ANALYZING VEGETATION DYNAMICS BY COMBINING REMOTE SENSING WITH PROCESS-BASED ECOSYSTEM MODELS

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ABSTRACT

Vegetation dynamics over large spatial extents are routinely monitored using data from sensors such as the NOAA AVHRR and MODIS, typically with vegetation indices. Due to the high temporal resolution of these data, both within-season and inter-annual information about these dynamics can be extracted. These patterns can then be related to disturbance, land management, and climate variations/trends. Combining process-based ecosystem models with high-temporal resolution remote sensing offers much potential for adding insights about the patterns and mechanisms underpinning observed vegetation dynamics at these spatial scales, but remains an underutilized avenue of research. In this study, we briefly explain the utility of such a combined approach for elucidating patterns and mechanisms of ecosystem dynamics. This includes direct comparison of remotely sensed data with ecosystem model output as well as assimilation methods. We highlight recent research conducted at Lund University, including disentangling the effects of people and climate on vegetation dynamics in the Sahel, simulating managed land in Africa, and the role of wild fires for simulating pyrogenic carbon emissions. We also outline some of the roadblocks that hamper such developments, drawing from our personal experiences working with data-model integration. In sum, there is untapped potential for the integration of remote sensing with process-based ecosystem models for refining our understanding of vegetation dynamics, as well as further contextualizing the role that terrestrial vegetation plays in the Earth system. These case studies show the benefits of such a synergy.

INTRODUCTION

In the context of scientific enquiry, Earth observation and ecosystem modelling exemplify two very different approaches. Earth observation provides the pattern, and can therefore be considered as 'top-down,' while ecosystem models provide the explanation behind the pattern, and can be considered as 'bottom-up.' These two approaches can therefore play important, complementary roles for studying vegetation dynamics within the Earth system.

In this paper, we discuss recent research that exploits the synergies between ecosystem models and remote sensing for documenting and understanding the causes of vegetation change at continental to global scales. We emphasize recent research carried out at Lund University, and draw partly from these experiences. Accordingly, we briefly review the two main approaches for combining ecosystem process models and remote sensing: A. Direct comparison of ecosystem process model output with remotely sensed data (in combination with ancillary information and sensitivity analyses, either in aggregated or spatially disaggregated mode), and B. Assimilation of satellite data into ecosystem process models in order to improve the accuracy by which the model can simulate various aspects of ecosystem function. Both 'diagnostic' and 'optimization' methods can be included in the second approach. Finally, we round off the paper by a discussion of some research priorities that would help advance this field.

DIRECT DATA-MODEL COMPARISON

Evaluation

Process-based ecosystem models are often used for establishing scenarios of global vegetation distribution and their dynamics decades into the future. It is therefore imperative that they be evaluated against independent data over similarly long spatial and temporal extents (1). The NOAA AVHRR record currently extends over a period of more than three decades with global coverage and can now be used for these ends. Additionally, if such models, driven by historical data on climate, atmospheric composition, and land use, are able to mimic observed long-term trends and inter-annual variability observed in vegetation indices derived for example from NOAA AVHRR and MODIS, much insight can be gained regarding the mechanisms underpinning those trends, as well as improving future prognoses. Data-model comparisons can show if the model correctly interprets its input data and captures a particular process to reasonable degree of accuracy (2). Additionally, where and when data-model divergence occurs can be used to point to where and how a model requires further development.

One of the challenges for the next generation of Earth System models (of which process-based ecosystem models are a subset) is to include realistic and interactive representations of human land use (3), and it is on this leading edge that researchers in Lund are currently active. A primary goal for the development of these models is to test the sensitivity of land management on simulated vegetation phenology and long-term vegetation trends. In this context, phenologies and trends derived from remotely sensed data can be used to gauge how realistically an ecosystem model can capture these patterns. For example, the process-based vegetation LPJ-GUESS (Lund-Potsdam-Jena General Ecosystem Simulator) (4) has recently been updated to include land use and cropland by adapting and modifying the land management algorithms included in LPJ-ml (5). In order to test the accuracy of the model for capturing phenological patterns across Africa with (and without) land use functionality, we have simulated monthly mean FPAR anomalies and compared with monthly maximum GIMMS NDVI anomalies for the period 1982-2006 for twelve regions where the fraction of cropland > 25% (unpublished experiments). Results show that the addition of the land use component improves the fit between FPAR and NDVI (both in terms of magnitude and seasonality timing) for many of the sites. The improvements in fit, however, depend on the climate zone, crop types and irrigation intensities. Consideration of inter-annual variability based on comparing maximum year NDVI and FPAR anomalies resulted in only a marginal improvement in correspondence in many cases.

Hypothesis Testing

Beyond strict model evaluation, data-model comparisons can also be used to isolate the drivers underpinning vegetation dynamics or to test hypotheses regarding direct human impact on vegetation dynamics at the continental scale. For example, (6) tested the extent to which climate and atmospheric CO_2 concentrations could account for the satellite data-observed greening trend (as well as its interannual variability) in the Sahel, using the LPJ-DGVM (Lund Potsdam Jena-Dynamic Global Vegetation Model, (7)). As the LPJ-DGVM was able to simulate the observed long-term greening trend (and its interannual variability) at the aggregated level, they were able to identify rainfall as the primary cause of the trend, with atmospheric CO_2 concentrations only causing a slight linear increase. They accomplished this by running the model several times, successively varying one input variable at a time while fixing the other driving variables at 1982-1998 averages. In a follow-up study, (8) mapped the level of agreement between vegetation amount simulated by the LPJ-DGVM (potential vegetation) and satellite-derived vegetation (actual vegetation) across the Sahel on a cell-by-cell basis for the period 1982-2002. They (8) provisionally rejected the hypothesis that people have had a measurable impact on vegetation dynamics in the Sahel because there was a lack of correspondence between degree of data-model agreement to state-of-the-art data sets on land use and population. Moreover, they showed that the LPJ-DGVM is able to faithfully capture vegetation dynamics for semi-arid grasslands, but not necessarily other biomes.

ASSIMILATION METHODS

Diagnostic Methods

In the first method, one or more ecosystem parameters or variables derived from satellite data are used directly in the model which operates in 'diagnostic mode' allowing for the analysis of changes in various ecosystem properties to be conducted with greater confidence. This can be equated with estimating 'unobserved parameters' (9). The LUE (Light Use Efficiency) model is the most popular of this class of methods and facilitates the transformation of vegetation indices (together with other environmental data, some derived from remote sensing) into primary production, which in turn can be used for assessing changes in the carbon balance of the vegetative pool at continental to global extents. In this approach, primary production is related to the products of incoming PAR (can be derived from a model that includes remotely sensed cloudiness data and atmospheric composition), FPAR (can be derived from vegetation indices) and a growth efficiency factor that takes into consideration suboptimal growth conditions such as drought or nutrient stressors. The growth efficiency factor in some cases is estimated from complex ecosystem models such as LPJ-GUESS (10). The Lund University Light Use Efficiency Model was applied to the Sahel (11) showing that the carbon sequestration rate for the vegetative pool was 3% of the total sequestration rate for the tropics, for the period 1982-1999. Recent work at Lund University has been dedicated to modelling vegetation productivity with the use of MODIS data for boreal and semi-arid ecosystems though the analysis of long-term vegetation dynamics over very large areas remains to be pursued (12-14).

In a novel application of the diagnostic approach, carbon emission dynamics were back-casted from African wild fires (2001-2005) by using the L3JRC burned area product (developed from SPOT VEGETATION S1 reflectance data) to parameterize and update the mechanistic fire model SPITFIRE while embedding it in a LPJ-GUESS framework at a resolution of 1 degree (15). This is a significant advancement in the estimation of carbon loading to the atmosphere because it capitalizes on the compatibility of the vegetation model to account for landscape-scale heterogeneity and vertical vegetation structure (important for determining burn area characteristics and fuel loads) with the spatio-temporal details of the L3JRC product. Moreover, it allowed for more realistic quantification of burn emissions in light of the strongly non-linear relationships amongst the main drivers; rainfall, NPP, and litter production.

Optimization Methods

In the second method, the ecosystem model is not driven by satellite derived inputs (with the exception of land use/land cover information for providing boundary conditions, if required) but rather, key model parameters are adjusted to bring them into alignment with remote sensing observations. This method is particularly effective because remote sensing can lend a spatio-temporal heterogeneity superior to conventional model 'drivers' such as climatologies derived from interpolation. Remote sensing data can therefore be used to capture a critical aspect of reality that is commonly missing in ecosystem models. This is particularly critical for the simulation of systems that display non-linear behaviour where model outcomes are potentially sensitive to initial conditions (9). Though assimilation techniques have a long history in other disciplines (e.g. meteorology, oceanography) their full potential for terrestrial applications remains to be exploited (16). In the context of vegetation dynamics, most work has been carried out in the context crop modelling (17). The general strategy is to simulate the temporal and spatial dynamics of state variables describing the biophysical and biogeochemical properties of the system. A few of these variables are closely related to satellite measurements, in the optical or thermal domain. With the addition of either simple empirical relationships or more complex radiative transfer models, the ecosystem model simulates the spatio-temporal variations of variables that are most comparable to satellite observations Optimization methods (there are many from which to choose) are then employed to minimize the differences between simulations and observations by readjusting the values of key parameters, thus improving the model (9, 16-17). Much work remains to be done within the global process ecosystem modelling domain but there are recent examples for carbon flux prediction and phenological modelling (18, 19). In sum, optimization methods have potential for improving the simulation of vegetation dynamics by reducing uncertainties and therefore adding explanatory value for understanding the functions and feedbacks in the Earth system.

RESEARCH PRIORITIES FOR DATA-MODEL INTEGRATION

Spatial Aggregation Issues

To date, ecosystem process models have not been constructed with remotely sensed data in mind and therefore several challenges remain to be tackled in order to advance the analysis of vegetation dynamics. Firstly, the spatial resolutions of many ecological process models are many orders of magnitude lower than Earth observation data, and bridging this gap is challenging from upscaling standpoints (3). Most ecosystem models assume a 'big-leaf' approach for simulating, for example, radiation regime photosynthesis. The implicit assumption is that the relations between predictor-response variables for a grid cell are the same as that of a single plant in a plot (1). Where predictor-response relations are non-linear, and where much heterogeneity exists within a grid cell (usually 0.5 degrees), significant aggregation error can result. Additionally, it is not always clear how remote sensing products such as vegetation indices or land cover should be aggregated to match the resolution of a modelling grid – different upscaling methods produce different results. Similar issues apply to the temporal domain. For this reason, a systematic survey across a range of ecosystem models and remote sensing data sets would be a clear benefit for assessing the spatial and temporal effects of aggregation on the comparability between observations and model output.

Comparability of Vegetation Indicators

Secondly, the difference between what is observed (from the standpoint of remote sensing) and what is represented (from the standpoint of an ecosystem system model) needs further clarification. Though vegetation indices are related to host of model ecosystem variables such as FPAR, LAI, NPP, etc., there is always a nagging sense that one is comparing 'apples and oranges.' Should the principle of parsimony be applied to rationalize the comparison of a vegetation index to a model output that requires the least number of assumptions to compute, or should the comparison be based on the output variable that is most compatible from a strictly biophysical standpoint? The question of which output variables will also depend on context, but a systematic survey across a range of models and data sets would help resolve some of the uncertainties and provide some guidelines. Additionally, global-scale process models could be modified to produce output that is most consistent with the radiation fields provided by remote sensing.

Poorly Simulated Biomes

Thirdly, a systematic study across and models and data sets should be carried out in order to locate geographical areas/biomes where comparisons are consistently unfavourable. For example, semi-arid regions and and agricultural areas have shown poor correspondence between LPJ-DGVM (without land use) FPAR/LAI and NDVI from the AVHRR (2, 8). Such an investigation would support model improvement (such as the inclusion of land management) or data sets used to drive the model, as well as highlight potential limitations in the satellite data.

Non-linear Vegetation Dynamics

Fourthly, observed, long-term vegetation change may not always occur gradually, but may better be characterized by abrupt shifts or non-linear trends (20). Though it has been demonstrated that ecosystem models can replicate observed inter-annual variability and long-terms changes in vegetation (6, 8) the extent to which they can simulate responses to abrupt (and potentially irreversible) shifts due to shock events such as severe drought requires investigation. Ecosystem models are now evolving toward the inclusion of ecological disturbance and managment (5, 15) so the evaluation of non-linear change should be a priority.

Consistency of Ecosystem Model Drivers

Fifthly, climate data sets of good, consistent quality are required to drive ecosystem models. Data-model correspondence in terms of both intra- and inter-annual vegetation dynamics, for example, can drop considerably over more sparsely vegetated areas where climate stations are few and far between (2,8). These difficulties could potentially be compensated for by the reconstruction of climate fields with the help of satellite observations.

Data Assimilation

Finally, progress is required regarding data assimilation (particularly optimization) at the resolutions, spatial extents, and levels of generalization appropriate for routine, global analysis of vegetation dynamics. Much of the challenge lies in modifying process based ecosystem models that can easily ingest and operate with remotely sensed data, and this requires progress in the various issues outlined above together will efficient computational methods/architectures that will better able to process large volumes of remote sensing data during model implementation (9,16).

CONCLUSIONS

In sum, leveraging process based ecosystem models with Earth observation (and vice versa) is fertile ground for studying vegetation dynamics. Comparing modelled and observed vegetation dynamics can lead to model (and data) improvements. Additionally, model-data comparisons can be exploited to test hypotheses regarding the mechanisms underlying vegetation dynamics. Assimilation methods can drastically reduce uncertainties in both models and data and are valuable for establishing initial conditions for future model predictions. Furthermore, these methods allow the recovery of information on ecosystem function with more realistic spatial heterogeneity, for the length of the satellite data archive. Certain challenges in data-model integration remain in terms of spatial data aggregation, comparability of vegetation indicators, biomes of consistently poor agreement, the quality of model drivers and the ability to simulate abrupt changes and non-linearity in vegetation dynamics. As we enter a data-rich era, data assimilation will attain greater importance as ground observation networks, remote sensing, and ecosystem models will be used together to provide a more coherent picture of the role of vegetation in the Earth system.

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