# Introduction

**Understanding how plant phenology is affected in space and time by climatic trends and accurately forecasting its trajectory is crucial for planning mitigation strategies for global climate change.** Remote sensing tools, like satellite imaging technology, allow for analyses of phenological patterns over time and broad spatial extents.Data obtained via remote sensing also make identifying drivers of these patterns possible. For example, plant phenology is highly dependent upon environmental cues, and rising global temperatures are expected to have strong impacts. Research indicates that trends in spring phenology have changed noticeably in recent decades, coinciding with rising temperatures ([White et al 2009](file:///D:\morrowcj\Documents\lab-resources\Papers\unorganized-PDFs\j.0030-1299.2008.16588.x.pdf)). Growing seasons are getting longer and starting earlier in many regions ([Hamunyela et al 2013](file:///D:\\morrowcj\\Documents\\lab-resources\\Papers\\unorganized-PDFs\\remotesensing-05-06159.pdf), [Zhang et al 2014](https://link.springer.com/article/10.1007/s00484-014-0802-z)). If these trends are shared worldwide and continue, they could have important impacts on ecosystems by altering species interactions and environmental processes ([Peñuelas & Filella 2001](https://science.sciencemag.org/content/sci/294/5543/793.full.pdf), [Post et al 2008](https://royalsocietypublishing.org/doi/full/10.1098/rspb.2008.0463)). There is a critical need for accurately predicting phenology from climatic drivers to prepare for effects of these alterations. It is also important to identify specific regions and biomes that might be especially sensitive to changes in climatic drivers in the future.

**Using remotely sensed data to answer questions about phenology poses a series of associated challenges.** All remote sensing data suffer from the “point vs. pixel” problem wherein a pixel of satellite data does not perfectly correspond to a true geographic location. Imaging error results in measurements taken from one pixel at multiple time points to cover slightly different geographical areas, which fail to be truly representative of the underlying points ([White et al 2009](file:///D:\morrowcj\Documents\lab-resources\Papers\unorganized-PDFs\j.0030-1299.2008.16588.x.pdf)). An additional challenge inherit to phenology specifically is that satellite derived land surface phenology (LSP) is not identical to plant phenology. LSP is nonetheless a useful proxy for species averaged plant phenology because the two are highly correlated ([Zhang et al 2003](https://www.sciencedirect.com/science/article/pii/S0034425702001359?casa_token=FqB5r5Jps20AAAAA:bfvDvBUlRraipaKSbnY3f9uID4tYptZqpulLut68_E-YywxJ-ESF9U2kXm4PRhvLl012J1yerg), [de Beurs & Henebry 2005](https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2486.2005.00949.x?casa_token=xjQqvrSFeBEAAAAA:81SF8hET1nqMwoOk9uWvjLkKLzsqOJqSURSM1TchDytUTet_Jlh69AaN91_urjVnK47d7PGxK_mpI-0)). However, conclusions from pixel-level LSP *trends* often contradict those made from ground observations (though there has been some effort to address this: see [Hamunyela et al 2013](file:///D:\morrowcj\Documents\lab-resources\Papers\unorganized-PDFs\remotesensing-05-06159.pdf) and [Melaas et al 2016](file:///D:\morrowcj\Documents\lab-resources\Papers\unorganized-PDFs\1-s2.0-S0034425716303571-main.pdf)). The challenges outlined above can be addressed with improved satellite accuracy, ground truthing, and proper calculation of phenology metrics from the spectral data but one additional challenge remains largely unaddressed.

**Perhaps the most problematic challenge facing predictions of global phenology is the presence of spatial and temporal autocorrelation.** An appropriate statistical model for a set of spatially distributed time series recognizes that observations are non-independent in both space and time. Unlike the challenges mentioned above, there has been little research that convincingly accounts for both types of autocorrelation when testing large-scale hypotheses ([de Beurs et al 2015](https://www.sciencedirect.com/science/article/pii/S0034425715301139), Ives et al in prep). This failure could help account for the contradiction between trends in remotely sensed LSP and ground observations over time. However, Ives et al (in prep) showed that their new method can correctly account for both types of autocorrelation in broad-scale hypothesis tests of remote sensing data. The method appropriately differentiates between real trends in a spatially distributed variable over time and stochastic variation. With modification, the method could be adapted to test the effects of climatic drivers on phenology and make comparisons among regions.

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|  |  | *(1)* |

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|  |  | *(2)* |

**This work aims to predict phenology from climatic factors while explicitly accounting for spatial and temporal autocorrelation by modifying an existing statistical method.** A spatiotemporal variable like phenology can be modeled with equation *(1),* which is modified from Ives et al (in prep). In this formulation, is the phenology metric of pixel at time which depends upon an intercept , the pixel’s value at the previous time point , time itself , a climatic factor that is also a function of time , and the values of nearby pixels. The spatial autocorrelation is contained in the residual error term where, for a given time point, . The modified method first estimates the parameter of interest for each pixel using conditional least squares (CLS) regression. The CLS estimator is distinct from a maximum-likelihood estimator because each is treated as independent in this step. is, however, an unbiased and relatively efficient estimator. Equation (2) shows the second step wherein is treated as a correlated variable in a generalized least squares (GLS) regression problem that tests for large-scale effects of on . The spatial correlations among   or any other parameter estimates from (1) can be derived from the correlation of the residuals . In (2), depends upon these residual correlations and a nugget that absorbs additional variation in the error termOptional explanatory terms in (2) allow for comparing effects of on by fixed pixel-level characteristics such as land cover class, latitude, and longitude.

**We will validate this method using simulated datasets and use it to test the effects of air temperature on LSP in the United States.** We will simulate 10,000 datasets with varying true values of and test the modified method for type I errors and statistical power. We will then use the validated method to answer questions about how temperature has affected LSP start of season (SOS), derived from MODIS 20-year greenness product, in the conterminous United States. Three separate metrics of air temperature will be used for comparison purposes: average winter pixel temperatures, average pixel temperatures from one month prior to SOS, and average overall pixel temperature that does not account for temporal variation. The following questions will be addressed: 1) Does air temperature drive SOS trends in the entire region? 2) Do the effects of air temperature on SOS differ among land classes? 3) Do the effects of air temperature on SOS change with increasing latitude and/or longitude?4) How does selection of an air temperature metric affect how conclusions are drawn?

# Contribution to Training

This work provides an opportunity to learn the skills necessary for developing valid statistical methods to solve complex problems. Like the genomics components of my dissertation, remote sensing problems involve massive data sets and require specialized tools to efficiently test hypotheses. A remote sensing phenology problem is superficially disjunct from the rest of my dissertation, which focuses on the role of intraspecific variation in plant-insect interactions. However, both research areas have complex statistical challenges that need to be addressed. Furthermore, developing a broad set of skills is crucial for someone interested in a career in quantitative ecology. My dissertation projects cover a range of approaches that demonstrate this versatility. 1) The resistance study uses classical experimental design to answer questions about variation within a population while controlling for external factors. 2) The insect community study combines a variety of data types and a novel statistical approach to answer questions about the effects of population variability on communities. 3) The remote sensing project validates and applies novel statistical tools towards answering ecologically important questions about the effects of climate on communities.