A BAYESIAN HIERARCHICAL MODEL FOR SPATIO-TEMPORAL PREDICTION AND UNCERTAINTY ASSESSMENT USING REPEAT LIDAR ACQUISITIONS FOR THE KENAI PENINSULA, AK, USA

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Abstract—Models leveraging repeat LiDAR and field collection campaigns may be one possible mechanism to monitor carbon flux in remote forested regions. Here, we look to the spatio-temporally data-rich Kenai Peninsula in Alaska, USA to examine the potential for Bayesian spatio-temporal mapping of terrestrial forest carbon storage and uncertainty.

INTRODUCTION AND MOTIVATIONS

Models leveraging repeat LiDAR and field collection campaigns may be one possible mechanism to monitor carbon flux in remote forested regions. Hopkinson et al. (2008) showed that it is possible to detect growth using repeated LiDAR collections for a pine plantation in Ontario, Canada. Plot-level field measures of forest height increment paralleled corresponding changes in LiDAR height, indicating that it may be possible to track forest growth by monitoring change in LiDAR metrics from year to year. Yu et al. (2008) constructed difference metrics by subtracting LiDAR variables derived from repeat LiDAR collections. Using these as predictor variables in a linear regression, they showed that forest height and volume increment can be predicted moderately well in a boreal forest in Finland. Hudak et al. (2012) developed biomass maps for two LiDAR acquisitions over a mixed conifer forest in Idaho, USA and showed that, even when LiDAR point densities differed dramatically between the datasets, it was possible to estimate change in biomass by subtracting the two predicted maps.

Considering the demonstrated ability of multi-temporal LiDAR to estimate forest growth, it is not surprising that there is great interest in developing forest carbon monitoring strategies that rely on repeated LiDAR acquisitions for remote areas. Allowing for sparser field campaigns, LiDAR stands to make monitoring forest carbon cheaper and more efficient than field-only sampling procedures. There are issues concerning the few procedures currently proposed to assess growth, and subsequently carbon flux, using multi-temporal LiDAR though. Most linear regression approaches implicitly assume that remote sensing and field data are collected in the same season, which is problematic for most large-area field inventory campaigns. To increase spatial field sampling coverage without incurring extra cost, typically, only portions of the network of permanent sample plots are remeasured each year. Since the LiDAR and field data need to be coincident for proper calibration, the researcher is forced to discard all inventory data from other years or otherwise assume temporal misalignments to be negligible. We need methods capable of using temporally disjointed data appropriately. Further, subtracting maps of separately predicted forest biomass does not allow for prediction uncertainty to be properly carried through to the estimation of carbon flux. Without an accurate and useful assessment of carbon flux uncertainty, we have no way of understanding if predicted values are reliable.

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Here, we look to the spatio-temporally data-rich Kenai Peninsula in Alaska, USA to examine the potential for Bayesian spatio-temporal mapping of terrestrial forest carbon storage and uncertainty. The modeling framework explored here can predict forest carbon through space and time, while formally propagating uncertainty through to prediction. Bayesian spatio-temporal models are flexible frameworks allowing for forest growth processes to be formally integrated into the model. By incorporating a mechanism for growth---using temporally repeated field and LiDAR data---we can more fully exploit the information-rich field inventory network to improve prediction accuracy.

MOTIVATING DATASET DESCRIPTION

LiDAR data for the Kenai Peninsula has been collected on four different occasions---spatially coincident LiDAR strip samples in 2004, 09 and 14, along with a wall-to-wall collection in 2008 (Table 1). There were 436 inventory locations measured at least twice between 2002 and 2014 (Figure 1). Plot locations exhibit a clustered configuration of up to 4 plots within a cluster (Figure 1, inset). Inventory data was collected according to the US Forest Service Forest Inventory Analysis plot design (Bechtold & Patterson, 2005). LiDAR information was acquired at least once over most of the inventory plots with many having LiDAR collected during 2, 3 or 4 different campaigns.

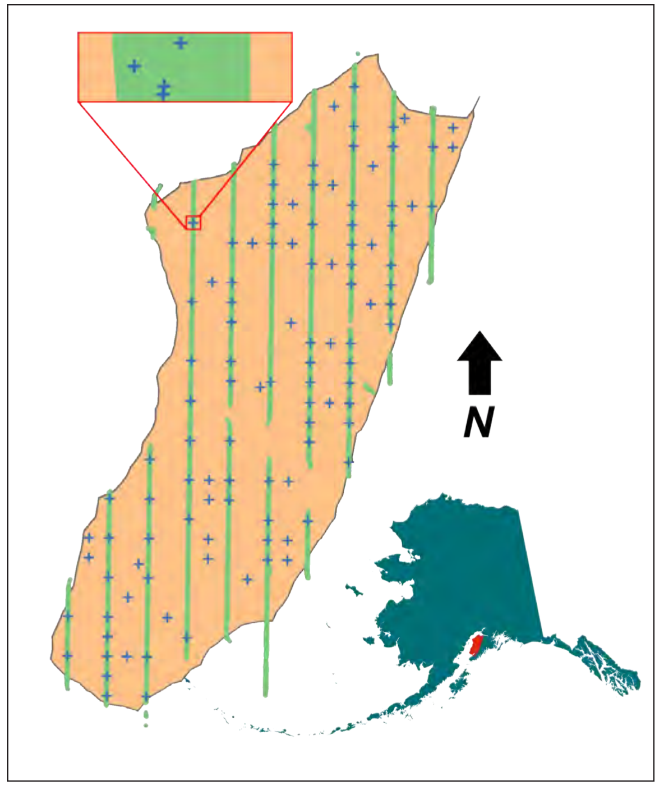

Figure 1—Kenai Peninsula study area. The orange region represents the coverage area for the 2008 wall-to-wall LiDAR dataset. The green areas represent the 2014 LiDAR strip dataset coverage. The 2004 and 2009 LiDAR datasets closely (but not completely) spatially coincide with the 2014 LiDAR dataset. The purple cross hairs locate the inventory plot locations (FUZZED). The inset map in the top left area of the figure zooms in on one cluster of plot locations. The Alaska state boundary map in the lower shows the location of the Kenai Peninsula in red.

Table 1—LiDAR acquisitions

Acquisition year	Strip sampling / wall to wall	Strip spacing, strip width	Average point density
2004	strip sampling	10 km, 300 m	7.88 points/m^2
2008	wall to wall	NA	1.81 points/m^2
2009	strip sampling	10 km, 300 m	4.13 points/m^2
2014	strip sampling	10 km, 300 m	7.38 points/m^2

MODEL FRAMEWORK

Bayesian hierarchical spatio-temporal modeling frameworks offer a useful solution to the problems of temporally misaligned data and uncertainty assessment (Cressie & Wikle, 2011). Here, we explore this class of models to develop a unified statistical framework capable of coupling the temporally misaligned and repeated measures of field inventory and LiDAR data for the Kenai Peninsula. This framework is able to predict forest carbon through space and time, while formally propagating uncertainty through to prediction. Bayesian spatio-temporal models are flexible frameworks allowing for forest growth processes to be formally integrated into the model. By incorporating a mechanism for growth—using temporally repeated field and LiDAR data—we can more fully exploit the information-rich field inventory network to improve prediction accuracy (Babcock et al., In Review). These frameworks also provide access to spatially and temporally explicit posterior predictive distributions useful for summarizing uncertainty. Because predictions of forest carbon for each year result from the same model in a spatio-temporal framework, it is possible to probabilistically assess uncertainty of carbon flux by summarizing posterior predictive distributions appropriately.

CONCLUDING REMARKS

Results from this research will impact how forests are inventoried. It is too expensive to monitor terrestrial carbon flux using field-only sampling and estimation strategies and currently proposed model-based techniques leveraging LiDAR lack the ability to properly utilize temporally misaligned data---we need new and innovative methods to track forest carbon dynamics in remote regions. Bayesian hierarchical spatio-temporal modeling frameworks offer a solution to these shortcomings and, further, easily allow for formal predictive error assessment. which is useful decision making about the certainty of our estimates and about when and where to collect future field and LiDAR data to best improve prediction accuracy.

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