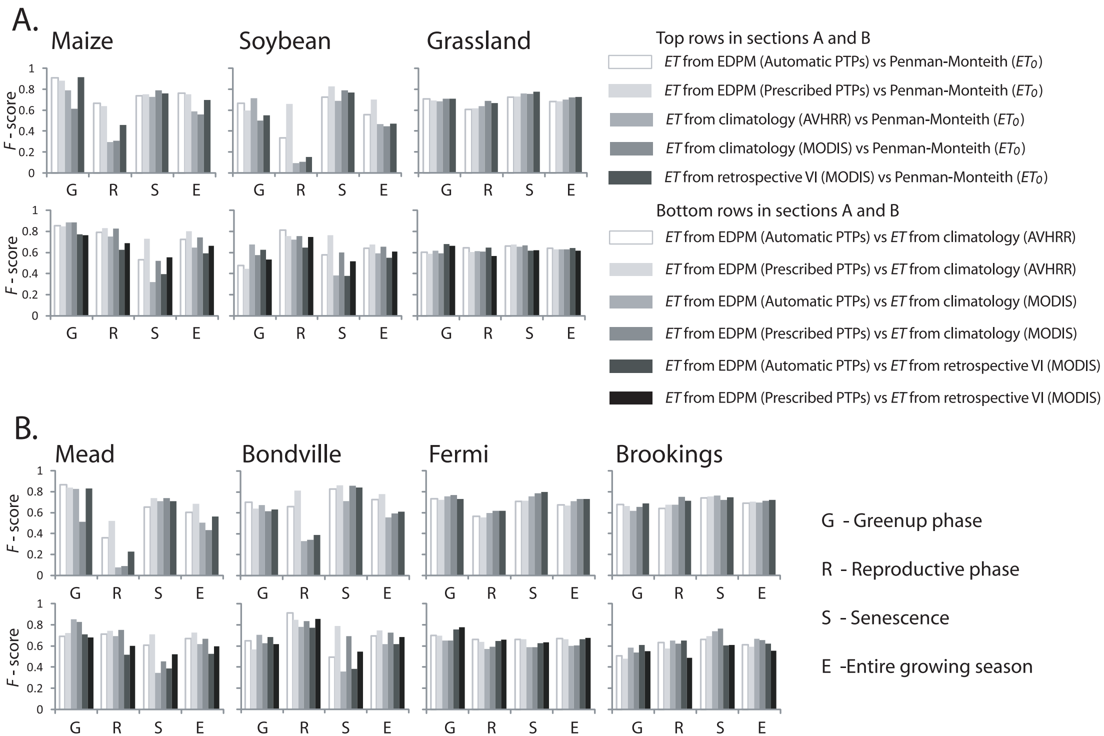

Fig. 6. Temporal details of VegET performance with different phenological forcings revealed by F-scores. Results arranged **(A)** by vegetation/crop type and **(B)** by location.

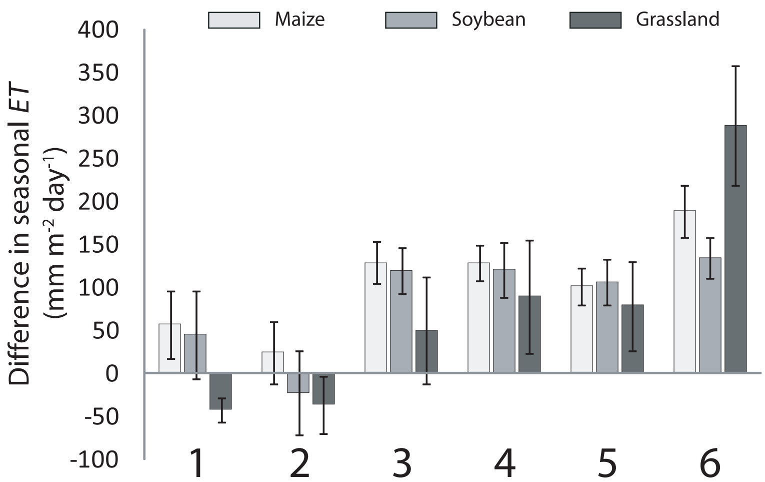

Fig. 7. Consequences of biases in VegET estimates and in total seasonal evapotranspiration: (1) *ET* obtained through VegET parameterized by K_{cp} from EDPM-A; (2) *ET* obtained with use of VegET parameterized by K_{cp} from EDPM-P; (3) *ET* derived via VegET driven by K_{cp} from AVHRR based climatologies; (4) *ET* derived via VegET driven by K_{cp} from MODIS based long term averages; (5) *ET* derived via VegET driven by K_{cp} transformed from retrospective MODIS time series; and (6) results from the Penman-Monteith equation. Error bars show standard errors.

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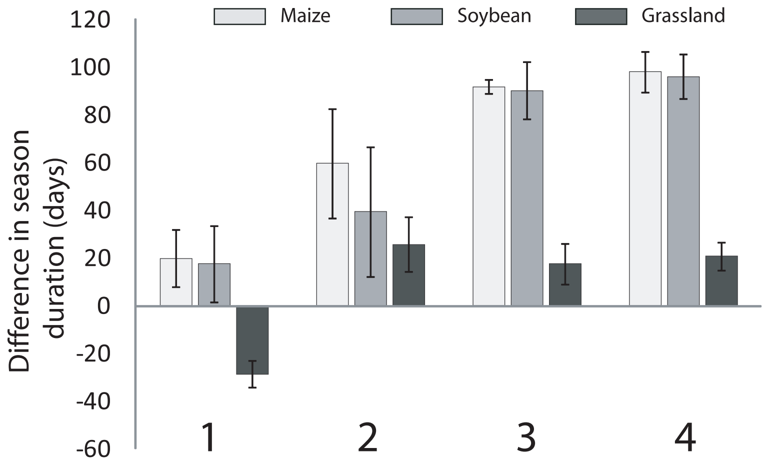

Fig. 8. Implications from choices of methods of determining growing season parameters: (1) differences between observed and estimated season duration from EDPM-A; (2) differences between observed and estimated season duration from retrospective MODIS time series; (3) differences between observed and estimated season duration from AVHRR based climatologies; and (4) differences between observed and estimated season duration from MODIS based long term averages. Error bars show standard errors.

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