Urban heat island impacts on plant phenology: intra-urban variability and response to land cover

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Title: Urban heat island impacts on plant phenology: Intra-urban variability and response to land cover

Short Title: Urban heat island impacts on plant phenology

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Abstract

Despite documented intra-urban heterogeneity in the urban heat island (UHI) effect, little is known about spatial or temporal variability in plant response to the UHI. Using an automated temperature sensor network in conjunction with Landsat-derived remotely sensed estimates of start/end of the growing season, we investigate the impacts of the UHI on plant phenology in the city of Madison WI (USA) for the 2012-2014 growing seasons. Median urban growing season length (GSL) estimated from temperature sensors is ~5 days longer than surrounding rural areas, and UHI impacts on GSL are relatively consistent from year-to-year. Parks within urban areas experience a subdued expression of GSL lengthening resulting from interactions between the UHI and a park cool island effect. Across all growing seasons, impervious cover in the area surrounding each temperature sensor explains ~50% of observed variability in phenology. Comparisons between long-term estimates of annual mean phenological timing, derived from remote sensing, and temperature-based estimates of individual growing seasons show no relationship at the individual sensor level. The magnitude of disagreement between temperature-based and remotely sensed phenology is a function of impervious and grass cover surrounding the sensor, suggesting that realized GSL is controlled by both local land cover and micrometeorological conditions.
1. Introduction

The urban heat island (UHI) effect is characterized by elevated temperatures in urban areas, relative to the surrounding countryside (Oke 1973, 1982, 1988). Though 60% of global population is expected to live in urban areas by the year 2030, the ecological impacts of the UHI remain poorly understood (Cohen 2006, Jochner and Menzel 2015). UHI-induced increases in temperature can affect plant phenology (the timing of developmental events such as leaf emergence and senescence) both within and around cities (Jochner et al 2012, Jochner and Menzel 2015). Understanding the UHI influence on phenology is critical, as the start of the growing season (SOS), end of the growing season (EOS), and total growing season length (GSL) can have substantial impacts on water, energy, and carbon exchange, which in turn have important feedbacks with climate (Penuelas et al 2009, Richardson et al 2013, Keenan et al 2014). UHI-induced changes in GSL have direct impacts on global food security, as 25-30% of global urban residents, most commonly from the poorest sectors of the population, are involved in food production and 60% of irrigated agriculture (35% rainfed) is within 20 km of urban areas (Orsini et al 2013, Thebo et al 2014). Moreover, UHI-driven advances in spring may compound shifts in growing season length that are already occurring due to climate change (Menzel and Fabian 1999, Schwartz and Reiter 2000) and thus increase the survival and activity of harmful insects and pathogens (Bradley and Altizer 2007).

2010). These studies primarily select one or several species to monitor phenology at discrete points and are not designed to capture variability within urban areas (Mimet *et al* 2009, Fotiou *et al* 2011, Comber and Brunsdon 2015). While sensor networks are widely used to describe UHIs (see Schatz and Kucharik (2014) for a summary of previous work), very few studies have investigated the spatial variability of UHI effects on GSL (Todhunter 1996, Smoliak *et al* 2015).

Due to the difficulty in studying phenological variability from the ground, satellite remote sensing is often used to study spatial variability in GSL to understand the impacts and extent of the UHI. For example, White *et al* (2002), Zhang *et al* (2004), Fisher *et al* (2006), and Elmore *et al* (2012) found increases in GSL ranging from 0-15 days associated with urban areas in the eastern USA, with a zone of influence extending up to 32 km from the urban margin. However, each of these studies relies on either masking out urban areas to study exclusively deciduous forest in or near urban areas or uses satellite data so coarse in resolution that spatial heterogeneity is obscured. These limitations reduce our ability to explore drivers of GSL within urban areas, where the impacts of UHIs on phenology would likely be both strongest and most variable.

In this study, we combine a network of temperature sensors of near unprecedented density and extent (Schatz and Kucharik 2014, Smoliak *et al* 2015) with Landsat-derived phenological metrics at 30 m resolution to study fine-scale degree day-based and remotely sensed response of SOS, EOS, and GSL to the UHI both within and around Madison WI (USA). Specifically, we answer two questions: (1) how do UHI impacts on GSL vary spatially and temporally within cities?; and (2) how does remotely sensed GSL ($GSL_R$) compare to GSL as defined by temperature-based metrics ($GSL_T$)? These questions address two critical knowledge gaps in urban phenological research: the unknown influence of urban composition on phenology.

2. Methods

2.1 Study Area

Our study domain is Dane County (WI, USA), at the center of which is the city of Madison. Madison is a mid-sized urban area located in north-central United States (43°N, 89°W) with a population of 233,000 and an estimated urban agglomeration population of 402,000 (U.S. Census Bureau 2010). The climate is humid continental, characterized by consistently below-
freezing winter temperatures and warm summers with precipitation dominated by convection-based storms. Madison is surrounded by an agricultural landscape intermingled with deciduous forest and lakes (Figure 1a).

2.2 Sensor Data

Beginning in March 2012, 151 HOBO U23 Pro v2 temperature/RH sensors (Onset Computer Corporation, Bourne MA) were installed on utility and streetlight poles in and around Madison. 135 sensors were installed in March 2012, with an additional 6 sensors installed in October 2012 and 10 more in August 2013. All sensors were equipped with radiation shields, installed at a height of 3.5 m, and logged instantaneous temperature every 15 minutes. Sensors were classified as Urban, Rural, Park, Lake, or Wetland at the time of installation. Specifically, urban sensors were defined as within the municipal limits of one of the cities or towns within the Madison metropolitan area (including Madison, Monona, Middleton, Sun Prairie, Fitchburg, Verona, Waunakee, and Stoughton), while rural sensors were outside of these boundaries. Park sensors were within municipal boundaries of a city or town, and inside an officially designated park; parks range in size from 1.7 ha to 520 ha, with a mean (median) size of 101 ha (39.2 ha). A full description of the sensor network, which is one of the most spatially dense and extensive in existence, can be found in Schatz and Kucharik (2014).

A detailed description of our approach for estimating SOS/EOS based on temperature data is described in Appendix S1. In short, we used a heating and cooling degree day (HDD and CDD) approach developed by Richardson et al (2006) for sugar maple, which is the Wisconsin state tree and an important component of Madison’s urban canopy. As this approach represents only a single species and was developed in New Hampshire, we also used a permutation-based
approach to quantify uncertainty associated with our estimate (Serbin et al 2014, Zipper and Loheide 2014). The HDD/CDD approach is based on the concept of thermal time and estimates the start and end of growing seasons based on cumulative temperature above/below a physiologically meaningful threshold (Cannell and Smith 1983, Fu et al 2014b).

As this approach represents only a single species and was developed in New Hampshire, we also used a permutation-based approach to quantify uncertainty associated with our estimate, in which temperature thresholds and other necessary parameters are randomly selected from a distribution in order to provide a range of values, from which both a mean and uncertainty can be estimated (Serbin et al 2014, Zipper and Loheide 2014). We selected a uniform distribution from -0.6°C to 4°C as our temperature threshold range for SOS thresholds for HDD accumulation, as this interval encompasses a range of vegetation, from cold-tolerant to warm-season, and these temperatures have been demonstrated as effective phenological predictors previously (Schwartz and Marotz 1986, Richardson et al 2006). As less data exists for the autumn phenological triggers, we varied our EOS threshold for CDD accumulation over the same 4.4°C range centered on the 20°C value reported by Richardson et al (2006) as most effective for sugar maple.

For each sensor and each growing season, cumulative HDDs beginning January 1 and CDDs beginning August 15 were used to identify the temperature-based SOS/EOS (SOSₜ and EOSₜ, respectively), and GSLₜ was calculated as EOSₜ – SOSₜ. The 2012 SOSₜ is an exception to this, as the sensors were installed in late March and therefore temperatures from a meteorological station at the University of Wisconsin-Madison Arboretum were adjusted for the UHI effect unique to each sensor and used prior to March 27. Differences between urban, park,
and rural sensor classes were tested for statistical significance using a pairwise t-test with significance defined as \( p < 0.05 \).

### 2.3 Satellite Data

A detailed description of the methodology for calculating phenology from remotely sensed data is presented in Appendix S2. We collected all Landsat images of Madison WI (path 24, row 30) over the period 2003-2013 with <40% cloud cover, for a total of 110 images (Figure S1). Each image was atmospherically corrected using the LEDAPS toolchain (Masek et al 2006), cloud-masked using the FMASK utility (Zhu and Woodcock 2012), and clipped to the boundaries of Dane County. We used a double-logistic model (Zhang et al 2003, Fisher et al 2006) to calculate a composite remotely sensed SOS/EOS (SOS\(_R\)/EOS\(_R\)) based on five different vegetation indices and calculated GSL\(_R\) as EOS\(_R\) – SOS\(_R\).

To compare remotely sensed and temperature-based phenology, we averaged SOS\(_R\)/EOS\(_R\)/GSL\(_R\) within a 500 m buffer surrounding each sensor, as this distance has been recommended as a zone of influence for sensor-based studies (Oke 2006) and previous work found that 500 m best describes local climate variability in our study area (Schatz and Kucharik 2014). It is important to note that this timestacking method produces a representative or average SOS\(_R\)/EOS\(_R\)/GSL\(_R\) for the period 2003-2013 at each pixel, rather than SOS\(_R\)/EOS\(_R\)/GSL\(_R\) for each individual growing season (Fisher et al 2006, Elmore et al 2012, Melaas et al 2013). Due to infrequent Landsat overpasses (Figure S1) and common summer cloud cover in the area, using Landsat imagery over a smaller time period such as 2012-2014 for direct comparison with temperature-based method is not possible. However, satellites with more frequent overpasses (e.g. MODIS, AVHRR) have spatial resolutions an order of magnitude coarser, which would
make studying the fine-scale UHI impacts on phenology impossible. While data fusion from multiple sensors shows promise at obtaining phenological estimates at high spatial and temporal resolution (e.g. Liang et al 2014), fusion approaches currently struggle when pixels have a mix of land cover types, and therefore are not well-suited to urban analysis (Walker et al 2012, Zhang et al 2013, Klosterman et al 2014).

To address potential problems associated with comparing 2003-2013 remotely sensed imagery with 2012-2014 temperature data, all pixels containing land use change between 2001 and 2011 (Jin et al 2013) were masked from analysis. Furthermore, we separately fit and estimated phenology using data from the complete Landsat period of record (1982-2013) and carried out all subsequent analysis to determine whether choice of the Landsat period has an impact on results. Only results using the 2003-2013 Landsat imagery are presented here, as using 1982-2013 data did not substantially impact either results or interpretation (data not shown).

2.4 Comparison between temperature-based and remotely sensed approaches

To compare remotely sensed and temperature-based phenology, we averaged SOS$_R$, EOS$_R$, and GSL$_R$ within a 500 m buffer surrounding each sensor, as this distance has been recommended as a zone of influence for sensor-based studies (Oke 2006) and previous work found that 500 m best describes local climate variability in our study area (Schatz and Kucharik 2014). Due to the different time periods of remotely sensed (2003-2013) and temperature-based (2012-2014) methods, it is important to note that a 1:1 relationship of phenological indicators between the methods is neither expected nor important, as the temperature regime controlling the timing of SOS/EOS varies interannually. However, temperature-based results show a consistent year-to-year relationship between SOS$_T$/EOS$_T$ and impervious cover (discussed in Section 3.1).
indicating that the spatial patterns of UHI impact on meteorological conditions conducive to plant growth are consistent from year-to-year. Therefore, we hypothesize that a positive correlation reflecting these patterns exists between $SOS_T/EOS_T$ from individual growing seasons and long-term average $SOS_R/EOS_R$. Our analysis focuses on the correlation and slope of the relationship between remotely sensed and temperature-based methods rather than bias between the two methods, as bias likely reflects the unique characteristics of the 2012-2014 growing seasons compared to the 2003-2013 average (see Ault et al 2013).

As a first-order attempt to quantify the impact of land cover on differences between remotely sensed and temperature-based growing season, we define three difference metrics. For each difference metric, a positive value indicates that remotely sensed estimates correspond to a longer growing season than would be predicted from meteorological data (e.g. $SOS_R < SOS_T$, $EOS_R > EOS_T$, and $GSL_R > GSL_T$):

1. $SOS_{Diff} = SOS_{T\text{Norm}} - SOS_{R\text{Norm}}$
2. $EOS_{Diff} = EOS_{R\text{Norm}} - EOS_{T\text{Norm}}$
3. $GSL_{Diff} = GSL_{R\text{Norm}} - GSL_{T\text{Norm}}$

For each difference metric, a positive value indicates that remotely sensed estimates correspond to a longer growing season than would be predicted from meteorological data (e.g. $SOS_R < SOS_T$, $EOS_R > EOS_T$, and $GSL_R > GSL_T$). To account for the different temperature-based growing seasons (2012-2014) within a single model, we calculated normalized values of $SOS_T$, $EOS_T$, and $GSL_T$ (denoted $SOS_{T\text{Norm}}$, $EOS_{T\text{Norm}}$, and $GSL_{T\text{Norm}}$) by subtracting the yearly mean value across all sensors from each individual sensor’s value, thus centering our data at 0 for all years. Similarly, we subtracted the overall mean value from each sensor’s value for the remotely
sensed metrics $SOS_R$, $EOS_R$, and $GSL_R$ to estimate $SOS_R_{\text{Norm}}$, $EOS_R_{\text{Norm}}$, and $GSL_R_{\text{Norm}}$. Using this technique, there are three difference metrics for each sensor (once for each growing season).

To account for potential impacts of land use change across the interval over which Landsat results were averaged, we eliminated from analysis all pixels classified as changing land cover between 2001-2011 in the National Land Cover Dataset (Jin et al., 2013). Furthermore, we repeated our analysis using $SOS_R$ and $EOS_R$ derived from a different Landsat time window (1982-2013) to check for the impacts of time domain selection on mean phenology, which had no substantial difference in results or interpretation (only 2003-2013 results shown below).

### 2.5 Land cover composition

We used two approaches to characterize the local estimates of the relative composition of impervious, tree, and grass cover at 30 m resolution (Figure 1b-d), both relying on spectral mixture analysis—spectral mixture analysis is a widely used technique for estimating relative composition of different land cover classes by comparing the spectral signature of each pixel to spectra from user-defined reference endmembers (Small 2001, Wu and Murray 2003, Wu 2004, Buyantuyev et al. 2007, Weng 2012). Inputs to both approaches were 30 cloud-free Landsat images collected between 2003-2013 with cropland and water masked (Gan et al. 2014), and spectral mixture analysis was conducted in ENVI 5.0 (Exelis Visual Information Solutions, Boulder, Colorado) and constrained to a unit sum.

In the first approach (referred to as the SMA method), we performed a linear spectral mixture analysis, trained with areas of homogeneous cover manually selected in each of the three classes. In the second approach (referred to as the hybrid method), we use percent impervious cover from the National Land Cover Dataset (NLCD; Xian et al. 2011), a national-level
impervious cover estimate widely used in the urban heat island literature (e.g. Georgescu et al. 2012, 2013, Zhang et al. 2014, Walker et al. 2015, Schatz and Kucharik 2015, 2016). We then used spectral mixture analysis to differentiate between tree and grass cover for the remaining percent land cover in each pixel not accounted for by NLCD impervious estimates. 30 cloud-free Landsat images and the native linear spectral unmixing function in ENVI 5.0 (Exelis Visual Information Solutions, Boulder, Colorado). Unmixing was forced to a unit sum and trained with areas of homogeneous cover manually selected in each of the three classes. Analysis was repeated using impervious cover from the National Land Cover Dataset.

We assessed the accuracy of each method by comparing results to manually digitized 2013 Dane County imagery from the US Department of Agriculture’s National Agricultural Imaging Program (NAIP). NAIP imagery was manually classified into ‘birds-eye view’ percent impervious, tree, and grass cover at 50 randomly selected 90 m x 90 m blocks, which were compared to 3 pixel-square blocks of Landsat-derived land cover (Wu and Murray 2003, Wu 2004, Gan et al. 2014). Comparison between the two methods revealed—no only minor substantial differences in results or which did not alter overall interpretation, but a slightly better performance of the hybrid method (Fry et al. 2011); thus, only results and analysis based on the hybrid method spectral unmixing are reported below in the main body text. Accuracy assessment results and—a comparison of the two methods is presented in Appendix S3. In all linear regressions, significance was testing using a two-tailed t test with significance defined as p < 0.05.

Due to the different time periods of remotely sensed (2003-2013) and temperature-based (2012-2014) methods, it is important to note that a 1:1 relationship between the methods is neither expected nor important, as the temperature regime controlling the timing of SOS/EOS
variants interannually (see Section 3.1). However, the consistent year-to-year relationship between 
SOS\(_T\)/EOS\(_T\) and impervious cover (Figure 3) indicates that the spatial patterns of UHI impact on 
meteorological conditions conducive to plant growth are consistent from year-to-year, and we 
thus hypothesize that a positive correlation reflecting these patterns exists between SOS\(_T\)/EOS\(_T\) 
within individual growing seasons and long-term average SOS\(_R\)/EOS\(_R\). Therefore, our analysis 
focuses on the slope of the relationship and the correlation between remotely sensed and 
temperature-based methods rather than bias between the two methods, as bias likely reflects the 
unique characteristics of the 2012-2014 growing season compared to the longer-term average 
(see Ault et al 2013). To account for potential impacts of land use change across the Landsat 
image interval, we eliminated from analysis pixels classified as changing land cover by Jin et al 
(2013), and also repeated our analysis using a different Landsat time window (1982-2013) to 
check for the impacts of time domain selection, which had no substantial difference in results or 
interpretation (only 2003-2013 results shown below).

3. Results & Discussion

3.1 Temperature-based growing season

The temperature-based growing season shows a strong influence of the UHI (Figure 2 and Figure 3). Median urban sensor SOS\(_T\) is advanced by 0.8, 0.9, and 2.0 days relative to the

**Figure 2.** SOS\(_T\) and EOS\(_T\) based on degree-day technique aggregated by sensor class. Hinges are at the class median, boxes span the interquartile range (IQR), and whiskers span 1.5*IQR with outliers plotted as circles. Letters in boxplots indicate statistically significant differences (p<0.05) tested using pairwise t-test.
rural sensors in 2012, 2013, and 2014, respectively, and urban $E_{OS_T}$ delayed by 4.2, 3.2, and 3.3 days. These changes in $S_{OS_T}$ and $E_{OS_T}$ lead to a statistically significant median increase in $GSL_T$ by 4.9-5.3 days in urban areas (Figure 2).

The changes in $S_{OS_T}$ and $E_{OS_T}$ are related most strongly to the percent impervious land surface cover (%I), a proxy for the density of the built environment, in the area surrounding the sensor (Figure 3). We averaged %I within 500 m of each sensor, as local climate variability in our study area is best described at this distance (Schatz and Kucharik 2014), but changes in buffer radius (100-1000 m) do not substantially alter results (data not shown). Across all years, $R^2$ for the %I-$S_{OS_T}$/-$E_{OS_T}$ relationships range from 0.49-0.58, indicating that physical urban density explains approximately over half of $GSL_T$ variability during most growing seasons. Uncertainty estimates generated using our permutation-based approach show similar trends as a function of impervious cover, indicating that variability in temperature thresholds or degree day accumulation intended to represent a range of potential urban species does not alter the relationship between the urban heat island and phenology.

Phenological shifts when considering rural and urban endmembers, which we define as the minimum (0.7%) and maximum (76.1%) observed impervious cover within a 500 m buffer of all sensors (1.8% and 69.2%, respectively), were even more extreme than shifts in median $S_{OS_T}$/-$E_{OS_T}$. The urban endmember $S_{OS_T}$ was advanced by 1.5-3.6 days and $E_{OS_T}$ delayed by 6.0-7.9 days relative to the rural endmember. This represents a potential UHI-driven extension of the growing season by 8.0-10.5 days, or 4.7-6.2% across our 3 study years.

The magnitude of UHI-driven changes in phenology are strongly determined by the prevailing weather conditions during seasonal transitions. The 2012 and 2014 $S_{OS_T}$ provide a
useful contrast to explore this dynamic. In 2012, much of the US including Madison WI experienced anomalously high late winter temperatures leading to a record-setting ‘false spring’ (Ault et al 2013). This was driven by a regional, synoptic-scale warm front which elevated temperatures above physiologically important thresholds more or less simultaneously across urban and rural parts of our study area, and therefore the small temperature differences caused by the UHI had relatively little effect. In contrast, 2014 experienced a relatively cool spring, which meant that small (1-2°C) increases in temperature due to the UHI were able to contribute a larger proportion of the degree day requirements to trigger the onset of spring. Therefore, the magnitude of urban impacts on $\text{SOS}_T$ were ~2.4 times as strong in 2014 compared to 2012, as measured by the difference in slopes between the two growing seasons (-0.020 days/% in 2012 and -0.048 days/% in 2014). This indicates that studies reporting UHI-driven increases in GSL on the basis of a single growing season (e.g. Schmidlin 1989, Zhang et al 2004) may not be generalizable across time without considering prevailing growing season weather conditions during spring and fall transition periods.

**Figure 3.** $\text{SOS}_T$ and $\text{EOS}_T$ based on degree-day technique, plotted as a function of impervious cover in the 500 m surrounding the sensor calculated using the hybrid method. Colors correspond to sensor type categories as shown in upper left panel. Points represent mean of 100 permutations and vertical lines one standard deviation around each point. Solid black line is a linear fit to means and dashed lines to $+1$ standard deviation outer range of uncertainty. All slopes and intercepts are significantly different from 0 tested using two-tailed $t$-test.
Park sensors tended to have intermediate values of $\text{SOS}_T$ and $\text{EOS}_T$ between the urban and rural sensors, indicating that they likely experience both a UHI effect elevating temperatures above the rural surroundings and a park cool island (PCI) effect reducing temperature relative to their urban surroundings (Taha et al 1991, Spronken-Smith and Oke 1999, Upmanis and Chen 1999, Spronken-Smith et al 2000, Yu and Hien 2006, Feyisa et al 2014). The PCI leads to a subdued expression of the UHI and median park $\text{GSL}_T$ 1.7-3.2 days longer than rural sensors ($p<0.05$ in 2013 & 2014) and 1.5-3.3 days shorter than urban $\text{GSL}_T$ ($p<0.01$ all years). This subdued phenological response to the UHI in parks may be particularly beneficial for native and migratory species which rely on vegetation phenological events for survival (e.g. budburst), as urban parks are often viewed as refugia for species threatened by the urbanization process (Dobrowski 2011, Stagoll et al 2012).

### 3.2 Remotely sensed growing season

$\text{SOS}_R$, $\text{EOS}_R$, and $\text{GSL}_R$ are shown in Figure 4a,c,e. Patterns of urban and peri-urban land surface phenology are consistent with those observed in other studies, with earlier $\text{SOS}_R$ and later $\text{EOS}_R$ observed close to the center of the city (Fisher et al 2006). Due to the elimination of agricultural lands surrounding Madison from analysis, phenological estimates are much less dense outside the urban margin. However, it is evident that $\text{GSL}_R$ is shorter in rural landscape surrounding Madison, with several patches of longer $\text{GSL}_R$ corresponding to small outlying cities and towns. Areas that are predominantly wetland (e.g. northeast and south of Madison) have the shortest observed $\text{GSL}_R$ within our study domain, indicating that the growing season of naturally cool areas is well captured.
Figure 4. Remotely sensed estimates of (a) \( \text{SOS}_R \), (c) \( \text{EOS}_R \), and (e) \( \text{GSL}_R \) with all agriculture, water, and failed fits masked (white areas). (b) and (d) compare \( \text{SOS}_R \) to \( \text{SOS}_T \) and \( \text{EOS}_R \) to \( \text{EOS}_T \), respectively. In (b) and (d), \( \text{SOS}_R \) and \( \text{EOS}_R \) points represent the average \( \text{SOS}/\text{EOS} \) in a 500 m buffer surrounding the sensor as described in Appendix S2; \( \text{SOS}_T \) and \( \text{EOS}_T \) represent the mean of the \( \text{SOS}/\text{EOS} \) from the 2013 and 2014 growing seasons at each sensor (2012 excluded due to false spring). (f) shows \( \text{GSL}_R \) as a function of distance from the city center, which is noted as a purple star in (e). Purple circles in (e) represent 2 km (inner) and 7 km (outer) from city center. Black line in (f) represents the mean and gray shading one standard deviation of all pixels a given distance from center.

Overall, at the county scale, \( \text{GSL}_R \) increases of \( \sim 10-25 \) days are observed within \( \sim 10 \) km from the city center (defined as the Wisconsin state capitol building; purple star in Figure 4e) and
maximum increases occur ~2-7 km from the city center (Figure 4f; purple circles in Figure 4e). These patterns exist due to the combined effects of the Madison lakes (suppressing GSL$_R$ within 2 km of the city center) and the urban-rural transition (occurring ~6.5-11 km from the city center).

We believe that GSL$_R$ is suppressed within the 2 km closest to the city center due to a unique characteristic of Madison, which is that the densest parts of the city are on an isthmus between two lakes (Figure 1). While these lakes visually dominate the landscape, previous work by Schatz and Kucharik (2014) has found that the lake’s zone of influence on temperature is relatively small (100s of meters), and impacts of lakes on temperature decay exponentially with distance from the lakeshore. Therefore, the 2 km closest to the city center (equal to the half-length of the isthmus and shown as the inner purple circle in Figure 4e) represents the area over which lakes contribute a larger proportional influence on temperature and phenology; however, previous work has shown the influence of the lakes on temperature is minor outside of this narrow zone on the isthmus (Schatz and Kucharik, 2014). Within this zone the lake effect leads to increased nighttime air temperature and daytime air temperature during the autumn, but decreased daytime air temperature during the spring and summer, which would lead to a delay in both SOS and EOS. Reduced GSL$_R$ in the 2 km closest to the city center may be due to central Madison’s unique position on an isthmus between two lakes, as the lake effect contributes a larger proportional influence on temperature and phenology within the narrow isthmus. Previous work by Schatz and Kucharik (2014) has found that the lake effect can be characterized by an exponential decay function within a relatively small zone of influence (100s of meters). Within this zone the lake effect leads to increased nighttime air temperature and daytime air temperature during the autumn, but decreased daytime air temperature during the spring and summer, which
would lead to a delay in both SOS and EOS. Overall, impervious cover is the dominant predictor on spatial temperature variability and explains 74% of average daily temperature variability (compared to 19% for lake proximity and 7% for topographic variation).

Instead, the urban-rural transition represents the primary control over observed patterns in GSL$_R$, a pattern similar that shown by Fisher et al (2007) in Providence RI and supporting recent work indicating that urban form determines the spatial extent of urban impacts on the thermal environment (Yang et al 2016). The city of Madison extends ~6.5 km south from the city center, and ~8-11 km on the east and west sides of town; therefore, the radial interval from ~6.5-11 km distance represents the urban-rural transition zone. This transition is evident in Figure 4f, where we can see a decrease in GSL$_R$ over this approximate interval, and relatively static baseline rural GSL$_R$ at distances greater than 11 km. The decrease in GSL$_R$ over this urban-rural transition zone can be explained by two mechanisms. First, this transition is characterized by a decrease in impervious cover with increasing distance from the city center (Figure 1). Based on the observed relationship between GSL$_T$ and impervious cover (Section 3.1), the meteorological period suitable for vegetation growth is longer in urban areas with denser impervious cover and a warmer temperature regime, leading to a lower GSL$_R$ in the surrounding rural areas. Second, urban areas are often characterized by exotic, ornamental, or invasive vegetation (McKinney 2002, Niinemets and Peñuelas 2008), including non-native evergreen plants, which may be characterized by a longer growing season (Shustack et al 2009, Nemec et al 2011). Thus, we suggest that decreases in non-native vegetation moving outward from the city center contributes to the observed decrease in GSL$_R$ over the urban-rural transition zone and reinforces previously described temperature effects. Overall, impervious cover is the dominant predictor on spatial
temperature variability and explains 74% of average daily temperature variability (compared to 19% for lake proximity and 7% for topographic variation).

3.3 Comparison between remotely sensed and temperature-based metrics

Due to the different time periods of remotely sensed (2003-2013) and temperature-based (2012-2014) methods, it is important to note that a 1:1 relationship between the methods is neither expected nor important, as the temperature regime controlling the timing of SOS/EOS varies interannually (see Section 3.1). However, the consistent year-to-year relationship between $SOS_T/EOS_T$ and impervious cover (Figure 3) indicates that the spatial patterns of UHI impact on meteorological conditions conducive to plant growth are consistent from year to year, and we thus hypothesize that a positive correlation reflecting these patterns exists between $SOS_T/EOS_T$ within individual growing seasons and long-term average $SOS_R/EOS_R$. Therefore, our analysis focuses on the slope of the relationship and the correlation between remotely sensed and temperature-based methods rather than bias between the two methods, as bias likely reflects the unique characteristics of the 2012-2014 growing season compared to the longer-term average (see Ault et al. 2013). To account for potential impacts of land use change across the Landsat image interval, we eliminated from analysis pixels classified as changing land cover by Jin et al. (2013), and also repeated our analysis using a different Landsat time window (1982-2013) to check for the impacts of time domain selection, which had no substantial difference in results or interpretation (only 2003-2013 results shown below).
While temperature-based and remotely sensed metrics show comparable patterns of longer growing seasons in urban Madison compared to the rural surroundings, when SOS/EOS are compared directly there is no statistically significant relationship between temperature-based and remotely sensed phenology at the individual sensor level (Figure 4b and 4d; $R^2 < 0.06$). This may be due to variability in species composition, as species-level response to temperature can vary dramatically (Shustack et al. 2009, Zhang et al. 2015), in addition to land cover heterogeneity within the 500 m buffer used for comparison between remotely sensed and temperature-based methods. Urban pixels are typically mixes of the built environment and vegetation (Gao et al. 2006, Klosterman et al. 2014, Walker et al. 2015, Lazzarini et al. 2015), leading to greater variability in both land cover and phenology (Buyantuyev and Wu 2012).

As noted in section 2.4, we did not expect there to be a 1:1 relationship between SOS$_T$/EOS$_T$ (which represents the individual 2012-2014 growing seasons) and estimated using the hybrid method. Positive values on y axis indicate that the remotely sensed predictions of GSL are longer than the temperature threshold estimates. In right set of plots, % Grass and % Trees in Pervious Area must add up to 100 and reported slopes are based on % Grass. Plots exclude sensors with >75% masked pixels within a 500 m buffer. All relationships are statistically significant (intercepts and slopes significantly different from 0 at $p < 0.05$.)
SOS$_R$/EOS$_R$ (which represents the mean of the 2003-2013 growing seasons); rather, we hypothesized that there would be a significant positive correlation between the two methods due to persistent interannual temperature effects on phenology described in Section 3.1, with a bias between methods due to the different sampling intervals. To study the drivers of differences between temperature-based and remotely sensed metrics, we introduced three difference metrics (SOS$_{Diff}$, EOS$_{Diff}$, GSL$_{Diff}$) in Section 2.4. For each difference metric, a positive value indicates that remotely sensed estimates correspond to a longer growing season than would be predicted from meteorological data (e.g. SOS$_R$ < SOS$_T$, EOS$_R$ > EOS$_T$, and GSL$_R$ > GSL$_T$).

We find significant relationships between our different metrics and the land cover in the area surrounding each sensor (Figure 5). Relationships between impervious cover (\%I) and our difference metrics are best explained by a piecewise linear function, with a breakpoint determined as the \%I which minimizes the sum of squared errors between model fit and difference metrics. Breakpoints are consistent across difference metrics at \%I of 35\% (SOS$_{Diff}$), 37\% (EOS$_{Diff}$), and 36\% (GSL$_{Diff}$) (Figure 5). Beneath this breakpoint, increasing \%I is associated with a longer realized growing season relative to meteorological potential at a rate of 6.5 days/10\%, with approximately even contributions from changes to SOS$_{Diff}$ and EOS$_{Diff}$. Above this breakpoint, increasing \%I is associated with a shorter growing season at a rate of 4.1 days/10\%, with ~2 times stronger effects on EOS$_{Diff}$ than SOS$_{Diff}$.

We attribute this piecewise pattern to two drivers: vegetation composition and urban stress regimes. First, moving outward from the city center, land cover transitions between the following classes: (Zone 1) high-density urban areas dominated by impervious cover, to (Zone 2) old neighborhoods with a thick urban canopy dominated by tree cover, to (Zone 3) recently developed areas with sparse urban canopies and a stronger grass signal, to (Zone 4) rural areas.
predominantly characterized by agriculture and trees (Figure 1c-e). Sensors with peak difference metrics (30% < %I < 40%) are primarily in low-density urban areas (Zone 3) surrounding Madison, as well as outlying towns and villages, where grass cover is highest, and the other sensors making up the increasing limb (%I < 36%) are in rural areas or the urban outskirts (Zone 4), where most remaining natural vegetation is trees. Therefore, the increasing limb of the %I relationships represents an increase in the relative proportion of cold-tolerant urban turfgrass within vegetated areas (%G), which is typically green from shortly after snowmelt in the spring until the first winter snowfall, moving from Zone 4 into Zone 3. This is supported by a significant positive correlation between %G and SOS\textsubscript{Diff} (R\textsuperscript{2}=0.24, p<0.001), as well as a weakly positive correlation with EOS\textsubscript{Diff} (R\textsuperscript{2}=0.02, p<0.05) (Figure 5). Overall, GSL\textsubscript{Diff} increases (i.e. the observable period of greenness grows longer relative to our temperature-based estimates) by 2 days for every 10% increase in %G, with ~75% of that change occurring at the beginning of the growing season. The decreasing limb of the %I relationships, then, may also be partially explained by the decrease in grass cover associated with the transition from low-density urban areas surrounding Madison (Zone 3) to the higher-density areas closer to the city center (Zones 1 and 2) in which %G decreases.

As a first-order attempt to quantify the impact of land cover on differences between remotely sensed and temperature-based growing season, we define three difference metrics:

\begin{align*}
(1) \text{SOS}_{\text{Diff}} &= \text{SOS}_T - \text{SOS}_R \\
(2) \text{EOS}_{\text{Diff}} &= \text{EOS}_R - \text{EOS}_T \\
(3) \text{GSL}_{\text{Diff}} &= \text{GSL}_R - \text{GSL}_T
\end{align*}
For each difference metric, a positive value indicates that remotely sensed estimates correspond to a longer growing season than would be predicted from meteorological data (e.g. $S_{OS_R} < S_{OS_T}$, $E_{OS_R} > E_{OS_T}$, and $G_{SL_R} > G_{SL_T}$).

Our difference metrics indicate that different land covers play a different role at the start and end of the growing season. We find that increases in the relative proportion of grass cover within pervious areas ($\%G$) has a significant positive correlation with $S_{OS_{Diff}} (R^2=0.20, p<0.05)$, and a weakly positive correlation with $E_{OS_{Diff}} (R^2=0.03, p<0.10)$, both of which indicate that the realized growing season is longer relative to the meteorological potential in grassier areas (Figure 5). We attribute this to the cold-tolerance of urban turfgrass, which is typically green from shortly after snowmelt in the spring until the first winter snowfall. Therefore, as the relative proportion of grass increases around a sensor, the observable period of greenness grows longer relative to our temperature-based estimates.

In contrast, we also find that increases in impervious cover ($\%I$) in the area surrounding the sensor is weakly correlated with decreases in $E_{OS_{Diff}} (R^2=0.05, p<0.10)$, indicating that the realized growing season is shorter relative to meteorological potential (Figure 5). As impacts of $\%I$ are not observed on $S_{OS_{Diff}}$.

Second, we suggest that the decreasing limb observed in $\%I$ relationships is may be due to vegetation in more urbanized areas experiences increased water or pollutant stress in denser urban areas (Zones 1 and 2), which can lead to early onset of senescence and effectively decouples $E_{OS_R}$ from meteorological conditions (Gratani et al 2000, Honour et al 2009, Sjoman and Nielsen 2010). This is supported by the observation that the slope of the decreasing relationship between $\%I$ and $E_{OS_{Diff}}$ is approximately double the slope of the decreasing relationship between $\%I$ and $S_{OS_{Diff}}$. While our analysis does not consider irrigation, variability
in water available to plants as a result of urban irrigation (e.g. Pataki et al 2011, Bijoor et al 2012, Vico et al 2014) may further decouple \( \text{EOS}_R \) from \( \text{EOS}_T \), e.g. by allowing irrigated vegetation to remain green during drought while non-irrigated vegetation may senesce. Note that 2012 data is excluded from Figures 4 and 5 due to the record-setting false spring which caused significant deviations in \( \text{SOS}_T \) from mean \( \text{SOS}_R \) values. Including 2012 in these analyses contributes to a larger magnitude of offset, but no substantial change in either the correlation between \( \text{SOS}_R \) and \( \text{SOS}_T \), or the slope/strength of the relationships between the difference metrics and land cover.

While our analysis is conducted at a plant functional type level (e.g. grass vs. trees), previous field- and plot-based studies have shown that phenological response to temperature varies at the species level (Bradley et al 1999, Chuine 2000, Primack et al 2004, Morin et al 2009, Vitasse et al 2009, Jochner et al 2013). A further complication is that non-native vegetation is common to urban areas and may be associated with earlier greening in the spring and a concomitantly longer \( \text{GSL}_R \), as discussed in Section 3.2 (McKinney 2002, Niinemets and Peñuelas 2008, Shustack et al 2009, Nemec et al 2011). If we assume that non-native vegetation common to urban areas has a longer growing season than native vegetation, this would cause an earlier \( \text{SOS}_T \) (downward shift of urban sensors in Figure 4b) and a later \( \text{EOS}_T \) (upward shift of urban sensors in Figure 4d), both of which would improve the correlation between temperature-based and remotely sensed phenological metrics. This may be due to variability in species composition, as species-level response to temperature can vary dramatically (Shustack et al 2009, Zhang et al 2015), in addition to land cover heterogeneity within the 500 m buffer used for comparison between remotely sensed and temperature-based methods. Urban pixels are typically mixes of the built environment and vegetation (Gao et al 2006, Klosterman et al 2014, Walker et
While our temperature-based method accounts for potential variability in species-specific biological responses to thermal conditions by varying input parameters to our HDD/CDD equations (see Appendix S1), this technique implicitly assumes a random and homogeneous distribution of all species by equally weighting all parameter combinations when calculating the mean \( \text{SOS}_T/\text{EOS}_T \) for each sensor. To account for spatial variability in species composition, the fitting parameters in Table S1 could be ‘tuned’ to maximize agreement between \( \text{SOS}_T/\text{SOS}_R \) and \( \text{EOS}_T/\text{EOS}_R \) at each sensor (e.g. Fisher et al 2007); however, this approach would assume that temperature is the only factor contributing to spatial variability in phenology, whereas factors such as intra-species variability in response to photoperiod or environmental stressors may contribute to spatial variability in phenology (Gratani et al 2000, Saxe et al 2001, Schaber and Badeck 2003, Honour et al 2009, Caffarra et al 2011). Urban pixels are typically mixes of the built environment and vegetation (Gao et al 2006, Klosterman et al 2014, Walker et al 2015, Lazzarini et al 2015), leading to greater variability in both land cover and phenology than natural areas (Buyantuyev and Wu 2012).

These results provide the first synthesis of remotely sensed phenology with a dense ground-based urban temperature sensor network, and highlight a disagreement between the two methods which is associated with fine-scale variability in land cover. As previous work has reported substantial bias between remotely sensed and observed phenology, \( \text{SOS}_R/\text{EOS}_R \) are typically used to compare the relative timing of phenological events, rather than the exact dates (White et al 2009, Cong et al 2012, Xu et al 2014). However, our results demonstrate here we show that remotely sensed observations of variability in land surface phenology cannot be used
as a proxy for UHI intensity, as the vegetative response to meteorological conditions is dependent on the highly variable land cover within and surrounding a point. Even when focusing on the response of a single plant functional type to the UHI, such as forests in Fisher et al (2006) and Elmore et al (2012), we find that the urban density land cover (particularly %I) surrounding a pixel alters realized GSL and needs to be considered before conclusions can be drawn about the strength of the UHI. These results extend previous work done at larger spatial scales showing a disconnect between meteorological conditions and phenological response (Fisher et al 2007) and indicates that local processes, particularly land cover composition, must be considered as an important control over the vegetative response to changes in land cover in addition to changes in climate.

4. Conclusions

Overall, we find that the UHI has a significant impact on urban phenology with intra-urban variability over fine spatial scales in response to local land cover composition. Across all growing seasons, we find that the UHI leads to statistically significant increases $GSL_T$ in urban areas, driven by earlier $SOS_T$ and later $EOS_T$, and $GSL_T$ (Figure 2) with a park cool island effect partially counteracting the UHI impacts on $GSL_T$ and a small and relatively localized lake effect near the lakeshore (Figure 2). Impervious cover in the area surrounding the temperature sensors explains ~50-70% of observed variability in both $SOS_T$ and $EOS_T$ (Figure 3). However, the magnitude of the UHI impact on phenology varies interannually, and is driven by the prevailing regional weather conditions during the spring/fall transitional seasons. As such, we conclude that studies based on a single year of data should consider meteorological conditions prior to generalizing are likely not generalizable to other growing seasons.
There is substantial intra-urban variability in both GSL$_1$ and GSL$_2$. Fine-scale heterogeneity in both SOS$_T$ and EOS$_T$, which determine GSL$_T$, is largely a function of the land cover, specifically %I, in the surrounding area (Figure 3). Furthermore, we find that the park cool island effect partially counteracts the UHI impact on GSL$_T$, creating an intermediate condition between the rural and urban endmembers (Figure 2).

We find that GSL$_2$ is longest 2–7 km from the city center and remains extended up to 10 km from the city center (Figure 4), which corresponds to the densest development in Madison. Fine-scale heterogeneity in both SOS$_T$ and EOS$_T$, which determine GSL$_T$, is largely a function of the land cover, specifically %I, in the surrounding area (Figure 3). Furthermore, we find that the park cool island effect partially counteracts the UHI impact on GSL$_T$, creating an intermediate condition between the rural and urban endmembers (Figure 2).

Comparison between remotely sensed and temperature-based phenology reveals that there is no relationship between remotely sensed and temperature-based SOS, EOS, or GSL at the individual sensor level (Figure 4b and 4d; $R^2$<0.06). We attribute this primarily to the impacts of variable land impervious cover and vegetation type cover within the 500 m zone of influence surrounding the each sensor on the realized phenological response to meteorological conditions. Our results indicate that differences between remotely sensed and temperature-based phenology are influenced by %I and %G around the sensor (Figure 5). Furthermore, our results demonstrate that remotely sensed phenology cannot be used as a simple proxy for UHI intensity due to potential confounding effects of local land cover composition. This corresponds with previous work indicating that EOS can be triggered by non-temperature variables such as photoperiod or environmental stressors (Gratani et al 2000, Saxe et al 2001, Schaber and Badeck).
2003, Honour et al 2009, Caffarra et al 2011). Critically, these results indicate that variability in remotely sensed greenness cannot be used as a proxy for UHI intensity, as the vegetative response to the temperature-based potential growing season is mediated by local land cover characteristics. These results represent a first step towards better understanding local drivers of phenological variability including environmental stressors, photoperiod, and plant species and functional type variability, which has been suggested by previous studies (Cleland et al 2007).

As impervious surfaces are the defining characteristic of cities worldwide and our results show that local-scale impervious cover represents the dominant control over observed intra-urban variability in phenology, we expect these process-based results conclusions to be broadly applicable to many other cities, particularly in temperate climates. This study represents the first comparison between temperature-based phenological estimates from an urban sensor network and remotely sensed estimates; Our results demonstrate substantial intra-urban variability in UHI impacts on phenology and demonstrate that remotely sensed phenology cannot be used as a simple proxy for UHI intensity. As urban meteorological networks become more common (e.g. Smoliak et al 2015), future work should focus on understanding the role of mechanisms by which land cover in determining influences the vegetative response to urban warming and implications of UHI-induced variability in phenology for water, energy, and nutrient cycling.

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Appendix S1: Estimating phenology from meteorological data

Though many factors such as photoperiod, environmental stressors, and water availability can impact the growing season of vegetation, temperature is the dominant control in high latitudes featuring a winter dormancy period (Bruns et al 2003). As such, a wide spectrum of models have been developed to estimate the start and end of the growing season (SOS and EOS, respectively) based on different temperature metrics, though existing models primarily focus on SOS due to increased difficulties predicting EOS (Schwartz et al 2006, Kucharik et al 2010, Fu et al 2014b, Ault et al 2015, Schatz and Kucharik in review). To estimate SOS and EOS for our study area, we used a heating and cooling degree day (HDD and CDD for spring SOS and autumn EOS, respectively) approach developed by Richardson et al (2006) for sugar maple, a common urban tree in Madison WI. As this method was developed in New England, we also performed a permutation-based test to quantify and account for uncertainty in the transferability of the SOS and EOS relationship across both locations and species, as the degree to which geographically isolated members of the same species respond to temperature conditions is unknown (Vitasse et al 2009, Morin et al 2009).

HDD/CDD approaches using the concept of thermal time, or the integral over time of temperatures exceeding some threshold, to relate daily meteorology to vegetation chilling and heating requirements (Campbell and Sugano 1975, Cannell and Smith 1983). For each day \( i \), the total HDDs and CDDs were calculated as:

\[
HDD_i = \max_{0} \left( T_{\text{Mean}_i} - T_{\text{BaseH}} \right) \quad \text{[Eq. S1]}
\]

\[
CDD_i = \max_{0} \left( T_{\text{BaseC}} - T_{\text{Mean}_i} \right) \quad \text{[Eq. S2]}
\]
where $T_{\text{mean}}$ represents the mean daily temperature, $T_{\text{BaseSOS}}$ is the base temperature for HDD calculations used to determine SOS, and $T_{\text{BaseEOS}}$ is the base temperature for CDD calculations used to determine EOS. Cumulative HDDs and CDDs were then summed for each growing season starting on January 1 (SOS) and August 15 (EOS) and the phenological indicator $P$ was calculated for each day $i$ using the logistic function:

$$P_i(DD) = \frac{4}{1 + \exp(B - M \times DD)} \quad \{\text{Eq. S3}\}$$

where $B$ and $M$ represent fitting parameters and $DD$ represents HDD (for SOS) and CDD (for EOS). The $B$ and $M$ parameters are analogous to intercept and slope in a linear equation, where changes to $B$ shift the $P$ response to $DD$ laterally and changes to $M$ shift the steepness of the $P$ response to $DD$. Equation S3 is bounded to the range 0-4, and $SOS_T$ and $EOS_T$ were calculated separately for each growing season and temperature sensor as the date when $P$ exceeds some threshold ($P_T$), which we follow Richardson et al (2006) in defining as 3 in the spring or 1 in the autumn, respectively.

Our iterative approach addresses uncertainty in both potential adaptations to local climate and the potential for different response to HDDs/CDDs between species by randomly varying the three input parameters for SOS ($T_{\text{BaseSOS}}, B_{\text{SOS}}, M_{\text{SOS}}$) and EOS ($T_{\text{BaseEOS}}, B_{\text{EOS}}, M_{\text{EOS}}$) over realistic ranges to generate a mean and standard deviation estimate of the $SOS_T$ and $EOS_T$ for each sensor and growing season, similar to the approaches used by Serbin et al (2014) and Zipper and Loheide (2014). For each sensor and growing season, $SOS_T$ and $EOS_T$ were calculated 100 times using randomly generated unique combinations of the 3 input parameters representing a reasonable range of potential values, selected using distributions described in Table S1. We selected -0.6°C to 4°C as the range for $T_{\text{BaseSOS}}$ as it represents a range of species sensitivities to cold temperature and have been demonstrated as effective phenological predictors.
previously (Schwartz and Marotz 1986, Richardson et al 2006). As less data exists for the autumn phenological triggers, we varied $T_{\text{BaseEOS}}$ over a 4.4°C range (equal to the $T_{\text{BaseSOS}}$ range) centered on the 20°C value reported by Richardson et al (2006) as most effective for sugar maple. Means and standard deviations for $B_{\text{SOS}}, M_{\text{SOS}}, B_{\text{EOS}},$ and $M_{\text{EOS}}$ were used based on reported uncertainty from Richardson et al (2006).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Distribution</th>
<th>Distribution Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{\text{BaseSOS}}$</td>
<td>Uniform</td>
<td>Minimum -0.6°C</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum 4°C</td>
</tr>
<tr>
<td>$B_{\text{SOS}}$</td>
<td>Normal</td>
<td>Mean 3.42</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Standard Deviation 0.09</td>
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<tr>
<td>$M_{\text{SOS}}$</td>
<td>Normal</td>
<td>Mean 0.028</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Standard Deviation 0.001</td>
</tr>
<tr>
<td>$T_{\text{BaseEOS}}$</td>
<td>Uniform</td>
<td>Minimum 17.8°C</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum 22.2°C</td>
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<td>$B_{\text{EOS}}$</td>
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<td>Mean 3.91</td>
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<tr>
<td></td>
<td></td>
<td>Standard Deviation 0.10</td>
</tr>
<tr>
<td>$M_{\text{EOS}}$</td>
<td>Normal</td>
<td>Mean 0.0117</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Standard Deviation 0.0003</td>
</tr>
</tbody>
</table>

**Table S1.** Values used to define distributions for permutation-based uncertainty analysis.

Using this permutation-based approach, the exact HDD and CDD threshold necessary to trigger SOS$_T$/EOS$_T$ will vary for each randomly selected set of parameters. To determine the HDD/CDD thresholds for a given permutation, equation S3 can be rearranged to solve for $DD$:

$$DD = \frac{B - \ln \left( \frac{4 - \frac{P_T}{P_T}}{P_T} \right)}{M} \quad \{\text{Eq. S4}\}$$

For the parameters of $B$ and $M$ defined in Table S1, Equation S4 solves to a mean expected HDD threshold of 161.4 °C-days for SOS$_T$, and a mean expected CDD threshold of 240.3 °C-days for EOS$_T$.

For the 2012 growing season, temperature sensors were installed in late March, but a complete record beginning January 1 is required for SOS$_T$ calculations. Therefore, daily mean temperature from a long-term meteorological station located in the University of Wisconsin-
Madison Arboretum (Figure 1) was used to gap-fill the temperature time series between January 1-March 27 (DOY 1-86), a period during which the Madison area experienced anomalously warm early season temperatures and a ‘false spring’ which caused widespread early SOS throughout much of the US (Ault et al 2013). To approximate the impacts of the UHI during this period, we calculated the average daily difference between the Arboretum meteorological station and each temperature sensor for DOY 1-86 in 2013 and 2014. This led to a shift in temperature that is uniform over time but unique to each sensor.

Appendix S2: Estimating phenology from Landsat data

We collected 110 Landsat images spanning the time domain 2003-2013. The distribution of images is shown in Figure S1. Pixels classified as agriculture or water by the 2006 National Land Cover Dataset (NLCD; Fry et al 2011) were masked, as the growing season is not physically meaningful for water and agricultural GSL is more a function of management than weather. To avoid potential errors due to land use change, we also masked pixels that changed classification between the 2001 and 2011 NLCD (Jin et al 2013). A variety of vegetation indices (VIs) have been used to estimate phenology from remotely sensed data in previous studies, most commonly EVI (Zhang et al 2003, 2004, Sakamoto et al 2005, Melaas et al 2013, Wu et al 2014) and NDVI (Reed et al 1994, White et al 2002, Bradley et al 2007, Robin...
et al 2007, Walker et al 2015). However, there is uncertainty in both the best vegetation index (White et al 2014) and the best mathematical model (Cong et al 2012, Xu et al 2014) for estimating SOS and EOS from remotely sensed data (SOS<sub>R</sub> and EOS<sub>R</sub>, respectively). We used a composite of the following 5 vegetation indices which have been shown to strongly track vegetation greenness in previous studies:

1. Enhanced Vegetation Index (EVI) (Huete et al 2002).

The following procedure was done separately for each of the five VIs: The measurement date was converted to day of year (DOY) for each image. For each non-masked pixel, we extracted all cloud-free values of VI. VI was then plotted as a function of DOY, and a double-logistic function was fit to the data (Zhang et al 2003):

\[
VI = m5 + m6 \left( \frac{1}{1 + e^{m1 + m2 \cdot DOY}} \right) - \left( \frac{1}{1 + e^{m3 + m4 \cdot DOY}} \right)
\]  

(Eq. S4)

VI corresponds to the vegetation index currently being fit, and \(m1-m6\) are fitting parameters estimated using the Matlab function \(fit\) (Matlab R2014a, The Mathworks Inc., Natick, Massachusetts). The maximum and minimum of the first derivative of Eq. S4 were used as \(SOS_R\) and \(EOS_R\), respectively. Figure S2 shows an example of a fit for a single pixel using SAVI.

After curve-fitting was complete, we had five estimates of \(SOS_R\) and five estimates of \(EOS_R\) at each pixel. We screened for failure of the logistic fit using the following six criteria:

1. \(SOS_R \geq EOS_R\)
(2) \( \text{SOS}_R \leq 60 \) (March 1)

(3) \( \text{SOS}_R \geq 182 \) (July 1)

(4) \( \text{EOS}_R \leq 182 \) (July 1)

(5) \( \text{EOS}_R \geq 335 \) (Dec. 1)

(6) \( \text{GSL}_R \leq 70 \) (10 weeks)

Any pixels that met any of these criteria for any of the five VIs were masked from all subsequent analyses. To generate a composite \( \text{SOS}_R \), \( \text{EOS}_R \), and \( \text{GSL}_R \), we took the arithmetic mean of all 5 estimates of \( \text{SOS}_R \) and \( \text{EOS}_R \) and calculated \( \text{GSL}_R \) as \( \text{EOS}_R - \text{SOS}_R \).

Figure S2. Example of technique for estimating start (\( \text{SOS}_R \)) and end (\( \text{EOS}_R \)) of growing season from Landsat data. Symbols are the same as in Figure S1.
Appendix S3: Comparison between land cover classification methods

We present here a comparison between the hybrid and SMA methods (described in Section 2.4) of estimating the percent impervious, grass, and tree cover over our study domain.

Figure S3 shows maps comparing calculated land cover composition between the two methods. Patterns of land cover composition are very similar between the two methods, with densest impervious cover in the downtown region on the isthmus between the two lakes, as well as outlying commercial developments at the margins of town. Towns and villages within Dane County but not contiguous to the City of Madison are also clearly visible. Grass cover is highest in relatively recent, low-density develops surrounding the City of Madison. Tree cover is dominant in most non-urban areas within the county. The primary differences between the two categories are a higher percent impervious cover and correspondingly lower tree cover in the hybrid method in the medium-density, historic neighborhoods immediate west of the lakes.

**Figure S3.** Comparison of % impervious, grass, and tree cover from (a-c) hybrid method and (d-f) SMA method. (a-c) are the same as (c-e) in Figure 1.
Results of the accuracy assessment for each method are presented in Figure S4. The two methods performed comparably overall (RMSE = 13.4% for hybrid method and 15.7% for the SMA method), with improved impervious surface estimation using the hybrid method (RMSE = 6.4%, relative to 13.7% for SMA method); overall, accuracy is on par with previous studies using SMA to assess impervious and vegetative cover in cities and comparable to the magnitude of error associated with manually digitizing aerial photographs (Small 2001, Wu and Murray 2003, Wu 2004, Kardi 2007, Michishita et al 2012). Impervious cover estimates are more accurate in the hybrid method (in which impervious cover is taken from the NLCD impervious surface area dataset; Xian et al 2011), with an RMSE of 6.4%, relative to 13.8% for the SMA method. Both methods have a slight tendency to underestimate impervious cover in denser urban areas (slopes < 1), though the hybrid method is very close to the 1:1 line.

The accuracy of the two methods is comparable for two vegetation classes, with an RMSE of 15.7% (17.1%) for grass and 15.9% (16.0%) for trees using the hybrid (SMA) methods. Errors in differentiating between vegetation...
classes are primarily driven by a few points with very large errors for both methods. These points occurred in wetland areas which, in this region, are dominated by emergent aquatic vegetation (e.g. cattails) which do not fall neatly into our grass vs. tree binary. Fortunately, wetlands make up a relatively small percentage of total land cover in Dane County (Figure 1a); furthermore, our analysis does not include wetland and lake sensors (our focus is urban, park, and rural classes), indicating potential land cover composition errors in wetland areas have little influence on our results.

Figure S5 shows the relationship between SOS$\text{T}$/EOS$\text{T}$ and impervious cover estimated using the SMA method surrounding each sensor for comparison with Figure 3, in which impervious cover is estimated using the hybrid method. The slope of these relationships, indicating the degree to which impervious cover advances SOS$\text{T}$ or delays EOS$\text{T}$, are virtually unchanged; however, the percent of observed variability explained by impervious cover is substantially higher when using the hybrid method, particularly for EOS$\text{T}$. Overall, however, we observe that we observe that impervious cover explains >49% of observed variability in SOS$\text{T}$ and EOS$\text{T}$.
regardless of land cover composition method chosen, and therefore represents a strong control over the temperature-based potential growing season.

Figure S6 shows difference metrics as a function of the land cover composition surrounding each sensor estimated using the SMA method, for comparison with Figure 5. The sign of all relationships is the same as calculations using the hybrid method, though model fit (measured using $R^2$) are lower when using land cover composition from the SMA method. We also observe that the slope of the relationship between difference metrics and %I gets shallower (closer to 0) for both the increasing and decreasing limbs, and the %I threshold for transition between the two relationships decreases from 36% to 29%. Thus, both methods agree on the sign and direction of the relationships between different metrics and land cover composition, which strengthens our confidence in the relationships described in the text.