A NOVEL STATISTICAL METHODOLOGY TO OVERCOME SAMPLING IRREGULARITIES IN THE FOREST INVENTORY DATA AND TO MODEL FOREST CHANGES UNDER DYNAMIC DISTURBANCE REGIMES

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Abstract— Forest inventory datasets offer unprecedented opportunities to model forest dynamics under evolving environmental conditions but they are analytically challenging due to irregular sampling time intervals of the same plot, across the years. We propose here a novel method to model dynamic changes in forest biomass and basal area using forest inventory data. Our methodology involves the following steps: 1) parameterize transition matrices for biomass using Gibbs sampling, 2) incorporate dynamic disturbance and forest growth scenarios and 3) simulate transient dynamics and stationary states using Markov chain model. We extend this method to further include changes in natural disturbance regimes and land-use practices, to predict the impact of changing climate and forest management practices. We apply this methodology on North American forests. We first assess the predictive power of the methodology, without including changing disturbance regimes, in two independent ways: (a) the first years of the dataset are used to predict the later years, and (b) the long-term predictions of two random partitions are compared. The model predicts consistent short-term increases in biomass. We then investigate the consequences of global warming scenarios including changes in forest fire rate in hardwood forests as well as possible growth enhancements due to increasing CO_2 and temperature. We conclude that ongoing increasing biomass trends are relatively unaffected in the short term by changing disturbances regimes. Overall, our original data-intensive methodology provides both descriptions of the short-term dynamics as well as predictions of forest development on a longer timescale.

INTRODUCTION

Existing national forest inventory programs collect a large number of individual tree records on permanent plots and sample forested ecosystems uniformly across the landscape. These databases provide unique opportunities to quantify and examine forest disturbances using a data intensive approach that involves data mining and the development of stochastic models (Lienard et al., 2015a, 2015b). In particular, one approach relying on Markov chain models has recently been developed to capture stand level dynamics from forest inventories (Strigul et al., 2012). These models operate with probabilities of forest state transitions. Markov chain models can be naturally linked with forest inventory data by considering every forest permanent plot as an independent realization of the underlying Markov chain process.

We propose here a novel approach to model stand biomass based on forest inventory data using inhomogeneous Markov Chain processes. We first develop a methodology to estimate the transition matrices based on survey data collected at irregular intervals. We then study how progressive dynamic changes in forest biomass resulting from variations in natural disturbance regimes and land-use practices.

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METHODS

Transition matrix estimation

We consider here an estimated 3-year transition matrix obtained using Gibbs sampling. This matrix is entirely deduced from empirical data and its shape is not constrained by any prior knowledge. Specifically, the matrix is estimated using the following methodology (explained in details in Lienard et al., 2015b):

1. Construct temporal sequences of uncorrelated characteristics depending on forest survey dates.
2. Use Gibbs sampling to infer the transition matrix. This algorithm consists of random initialization of missing values followed by iteration of parameter estimation (a) and data augmentation (b):
   a. Parameter estimation: Compute the transition matrix using the (augmented) sequences of plot transitions.
   b. Data augmentation: Draw new sequences conditional on the new transition matrix.

Dynamic changes of growth and disturbance

We further model hypothetical, dynamic changes of growth and disturbance probabilities with the inclusion of time-dependent terms within the biomass transition matrix (inhomogeneous Markov Chain model). We employ these terms to model forecasted changes in forest fire frequency caused by global warming, and the possible enhanced growth effect resulting from the greater temperature and greater availability of atmospheric. Specifically, we derive lower and upper bounds among the published predictions of forest from the study of Bergeron et al. (2005) and Drever et al. (2009). In accordance with meta-analyses of data gathered in Free-Air CO_2 Enrichment (FACE) experiments and to avoid over-estimation of boosted growth, we settled for a rather conservative growth enhancement of 20 percents until the $3xCO_2$ concentration is reached, around 2090. Figure 2a summarizes the scenarios used in this study.

RESULTS

Estimation of transition matrices

The methodology is able to estimate transition matrices even with irregular survey intervals (e.g. when the time between two successive measurements varies along the years due). In the biomass transition matrix shown in Figure 1, each value at row i and column j corresponds to the probability of transition from state i into state j after 3 years. By definition, rows sum to 100%. This transition matrix is dominated by its diagonal elements, which is expected because few plots show large changes in a given 3-year period. The values below the diagonal correspond to transitions to a lower state (hence, they can be interpreted as the probabilities of disturbance), while values above the diagonal correspond to transitions to a higher state (i.e., growth). The transitions in the first column of the matrix correspond to major disturbances, where the stand transitions to a very low biomass condition. As the probabilities above the diagonal are larger than below the diagonal, the overall 3-year prediction is of an increase in biomass. This matrix also shows that plots with a biomass larger than 40,000 kg/ha have a roughly uniform 10% probability of ending with a biomass of less than 20,000 kg/ha 3 years later, which is interpreted as the probability of high-biomass stand to go through a moderate to high disturbance.

We performed a cross-validations of our methodology by estimating the transition matrix with data from 1970 to 1988, and then used the model to predict forest for the period corresponding to 1989 to 2007. The comparison of the predicted dynamics with the aggregated distribution of the second half of the dataset shows accurate predictions, with R^2 coefficients ranging from 0.8 to 0.95. This indicates that the second half of the dataset is overall predictable with a Markov chain model based solely on the first half.

at time = t + 3 years

at time = t

(in %)	0−2	2−4	4−6	6−8	8−10	10−12	12−14	14−16	16−18	18−20	20−22	22−24	24−26	26−28	28−30	30−32	32−34	34−36	36−38	38−40	40−42	42−44	44−46	46−48	48−50
0−2	65	18	10	2	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2−4	2	53	21	13	5	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4−6	0	5	50	14	11	9	4	2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6−8	0	2	3	53	13	9	7	5	3	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
8−10	0	1	2	2	55	10	9	7	5	2	2	1	1	1	1	0	0	0	0	0	0	0	0	0	0
10−12	0	0	2	3	2	57	8	10	5	4	2	2	1	1	1	1	0	0	0	0	0	0	0	0	0
12−14	0	0	1	3	2	1	58	6	9	7	4	3	1	1	1	0	1	1	0	0	0	0	0	0	0
14−16	0	0	1	1	2	2	2	56	7	8	5	5	2	1	1	1	1	1	1	1	0	0	0	0	0
16−18	1	0	1	2	1	2	1	1	58	5	7	6	5	2	2	1	1	0	1	0	1	0	0	0	0
18−20	0	0	0	1	1	2	1	1	2	60	4	6	4	5	3	1	1	2	1	1	1	1	0	0	0
20−22	1	0	0	0	2	2	1	1	2	2	58	3	5	6	6	3	1	2	1	0	0	1	1	0	0
22−24	0	0	1	1	1	1	1	1	1	1	1	60	5	7	5	3	4	2	0	1	1	1	1	0	0
24−26	0	0	0	0	1	0	1	1	1	1	2	3	58	3	5	6	6	5	1	1	1	1	1	1	0
26−28	0	0	0	0	0	1	2	1	1	1	1	1	2	60	3	6	5	4	4	2	2	1	2	1	1
28−30	0	0	0	0	1	0	1	1	0	1	1	2	1	3	59	5	4	6	4	3	1	2	1	1	1
30−32	0	1	1	0	0	0	1	1	0	1	1	1	1	1	2	61	3	2	9	5	2	2	1	1	1
32−34	0	0	0	1	1	0	1	1	1	1	1	0	1	2	2	1	58	4	5	5	5	2	5	3	1
34−36	0	0	0	0	1	1	0	1	0	0	1	2	1	1	0	1	0	64	2	5	7	6	2	2	1
36−38	1	0	0	0	0	0	0	0	1	1	1	1	2	1	1	1	0	2	62	3	2	5	5	5	3
38−40	1	0	0	0	0	1	1	0	0	1	1	1	1	1	1	1	2	3	2	63	3	4	5	3	4
40−42	0	1	1	0	1	1	1	1	1	1	2	1	2	1	1	1	1	1	2	1	61	5	8	4	4
42−44	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	60	6	8	9
44−46	1	1	0	1	0	1	1	1	1	1	1	1	3	1	1	4	1	2	1	3	1	3	63	3	7
46−48	1	1	1	1	1	1	1	1	1	1	1	1	2	3	1	1	2	1	1	2	3	4	3	64	3
48−50	1	1	1	1	1	1	1	1	1	1	1	2	1	1	2	1	1	2	2	3	2	2	2	3	67

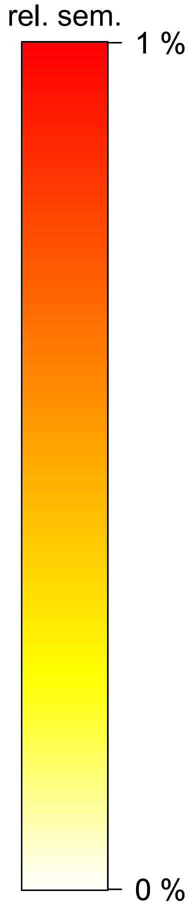

Figure 1—3-year transition matrix for the biomass. The states are the biomass ranges in 10^3 kg/ha, spanning from 0-2 to 48-50 10^3 kg/ha, and represented here on the left and on top of the matrix. The values M(i,j) inside the matrix correspond to the rounded probability of transition from state i to state j, in percents. The color represents the relative standard error of the mean and indicates the uncertainty in the matrix coefficients.

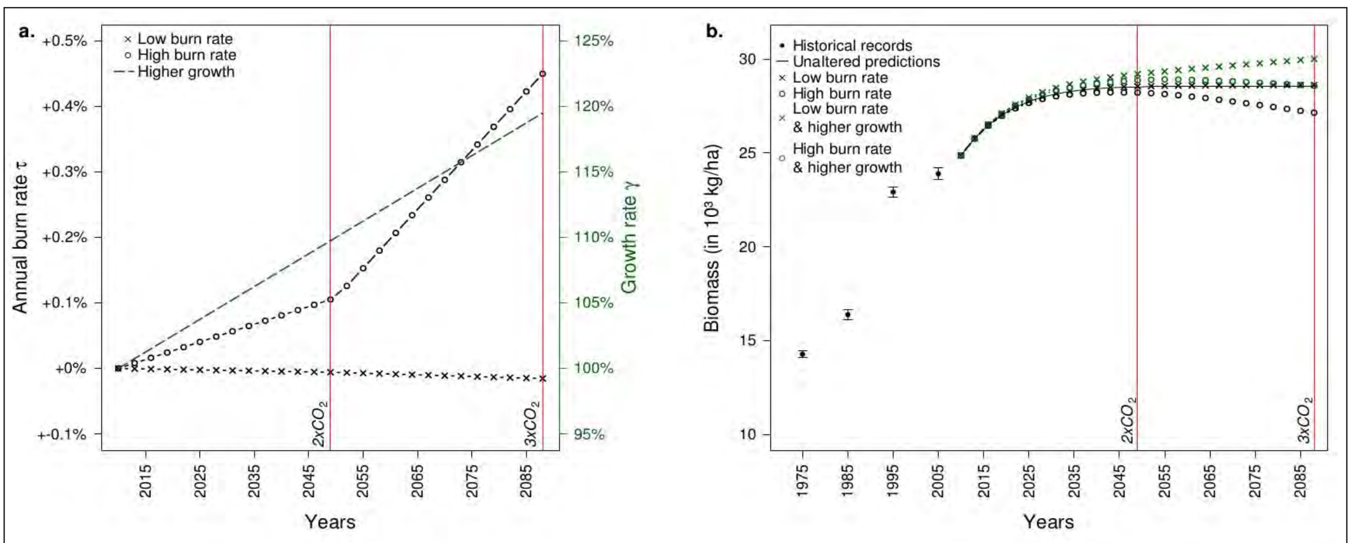

Figure 2—climate-change scenarios and predicted average biomass changes. Panel a: forest fires scenarios (black, left y-axis) and possible growth enhancement (green, right y-axis) in hardwood forests. The two burn rate scenarios were derived from Bergeron et al. (2006); Drever et al. (2009) (see methods for details). Panel b: average biomass predicted with no change in current disturbance regime (solid line) and in the two future burn rate scenarios computed with or without the addition of enhanced growth. Historical biomass records from the forest inventory are displayed in 10-year bins with standard error of the mean.

Climate change scenarios

The average biomass in Quebec hardwood forests displays distinct trajectories and dynamics under the different scenarios (Figure 1b). The unaltered projections show a continuous increase of biomass until 2050, consistent with the trend observed in the database (historical records in Figure 1b). In the "low burn rate" scenario, the average biomass is almost not discernible from the unaltered predictions; the slight decrease of burn rate considered in this scenario does not significantly affect the average biomass dynamics. In the "high burn rate" scenario, a departing from the unaltered predictions is apparent after reaching the 2xCO_2 threshold. The addition of the "higher growth" condition changed substantially the dynamics with a marked increase in both scenarios. In the "low burn rate" scenario the boosted growth is able to sustain an increasing trend until 2090, while in the "high burn rate" scenario the boosted growth negates the effects of increased burn rate for the average biomass.

DISCUSSION

In this work we have developed an inhomogeneous Markov chain approach to model forest changes under nonstationary environmental conditions. This approach integrates mechanistic models of growth and disturbance into empirically-derived transition models. Its practical realization involves three consecutive steps: 1) biomass transition matrices are estimated from forest inventory data using data mining and Bayesian methods, 2) different scenarios of disturbance and forest growth are formulated according to climate change projections, 3) biomass forecasts are obtained via time-dependent alterations of the transition matrices according to these scenarios.

Markov chain models have a rich history of application in ecology, and, in particular, in forest modeling. This modeling framework has been employed in particular to describe forest transitions at different scales with various focal variables, for example, succession models defined on the species and forest type level, gap mosaic transition models, or biomass transition models. The Bayesian methodology proposed in this study allows to extend the scope of transition matrices by allowing their computation directly from forest inventory data.

On well-known limitation of Markov chain models is the time-homogeneity (stationarity) assumption, meaning that transitional probabilities remain the same over the focal time horizon (Usher, 1979, Waggoner and Stephens, 1980). While this assumption is often justified on small and intermediate time scales that span from years to decades, time-homogeneous Markov chains will likely provide unrealistic predictions in case disturbance or growth regimes change substantially over longer time horizons (decades to centuries). With the inclusion of time-dependent growth and mortality terms in the transition matrices, we relax this assumption and extend the scope of application of Markov chain biomass models.

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