Land surface phenology as an integrative diagnostic for landscape modelling

Henebry, G.M.

Geographic Information Science Center of Excellence, South Dakota State University, 1021 Medary Ave., Wecota 506B, Brookings, SD, 57007-3510 USA, Geoffrey.Henebry@sdstate.edu

Abstract: Integrative landscape modelling requires integrative diagnostics to enable both model developers and model users to calibrate and validate against trusted reference data and to evaluate the consequences of simulation experiments. Land surface phenology can serve as such an integrative diagnostic. What phenology is in general and land surface phenology in particular is reviewed. How land surface phenology is well-suited to model tuning and simulation experiments is then discussed. The paper concludes with an example of modelling future land use change in the Northern Great Plains of North America if large areas of croplands currently in maize/soybean rotation shift to perennial grasses harvested for feedstock to cellulosic ethanol biorefineries.

Keywords: land surface phenology; biofuels; switchgrass; maize; Northern Great Plains; North America

1. Phenology and Land Surface Phenology

1.1. Phenology

The seminal conservationist Aldo Leopold observed: "Phenology, in short, is a 'horizontal science' which transects all ordinary biological professions. Whoever sees the land as a whole is likely to have an interest in it" (Leopold and Jones, 1947). This quotation points to the crucial role that phenological data, both observations and simulations, should play in integrative landscape modelling. But what is phenology?

There are several definitions of phenology in circulation. The following statement, first articulated by the US/IBP Phenology Committee, is particularly concise and insightful:

> Phenology is the study of the timing of recurring biological events, the causes of their timing, their relationship to biotic and abiotic forces, and the inter-relations among phases of the same or different species. (Lieth, 1974)

Note that phenology is about the *timing of biotic phenomena*. It is important here to distinguish phenology from seasonality. Seasonality refers to temporal patterns of abiotic variables occurring at annual or sub-annual timescales. Phenology and seasonality are thus complementary aspects of ecosystem function that interact: abiotic forces elicit biotic processes and biotic forces shape abiotic processes (Henebry, 2003).

1.2. Land Surface Phenology

Land surface phenology (hereinafter LSP) describes the spatio-temporal patterns of the vegetated land surface as observed by remote sensors at spatial resolutions and extents relevant to meteorological processes in the atmospheric boundary layer (de Beurs and Henebry, 2004). LSP tracks the seasonal timing and progression of interactions between the land surface and the lower atmosphere, such as the onset of spring in the extra-tropics, heralded by leaf flush and canopy development that lowers the surface albedo and increases the net radiation at the surface bringing a burst of evapotranspiration and moderation of the diel temperature range (Schwartz, 1990; Fitzjarrald *et al.,* 2001). LSP can be influenced by human action: land use and land management practices affect the dynamics of the vegetated land surface—agriculture being the most obvious example. Thus, LSP is central to the modelling and monitoring of weather and climate, the water and carbon cycles, and the human dimensions of regional and global change.

We can observe LSP from orbital platforms by sensing *reflected solar* radiation as visible through shortwave infrared (e.g., Zhang *et al.,* 2006; Wardlow and Egbert, 2008) or *emitted terrestrial* radiation as middle infrared through thermal infrared and microwaves (e.g., Smith *et al.,* 2004; Kimball, 2006), or *backscattered anthropogenic* radiation as radar or lidar (e.g., Kimball *et al.,* 2004; Chasmer *et al.,* 2008). In contrast to the species-centric perspective of traditional phenology, LSP is intrinsically multiscale due to signal mixing arising from sensor spatial resolutions that are coarse relative to the spatial heterogeneity of the observed surfaces, which may include many different plant species as well as abiotic surfaces such as snow, soils, water, and the building materials used in human settlements.

2. Using LSPs in Integrative Landscape Modelling

2.1. LSP as a Model Diagnostic

LSP has long been tracked using the Normalized Difference Vegetation Index (NDVI) that exploits the strong spectral contrast between the near infrared (bright, high reflectance) and red (dark, low reflectance) in healthy green vegetation (e.g., Goward *et al.*, 1985; Justice *et al.*, 1985). LSP has been represented in mesoscale meteorological models by climatologies of fractional vegetation cover (fVeg) or leaf area index (LAI) keyed to specific land cover categories (e.g., Chen and Dudhia, 2001a,b; Skamarock *et al.*, 2008).

NDVI, fVeg, and LAI are all measures of intensive properties (like temperature or density) rather than extensive properties (like heat capacity or biomass). The scale dependency of an intensive property is not known *a priori*; indeed, this scale dependency itself depends on the context of phenomena under investigation, including the specifics on how measurements or simulations are carried out. While this lack of extensivity can complicate inferences about causal influences in observational studies, it can offer some advantages in integrative modelling. I mention here only three.

First, LSPs of complex landscapes can be synthesized through the use of phenological endmembers. Although the NDVI (or another nonlinear spectral vegetation index) is not susceptible to linear (un)mixing, the linear models of the temporal profiles of the NDVI can be mixed (and unmixed). Simple quadratic models that link NDVI to the temporal progression of accumulated growing degree-days (or thermal time, accumulated from January 1st using a base of 0 ^{o}C) have been successfully applied to a variety of settings and scales (de Beurs and Henebry, 2004, 2005, 2008, 2010; de Beurs *et al.*, 2009).

Second, LSPs can be used as a flexible model forcing in simulation experiments. In many models of land surface dynamics, land cover classes are linked to a suite of biophysical attributes. Changing land cover class triggers a cascade of abrupt changes in land surface properties. LSPs can be used to finesse the effects of land management practices or land use changes within land cover classes. Replacing fVeg climatologies in land surface models with LSPs based on remotely sensed observations can elicit significant changes in regional hydrometeorology (e.g., Stauffer *et al.*, 2009).

Third, LSPs bring together the temporal dimension, by tracking the unfolding of vegetation growth and development during the growing season, and the spatial dimension, by articulating the collection of seasonal trajectories within a geospatial reference frame. LSPs can, thus, be characterized by a time series of spatial pattern metrics (Henebry, 1993; Henebry and Su, 1993; Viña and Henebry, 2005). Model diagnostics—whether sensitivity, error, or uncertainty analyses—can be keyed to LSPs either as forcing or response within a Monte Carlo (Henebry, 1995) or resampling (Henebry, 1993; Sherman and Carlstein, 1996) framework.

2.2. Shifting LSPs: From Maize to Switchgrass

Land cover change across the Northern Great Plains of North America over the past three decades has been driven by changes in agricultural land management (shift to conservation tillage; expansion of irrigation; reduction in herbicide applications), government incentives (Conservation Reserve Program; subsidies to maize-based ethanol production), crop varieties (development of cold-hardy soybean and herbicide-resistant maize and soybean), and market dynamics (increasing world demand and crop prices).

Climate change across the Northern Great Plains over the past three decades has been evident in trends toward earlier warmth in the spring and a longer frost-free season. Together these land and climate changes can induce shifts in local and regional LSPs. Any significant shift in LSP may correspond to a significant shift in actual evapotranspiration, with consequences for regional hydrometeorology. For an ongoing study, we are projecting how the regional land surface dynamics could appear across a five-state region (North and South Dakota, Nebraska, Minnesota, and Iowa; Figure 1) under a scenario of widespread cultivation of switchgrass (*Panicum virgatum* L.) or other perennial grasses as cellulosic feedstock for ethanol production. Land use change in the Northern Great Plains associated with ethanol feedstocks (whether a grain like maize or a cellulosic source like switchgrass or maize stover) is likely to be restricted to areas near existing and planned biorefineries.

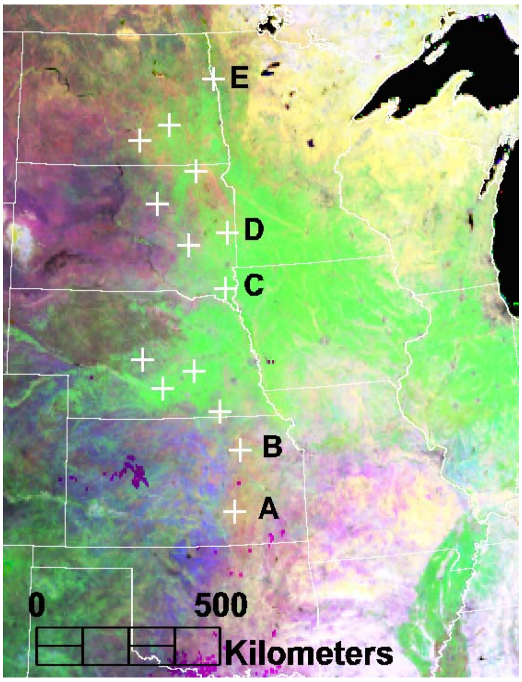

Figure 1. False color composite of three NDVI images derived from MODIS data. Red, green and blue color planes display May 25, August 13, and April 7, 2006, respectively. White crosses indicate weather stations used in the analysis. Refer to Table 1 for detail on labeled sites.

Switchgrass and other perennial C_4 grasses can be found in abundance in the Flint Hills of Kansas, the largest remnant of tallgrass prairie, which is located south of the study region in eastern Kansas (orange elongated elliptical area to the left of labels A and B in Figure 1).

2.3. Toward LSP Transfer Functions

A key problem in projecting future landscapes is simulating the associated land surface phenologies. A recent study of top land surface models concluded that the representations of crop phenologies among the models diverged sufficiently to impede a useful intercomparison of simulation results from their associated climate models (Pitman *et al.*, 2009). Grass phenologies are far more complicated than crop phenologies due to multiple forcing factors, photosynthetic pathways (C_3 vs. C_4), and spatial heterogeneities in resource availabilities and land management practices (Henebry, 2003). Furthermore, many tallgrass species (such as switchgrass) are widely distributed across temperature, but not moisture, gradients, resulting in significant ecotypic variation across the species' geographic range. Thus, how feasible is "transplanting" tallgrass LSPs across isotherms—but along isohyets—to simulate shift from maize to switchgrass?

Hopkins (1918) set forth a ruleset to estimate the offset in the onset of spring in the US east of the Rockies Mountains as a function of latitude (4 days per degree northward), longitude

(1.25 days per degree westward), and elevation (1 day per 100 feet higher). While this widely referenced "bioclimatic law" does capture some geographic patterns, it falls short of an effective transfer function for LSPs.

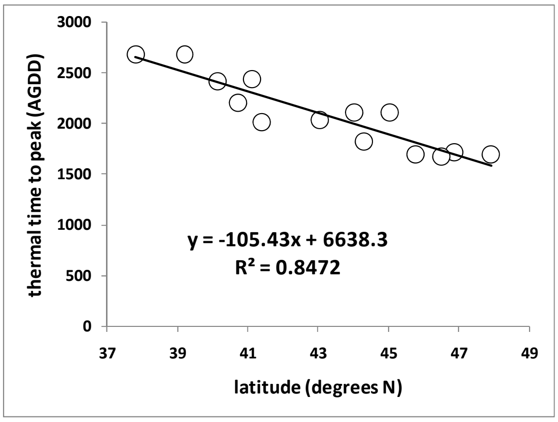

Figure 2. Relationship between the thermal time to peak NDVI (TTP) and latitude.

As noted above, a quadratic model can provide a parsimonious link between an NDVI time series and thermal time:

$$NDVI_t = \alpha + \beta AGDD_t + \gamma AGDD_t^2$$

where $AGDD_t$ is accumulated growing degree-days at day t, which is calculated as:

$$AGDD_t = AGDD_{t-1} + \max(TempAvg_t\text{-}BaseTemp, 0)$$

where $TempAvg_t$ = the simple arithmetic average of maximum and minimum temperatures at day t and BaseTemp is the base temperature (here 0 ^{o}C) and max() is the maximum operator.

The thermal time to peak NDVI (TTP) is a simple function of the parameter coefficients of fitted model (de Beurs and Henebry 2004, 2010):

$$TTP = -\beta/2\gamma$$

Based on LSP quadratic models fit to MODIS NDVI and weather station data at 14 sites from 2000-2009 (shown in Figure 1), Figure 2 shows a strong latitudinal gradient in TTPs in the Northern Great Plains. This gradient results in part from a strong, nearly linear, gradient in accumulated daylight hours between 30 and 50 degrees north. AGDD, however, improves upon accumulated daylight by providing sensitivity to the variability of growing season weather. In turn, there is a geographic pattern in the quadratic parameter coefficients as a function of the TTP, although it is more variable at shorter TTPs (Figure 3). Estimating a quadratic LSP model within the domain is then a four-step process. First, the TTP is calculated as a function of latitude; second, the quadratic coefficient is calculated as a function of TTP; third, we solve for the linear coefficient; and, finally, an intercept must be selected (here 0.20).

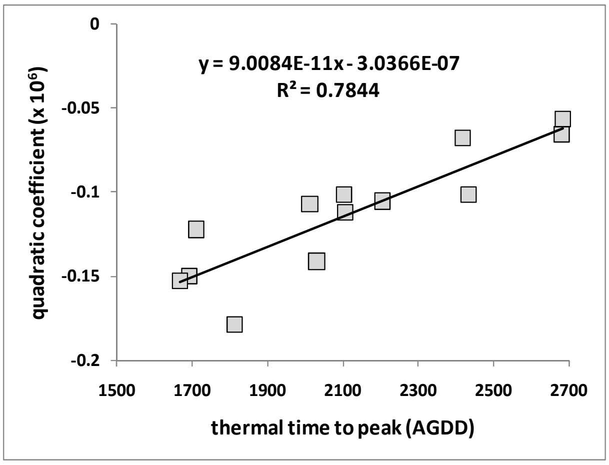

Figure 3. Relationship between quadratic coefficients and TTPs.

This LSP transfer function was implemented at five sites (Table 1). The fits are reasonable except for the most northerly site, Grand Forks, North Dakota, that exhibits in the decade of data two distinct LSP patterns with earlier and later TTPs (Table 1) that the transfer function fails to capture.

Table 1. Characteristics of sites labelled in Figure 1. TTP = Thermal Time to Peak NDVI in accumulated growing degree-days (base 0 °C) calculated from LSP model fit to site data. TTP = TTP estimated by LSP transfer function.*

Label	Site	Latitude (°N)	Longitude (°W)	TTP (°C)	TTP* (°C)
A	El Dorado, KS	37.82	-96.84	2642	2651
B	Manhattan, KS	39.21	-96.60	2520	2504
C	Centerville, SD	43.04	-96.90	2130	2100
D	Brookings, SD	44.32	-96.77	1944	1966
E	Grand Forks, ND	47.92	-97.10	1676 (early) 1801 (late)	1586

Figure 4 shows an estimated switchgrass LSP contrasting with against three years of crop LSPs at Centerville, South Dakota. The change from annual summer to perennial crops affects water and energy exchanges. Integrating under the LSP curves in Figure 4 illustrates this difference; the switchgrass AUC equals 1778 versus 1896, 1962, and 1745 for the crop AUCs in 2000 (mesic), 2006 (hotter, drier) and 2008 (cooler, wetter), respectively, over the period from May 1st to the autumnal equinox. However, the contrast is more pronounced in the early growing season. Integrating from May 1st to June 1st the switchgrass AUC is 282 versus 226 (2000), 306 (2006), and 248 (2008), for the crops.

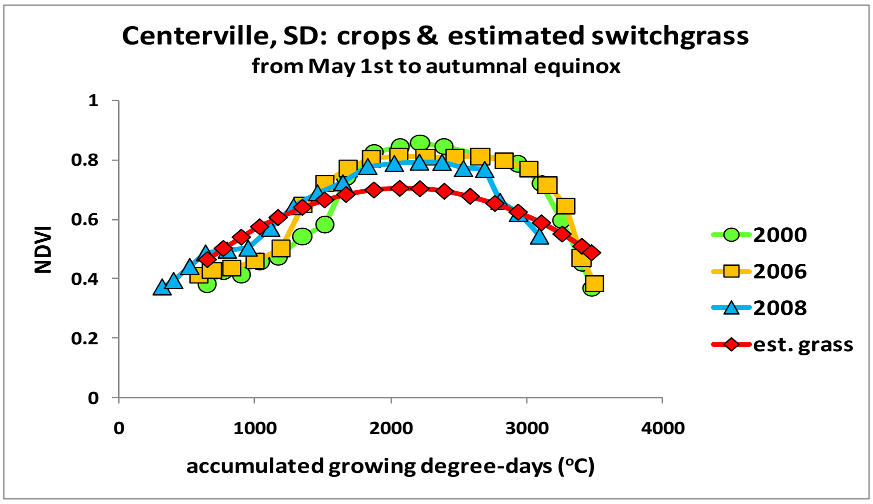

Figure 4. Crop-dominated LSPs versus a switchgrass LSP estimated by the LSP transfer function.

Conclusion: Future Directions for LSP Modelling

Although this LSP transfer function shows some promise, it clearly needs refinement, particularly to be able to capture later season moisture limitations. Indeed, devising a concise, effective parameterization scheme for land surface phenology in moisture-limited landscapes is one of the key challenges for future LSP research.

A recent intercomparison of methods to derive the apparent start-of-season from older optical remote sensing data found that every algorithm evaluated exhibited shortcomings, particularly when exercised across a range of ecosystem types (White *et al.*, 2009). Most of these methods rely solely on a single spectral vegetation index, such as the NDVI. A methodological advance is needed to improve the LSP modeling and monitoring of changes and trends in LSPs.

One promising avenue is the use of multiple remote sensing modalities at multiple spatial and temporal scales. By complementing the NDVI with datastreams from the thermal and microwave regions of the electromagnetic spectrum, a broad range of spatial and temporal resolutions can be brought to bear on the problem, including next generation products from the vast Landsat data archive (Roy *et al.*, 2010).

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