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Effect of the current major insect outbreaks on decadal phenological and LAI trends in southern Rocky Mountain forests

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Remote sensing is a valuable tool for monitoring the impact of landscape-scale disturbances on ecosystem structure and function. We explore the impact of the ongoing insect outbreaks (*Dendroctonus ponderosae*, *D. rufipennis*, and *Ips* spp.) on southern Rocky Mountain forests, with the goal of assessing the sensitivity of leaf area index (LAI) and phenology metrics to different disturbance severities. Specifically, we investigate the influence of the outbreaks on two important ecosystem metrics, LAI, and phenology (e.g. green-up date, green-up speed, amplitude, etc.). Both were assessed via MODIS: 1000 m LAI (MOD15A2) and 250 m NDVI (MYD13Q1) for the phenology assessment. Trends (2002–2010) in phenology metrics and LAI were compared to different cumulative severities and timing of tree mortality, as determined from aerial surveys. Trends in phenology were significantly correlated with disturbance severity but with very low predictive power. This seems likely due to yearly variations in the onset of snow-fall and snow-melt, which dominate the phenologic signal at the regional scale of this study. Trends in LAI were associated more strongly with both disturbance severity and timing, with landscapes disturbed early in the observation period showing recovery (e.g. a positive trend) in LAI. The LAI, which is related to various vital ecosystem properties like water use and gas exchange, seems to be fairly resilient to even heavy mortality. Further work determining the relative contribution of the various functional groups (trees, shrubs, and grasses) to the LAI recovery is needed to better understand the implications of this large-scale, pervasive disturbance on forest structure and function.

1. Introduction

Fires, insect outbreaks, and other landscape disturbances often cover a large spatial and temporal extent and are key to ecosystem structure and functioning. The unique view afforded by remote-sensing instruments allows for a comprehensive perspective on these phenomena. The current insect outbreaks (mainly mountain pine beetle (*Dendroctonus ponderosae*), spruce beetle (*D. rufipennis*), and engraver beetle (*Ips* spp.)) affecting conifers throughout the southern Rocky Mountains are a case in point. The historic scale and severity of the current outbreaks (ca. 1997 to present) have raised concerns regarding the future of the forests, ecosystem services, and various processes dependent on those forests (e.g. Kurz et al. 2008; Pugh and Gordon, Forthcoming). In this research, we explore the regional

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impact of the current mortality on trends in forest phenology and LAI, two measures of forest health with direct implications for a number of ecosystem processes.

The southern Rocky Mountains are covered with extensive forests dominated by several species of conifer, including lodgepole pine (*Pinus contorta*), ponderosa pine (*P. ponderosa*), Engelmann spruce (*Picea engelmannii*), and subalpine fir *(Abies lasiocarpa)*. While insect outbreaks are not uncommon and in fact are an integral part of the disturbance regime (Romme, Knight, and Yavitt 1986; Raffa et al. 2008; Safranyik and Carroll 2006), the current outbreaks are unprecedented in known historical terms, both in severity and extent (Raffa et al. 2008). They have received substantial attention because the region is dependent on various forest ecosystem services for factors such as scenic value, water supplies, timber, and recreation.

Forest insect epidemics are major landscape-scale disturbances (Raffa et al. 2008); however, rather than a sudden, discrete disturbance like a wildfire, insect outbreaks occur over a span of years. The current outbreaks have been occurring over the last decade, with cumulative mortality levels reaching extremely high values in some locations. It is a gradual process. In the case of the mountain pine beetle, *D. ponderosae,* which caused over half of the observed mortality (see Section 2), beetle emergence in mid- to late-summer is followed by dispersal, infestation of new host trees, and egg laying. The next generation emerges the following summer and repeats the cycle. Infested trees typically remain green for 1 year, and then the needles gradually turn red ('red stage') and fall off ('grey stage'), usually within 4 years. Beetle flight is spatially limited, so the current outbreaks represent the synchrony of many local-scale infestations, rather than a single, runaway outbreak. This has important implications for remote-sensing studies. Rather than discrete changes in reflectance, longer time periods are needed to see major changes as the cumulative effect grows. However, growth by understory plants, young trees, and other plants may partially or completely compensate, masking the signal of dead trees.

NASA's two Moderate Resolution Imaging Spectrometer (MODIS) instruments, launched in 1999 on the Terra platform and in 2002 on the Aqua platform, are well suited for dynamic disturbance modelling. MODIS represents a compromise between high temporal resolution and moderate spatial resolution (250–1000 m), with spectral bands chosen for vegetation health monitoring (among other things). MODIS has been successfully used to map the occurrence of insect disturbance (Eklundh, Johansson, and Solberg 2009). Forest ecosystem functioning is related to leaf area index (LAI, measured as leaf area per area ground, or $m^2\ m^{-1}$). LAI is tied to a number of important processes, such as evapotranspiration rates and canopy transmissivity, and is an integral part of many ecosystem models. Changes and differences in LAI are therefore vital indicators of the changes in a number of processes. For example, Coops et al. (2009) found that susceptibility to mountain pine beetle mortality could be predicted by remotely sensed LAI estimates (% of maximum LAI). Disturbances, such as insect-caused mortality, generally reduce LAI, at least temporarily, and the ability of MODIS to monitor LAI over large areas at high temporal resolution is particularly useful in monitoring the effects of and recovery from disturbances (Zheng and Moskal 2009). MODISLAI (MOD15A2) estimates are continuously refined, and the current collection (col. 5) has a strong validation history (e.g. Sea et al. 2011; McColl et al. 2011); expected uncertainty (RMSE) across all cover types except deciduous forests is $0.5\ m^2\ m^{-2}$ (MODIS Land Validation project 2011; see website for supporting studies: http://landval.gsfc.nasa.gov/).

The high temporal resolution of MODIS also allows for time-integrated analyses of forest health, as opposed to single snapshots (e.g. single-scene LAI). One class of these analyses is phenologically based, such as analysis of the amplitude of seasonal fluctuations

in a selected reflectance value, often NDVI (e.g. van Leeuwen 2008). NDVI, a common vegetation index associated with healthy green vegetation, should be reduced by tree mortality. Yearly patterns of NDVI (the phenology) can therefore be used to diagnose disturbance events; for example, the ForWarn online data product attempts to map the disturbances by comparing historical and current NDVI values (forwarn.forestthreats.org). Example phenological metrics include the rate of green-up and brown-down, the length of the season, and more (Figure 1, left). These metrics have the advantage of integrating the information recorded across an entire year, providing unique data that single-image data cannot. They also represent fundamentally important ecological processes, both for natural systems and ecosystem services. All, for instance, are correlated with various aspects of forest growth and therefore carbon sequestration (Leinonen and Kramer 2002); other studies have tied trends in phenological variables to various disturbance effects (van Leeuwen 2008; Eklundh, Johansson, and Solberg 2009; van Leeuwen et al. 2010). Changes in these phenological attributes that can be attributed to disturbance can therefore be used as potential indicators of changes in their governing processes and tied to potential alterations related to ecosystem services. Tree mortality may affect these metrics in various ways, by increasing snow infiltration into the understory, decreasing canopy interception, or increasing the rate of green-up in the spring through exposure of herbaceous understory.

The purpose of this study was to determine how insect outbreaks affect LAI and phenology over a decadal timescale. We used a trend analysis to look at the increasing mortality due to insects (cumulative, from 2002 to 2010) and the trajectory in the MODIS metrics at the same points over the same time period, along with climatic variables (trends in mean precipitation and max. temperature). Trend analyses are useful in overcoming noise from stochastic yearly fluctuations due to weather, timing, sun angle, and clouds (which can affect pixel quality) and better reflect the long-term dynamics of forests (Kennedy, Yang, and Cohen 2010); the current timeline of the MODIS instruments allows for decadal trends to be investigated. Trend analyses have proven very useful in other forest health and dynamics contexts (e.g. Verbesselt et al. 2009; Kennedy, Yang, and Cohen 2010).
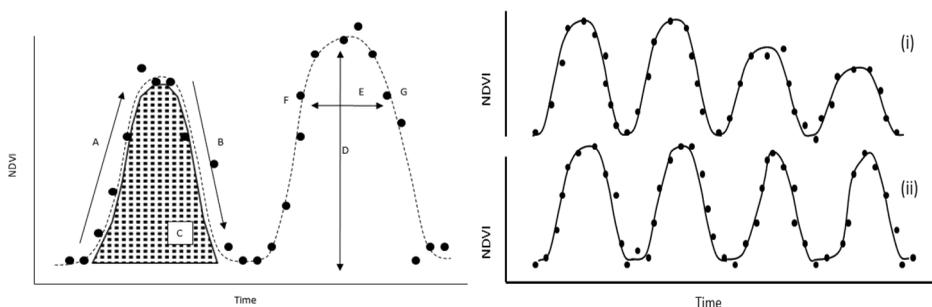

Figure 1. Left: basic phenological metrics. Each metric is computed from 23 measurements/year, weighted by quality. Dots show simulated measurements, the dashed line is the best-fit yearly curve (see Section 2). From the dashed line, several metrics are computed. A: rate of green-up (left derivative). B: rate of green-down (right derivative). C: area under the curve, or the cumulative effect of vegetation on NDVI. D: seasonal amplitude. E: length of season. F: season start date (defined as 90% of maximum). G: season end date (defined as 90% of maximum). Right: hypothetical examples of trend analysis, limited to four years. (i) Decreasing amplitude and max. NDVI without change in any other metrics. (ii) Increasing green-up rate and a decrease in length of season with no change in the other metrics. Note that these are not necessarily realistic, but rather simplified examples of potential changes; in reality all of the metrics would likely be changing concurrently.

Specifically, focusing at the regional scale of the Colorado Rocky Mountains, we asked:

(1) Are MODISLAI estimates reliable when compared to ground estimates in insect-killed forests?
(2) How are trends in summer LAI (maximum and mean) related to cumulative mortality?
(3) How are trends in phenology metrics related to cumulative tree mortality?
(4) Are observed LAI trends dependent on the timing of mortality and are there any indications of recovering LAI?

It is also important to consider the practical application of these products, and their usefulness to the end user (e.g. land managers, using the products with minimal post-processing). For example, the MODIS LAI product may be used as an input to regional hydrology models. Therefore their sensitivity to large-scale disturbances, such as the current insect outbreaks in the study area, is an important consideration. So, we discuss these results from that perspective as well.

2. Methods

2.1. Initial Processing and Study Area

The study area was identified as the majority of the Colorado Rocky Mountains, which have seen extensive mortality over the last decade driven by widespread insect outbreaks. The complete time series of MODIS NDVI ($\sim$250 m resolution, 16 day temporal resolution MOD13Q1, ver. 5) and LAI ($\sim$1000 m resolution, 8 day temporal resolution, MCD15A2, col. 5) maps were obtained through the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LPDAAC). Maps were mosaicked and reprojected through the MODIS Reprojection Tool (https://lpdaac.usgs.gov/tools/modis_reprojection_tool). The final extent of the analysis area was from $\sim$37° N 108° W (lower left; UTM 172897 4150354 zone 13, NAD83) to $\sim$41° N 105° W (upper right; UTM 517897 4545354), covering approximately 136,000 km^2 (Figure 2).

Because this covers a large area, the climate varies, but it all has a continental climate with warm summers and cold winters. The precipitation is primarily winter snow-dominated, although summer thunderstorms and monsoons can provide large amounts of moisture. The coniferous forest of the region, where this study is focused, is composed primarily of lodgepole pine (*P. contorta*), Engelmann spruce (*P. engelmannii*), and subalpine fir (*A. lasiocarpa*), with ponderosa pine (*P. ponderosae*) at the lower elevations. Limber pine (*P. flexilis*) can be locally common as well, especially in the northern regions. Most of the recorded mortality has been in lodgepole pine and spruce–fir forests (see Section 2.3). LAI in undisturbed stands varies between species and stand densities. Kaufmann, Edminster, and Troendle (1982) describe the relationship between stand basal area and LAI. They estimate that for a lodgepole pine stand at 70 m^2 ha^{-1} (their approximate maximum for the southern Rocky Mountains), the projected LAI values would be approximately 2.3. A spruce–fir forest at the same basal area would be approximately 6.7. Actual density values are often lower, and Kueppers and Harte (2005) estimated LAI values as 2.14 to 4.8 in a spruce–fir forest (approx. 20–50 m^2 ha^{-1} basal area) in the Fossil Ridge Wilderness, which is near the centre of the study area (Figure 1). It should be noted that because our analysis follows a single point through time, it is not the absolute magnitude of LAI that is being investigated, but rather the relative increase or decrease.
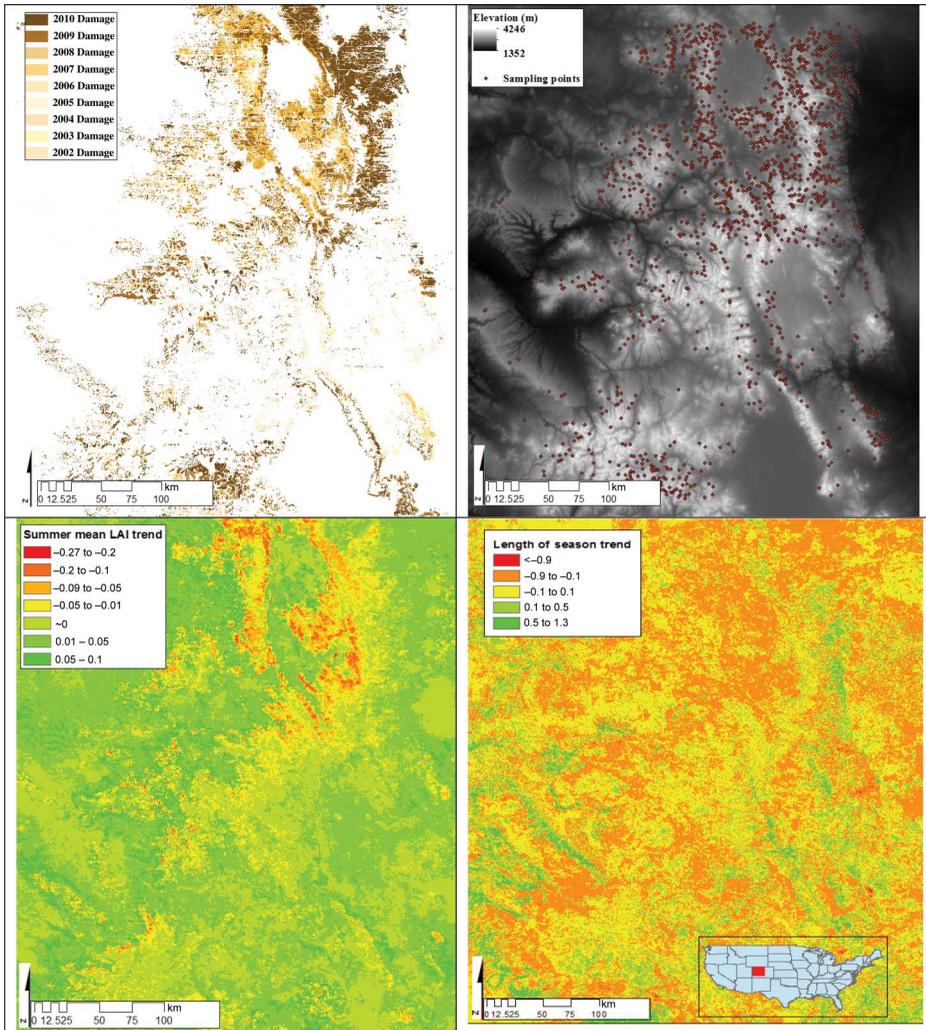
Figure 2. Examples of input and output variables and the entire spatial extent of the study area (inset, lower right). Top left: aerial survey damage maps, showing where at least one instance of tree mortality was observed for study years. Top right: input DEM and final sampling points ($n = 1458$). Bottom left: mean LAI trend over the entire study extent; sharply negative trends are seen in areas with recent beetle kill. Units are in terms of the mean change in LAI/year. Bottom right: length of season (in 16 day increments to match the MODIS product) trend over entire study extent. Seasonal trends are highly variable across the study area, likely because of yearly changes in snow onset/melt. Inset shows study coverage area (red). Coordinates in text. Maps of summer LAI mean and max. trends, corresponding r^2 and significance values, and total tree mortality can be found in the Appendix.

2.2. Ground data

While MODIS level 4 products are highly validated and continuously being improved, there is still a substantial variation in their quality and, thus, products should always be tested to ensure they are representative of local conditions (De Kauwe et al. 2011). MODISLAI (col. 5) values were compared to 24 field-based plots where effective LAI (LAI$^\circ$) was estimated in 2009 and 2010. Plots were divided into mortality classes (living, red stage, and

grey stage) and the non-parametric Kruskal–Wallis test was used to compare MODISLAI and ground LAI$^\circ$ estimates for each class. These plots spanned a range of basal areas (green, 41.1 (9.3) m^2 ha^{-1} (mean (standard deviation)); red, 34.0 (10.6) m^2 ha^{-1}; grey, 38.7 (11.4) m^2 ha^{-1}) and infestation severities (green < 35% mortality, red/grey > 50%). Twelve hemispherical photographs per plot were taken at 1 m height and assessed for LAI$^\circ$; the average of these 12 measurements was used (see Pugh and Small 2011 for general methods). Two methods of hemispherical estimation were used (0–60° vs. 0–75° view angle) for comparison. Because of the different scales (∼50 × 50 m field plots vs. 1000 × 1000 m pixels), the average difference of the paired observations was also recorded. This allows us to assess whether the difference in observation methods is within the expected 0.5 LAI uncertainty of a MODIS pixel. MODISLAI values were taken from the compositing period around Julian date 241 (29 August, both years), which was the latest date that was consistently snow free (personal observation); ground dates were taken from Julian date 305 (1 November, both years). There was no snow present in tree canopies when ground measurements were collected, although some snow may have been on the ground.

2.3. Climate and insect data sets

Two climate variables were considered – maximum annual temperature and mean annual precipitation, both taken from ∼4 km resolution PRISM data sets (Daly, Taylor, and Gibson 1997; available at http://prism.oregonstate.edu). Annual means were chosen because they correspond to the integrated annual perspective afforded by the phenology variables. Elevation data were obtained from the USGSGMTED2010 data set (Danielson and Gesch 2011). These variables were used to limit the influence of topography and climate on observed trends.

Tree mortality data was acquired from the USFS aerial surveys, which are conducted annually across the southern Rocky Mountains. Briefly, trained observers sketch-map mortality from a low-altitude aeroplane (Ciesla 2006). Results are broadly accurate, and while accuracy at any given point may be relatively low (61.1% on a point-basis), the general occurrence trends across a region are more accurate (78.6% accurate with 500 m spatial error tolerance, Johnson and Ross 2006). For an analysis of the scale of this study, this data set is appropriate (Johnson and Ross 2006), but it should be noted that this limits the study area to places with concurrent areal data. The observed density of trees (dead trees/ha) killed in the previous year was reprojected to a 250 m grid (nearest neighbour resampling) and used in the analysis. Cumulative annual mortality maps for the beginning of the observation period (2002–2004), the end of the observation period (2007–2010), and the entire observation period (2002–2010) were made by simple addition of the observed new mortality each year during that span (Figure 3). Because of the yearly additive nature of insect disturbances, cumulative maps were deemed more appropriate than annual. We did not distinguish between damage-causing agents in the analysis, as we are primarily focused on disturbance drivers of the trends in LAI, rather than the specific cause of those disturbances. So, the mortality maps reflect all mortality recorded, and potentially are confounded with competition or single-tree blowdown events. However, the damage agents were predominantly identified as mountain pine beetle, *D. ponderosae* (56% of observed points), and the spruce beetle, *D. rufipennis* (10%). Twenty-seven per cent of the observed mortality was classified as non-specific/unknown insect or disease in spruce–fir forests. These data are provided as mapped polygons, and were resampled to 250 m raster resolution (MODIS resolution) using the nearest neighbour assignment. The cumulative mortality map can be found in the Appendix.
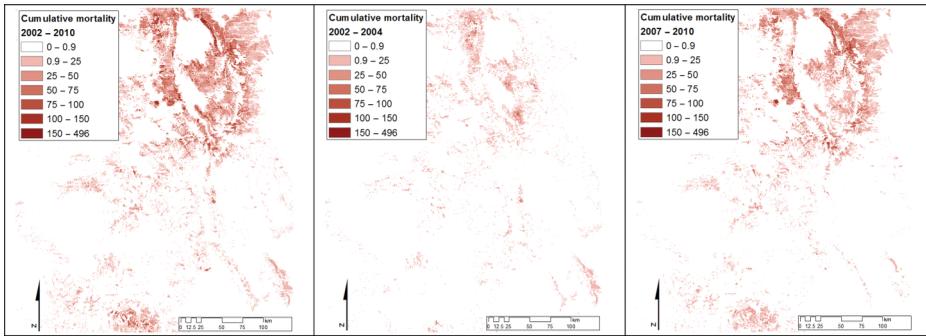
Figure 3. Timing and intensity of observed mortality from USFS aerial survey. Total cumulative mortality is on the left; the early period (2002–2004) and recent (2007–2010) are the maps used in the analyses. Mortality is in TPH. Scales are held constant to aid in visual comparison, although not all classes are on each map. Survey polygons reprojected to 250 m grid. Area shown is the same as Figure 2.

2.4. Point selection

Ten thousand random points were assigned across the region in ArcMap, and corresponding variables were extracted at each point using the nearest neighbour assignment. Analysis was limited to points that saw at least one occurrence of insect-related mortality ('minimum severity criterion' = 1) during the observation period. This ensures that a lack of observation by the aerial surveys would not be responsible for inflated zero-mortality values. This stipulation left 1458 data points, all within subalpine forests, ranging from 1877 to 3749 m elevation, and a minimum spacing of 1002 m between points (median = 134,292 m). Although low levels of long-distance dispersal are possible, most mountain pine beetle dispersal is limited to ∼30 m year^{-1} (Safranyik and Carrol 2006), and so the rate of yearly spread of any specific infestation is relatively short. Disturbances are, by their very nature, spatially autocorrelated (Wiens and Parker 1995). Gradient analyses are a way to minimize the potential confounding effects of that spatial autocorrelation (Wiens and Parker 1995; Parker and Wiens 2005), and the 1 km spacing was intended to isolate points from each other in terms of single-year beetle dispersal distances. This distance also spaces each point into a different LAI and NDVI pixel.

2.5. Phenology analysis

TIMESAT was used for the phenological analysis (Jonsson and Eklundh 2004; Eklundh and Jonsson 2010) and seven metrics selected for analyses (Table 2). A double logistic model was chosen as the base model, as it is well suited to smoothing out anomalous points and works well in highly seasonal environments, where there is a discrete start and end of the growing season (snow-melt and snow-fall, respectively; Eklundh and Jonsson 2010). The fitting used three envelope iterations with adaptation strength of 2 and forced a minimum of 0.2. Spikes were removed via a median filter. Low-quality pixels (MODIS Quality data) were weighted at 0.1. Season start/stop times were defined as when NDVI equals 75% of the maximum amplitude for the given year; this value was chosen to avoid potential influence of spring/fall snowstorms. After processing, any pixel which reported an error for a given year (e.g. no season was found at that pixel for that year, which was rare) was replaced with the mean of 1000 randomly sampled values from the same year (a

conservative correction that tends to reduce any trend). These pixels were primarily located in urban areas and were thus excluded from the analysis by the minimum-severity criterion from Section 2.4.

2.6. Trend calculation

The decadal trends for mean annual precipitation, maximum annual temperature, mean and maximum LAI, and the phenology metrics were calculated by taking the value at each pixel for each year (in the case of LAI, the max. and mean observed for the snow-free period were assigned to a given pixel for each year) and computing a simple linear regression. Points were extracted in ArcMap (ESRI 2011); all further analyses were done in R (R Development Core Team 2011). The slope was taken as the trend (Figure 1, right). To eliminate the potential confounding influence of trends in precipitation, temperature, and topography on observed trends, LAI/phenology trends were first run through a linear model with those variables, and the residuals kept. This is one way to account for the spurious influences of those variables ('statistical partialling').

LAI residuals (which had the climate/topography influence removed) were then regressed against the cumulative tree mortality (see Section 2.3) using a polynomial function, residuals $= b + mx + mx^2$, where x is cumulative mortality ($\log_{10}$ transformed for normality). Phenology residuals were run with an exponential function as well, but a standard linear regression against the residuals was found to fit the data more parsimoniously, and so the linear function results were reported.

3. Results

3.1. Is MODISLAI comparable to ground-measured effective LAI estimates?

The average difference between the observed and MODISLAI paired points ranged from 0.15 to 0.22 (Table 1), well within the expected 0.5 error rate from the MODIS platform. The significance of the differences between the two estimates depended on the mortality stage, with living and red-stage plots showing no difference, but grey-stage plots showing significantly higher LAI estimates from the MODIS product (Table 1, Figure 4). The ground-observed LAI° had a fairly small range (0.72 and 0.70 for 60° and 75° methods, respectively) relative to the variance expected in a MODIS pixel. Nonetheless, the MODISLAI estimates were generally close to the observed LAI° as indicated by the small average difference between the two estimates for the green and red stages.

Table 1. Comparison between ground-based LAI values and MODIS estimates ($n = 24$). There was no significant difference between the green- and red-stage LAI estimates, and the mean differences were small and within the expected variance of the instrument (0.5). Significant differences is shown in bold. Range is shown in parentheses.

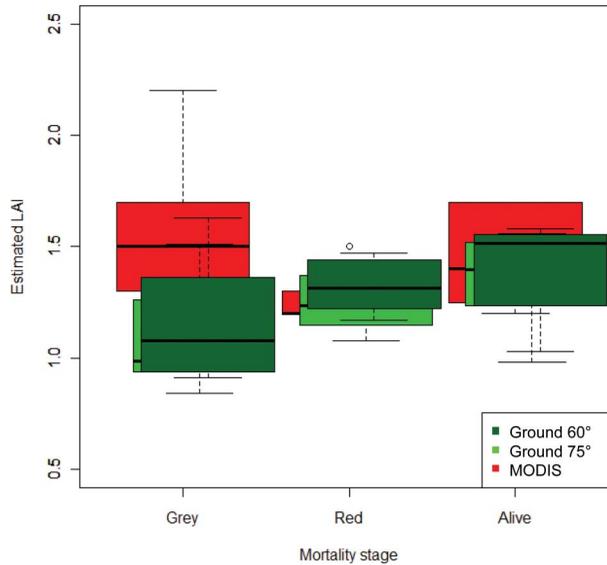| | | | | | Kruskal–Wallis *p*-value | |
Ground LAI°	Observed range ground LAI°	Observed range MODIS	Mean difference MODIS – ground	Alive	Red stage	Grey stage
60°	0.91−1.63 (0.72)	1.2−2.2 (1.0)	0.15	0.67	0.42	**0.02**
75°	0.84−1.56 (0.70)	1.2−2.2 (1.0)	0.22	0.56	0.74	**0.006**

Figure 4. Comparison between ground-estimated LAI° (60° and 75° methods) and MODISLAI. Results varied by mortality stage: For live plots ($n = 8$) and red-stage tree mortality plots ($n = 6$), there was no significant difference. For grey-stage plots ($n = 10$), MODISLAI was significantly higher.

3.2. How are trends in summer LAI related to cumulative mortality?

Significant relationships ($p < 0.05$) existed for both mean and maximum summer LAI values with total cumulative mortality (2002–2010), although predictive power was low. After the statistical partialling procedure, significant relationships remained for cumulative tree mortality and both residual mean LAI trends ($p \approx 0$, $r^2 = 0.11$) and residual max. LAI trends ($p \approx 0$, $r^2 = 0.07$), indicating that the relationships are not simply due to climate/topography (Figure 5). A multiple regression containing all terms (climate, topography, and mortality) had higher predictive power (mean LAI: $p \approx 0$, $r^2 = 0.23$; max. LAI: $p \approx 0$, $r^2 = 0.16$), with all terms except the first-order cumulative observed mortality and precipitation trends being significant. Summer mean and max. LAI trend maps and corresponding r^2 and significance maps are found in the Appendix.

3.3. How are trends in phenology metrics related to mortality?

The initial regression against climate and topography indicated that trends in these variables were influencing, to a small extent, trends in the observed phenology (Table 2). The residual analysis against the mortality data was generally significant but with very low r^2 values (Table 2). Because the length of the season is highly variable due to high year-to-year variability in snow onset/melt dates, we also analysed correlations between the length of the season and the phenology variables (on a yearly basis) in an attempt to determine to what extent variability in season length may overshadow the influence of insect mortalities. These correlations were significantly higher than those with the tree mortality data (Table 3), indicating that much year-to-year variability in phenology metrics, which would reduce the significance of any trend in those metrics, is driven by the changes in season length.
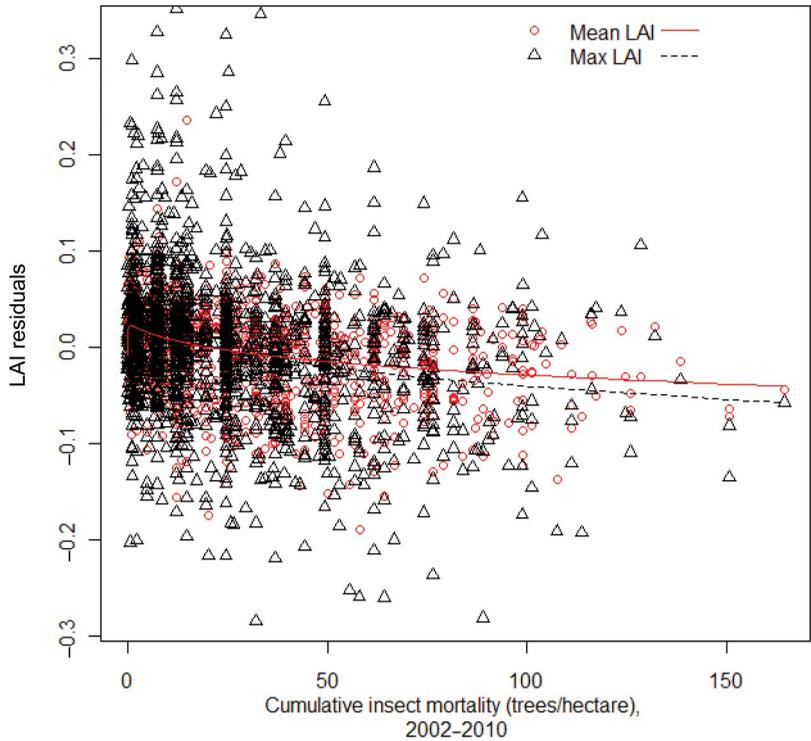
Figure 5. Plot of residual LAI (from linear model: LAI trends ~ elevation + precipitation trends + max. temperature trends) *versus* cumulative tree mortality. Results show similar patterns between max. and mean LAI values, both decreasing. Low levels of mortality (also associated with early period mortality, see Figure 5) are associated with positive or neutral LAI trends, whereas high levels of mortality are associated mainly with negative LAI trends. The trends are both significant (mean LAI: $p \approx 0$, $r^2 = 0.11$/max. LAI: $p \approx 0$, $r^2 = 0.07$).

Table 2. Relationship between trends in phenological metrics and climatic variable trends, and residual correlation with tree mortality (trees killed/ha (TPH)). Metric trends were first regressed against elevation and climate trends, then the residuals regressed against the $\log_{10}$ transformed mortality numbers ($n = 1458$). NA indicates no significant relationship.

Phenologic metric	Climate/elevation regression			Trend residuals ~ Cumulative TPH 2002–2010	
	p	r^2	Variables	p	r^2
Large integral	0.004	0.007	Elevation, precipitation trend	0	0.01
Length of season	0.002	0.008	Precipitation trend, temperature trend	0.009	0.004
Green-up rate	0.61	0	NA	0.03	0.003
End of season	0.06	0.002	Precipitation trend	0.06	0.002
Amplitude	0.01	0.005	Temperature trend	0.41	0
Green-down rate	0	0.02	Elevation	0.07	0
Start of season	0.01	0.006	Temperature trend	0.07	0

Table 3. Correlations between the length of the season and various phenologic variables for all of the investigated years at sample points ($n = 1458$). Season length is largely driven by snow-melt/snow-fall, which are both highly variable (see text). Start- and end-of-season times are the strongest, although all variables show significant relationships for most years. Correlations between length and the other phenology variables are generally substantially higher than between insect infestation severity and the phenology variables.

Year	Start		Green-up rate		Amplitude		Large integral		Green-down rate		End	
	r^2	p	r^2	p	r^2	p	r^2	p	r^2	p	r^2	p
2000	0.10	0.00	0.09	0.00	0.07	0.00	0.07	0.00	0.02	0.00	0.55	0.00
2001	0.17	0.00	0.01	0.01	0.03	0.00	0.12	0.00	0.15	0.00	0.51	0.00
2002	0.25	0.00	0.00	0.12	0.01	0.00	0.08	0.00	0.04	0.00	0.29	0.00
2003	0.18	0.00	0.04	0.00	0.07	0.00	0.08	0.00	0.01	0.00	0.44	0.00
2004	0.35	0.00	0.02	0.00	0.05	0.00	0.06	0.00	0.02	0.00	0.49	0.00
2005	0.22	0.00	0.03	0.00	0.04	0.00	0.13	0.00	0.00	0.03	0.43	0.00
2006	0.20	0.00	0.08	0.00	0.12	0.00	0.13	0.00	0.02	0.00	0.41	0.00
2007	0.51	0.00	0.09	0.00	0.15	0.00	0.10	0.00	0.07	0.00	0.49	0.00
2008	0.20	0.00	0.10	0.00	0.11	0.00	0.14	0.00	0.00	0.04	0.31	0.00
2009	0.17	0.00	0.08	0.00	0.11	0.00	0.15	0.00	0.03	0.00	0.52	0.00
2010	0.26	0.00	0.09	0.00	0.09	0.00	0.10	0.00	0.02	0.00	0.41	0.00

3.4. Are the observed trends dependent on the timing of mortality, and is there any indication of recovery?

It seems reasonable to expect that the timing of mortality would have an influence on observed trends. Recent mortality was subtracted from early-period mortality (see Section 2.3 for details), and the result gives a sense of timing: Negative results indicate areas dominated by late mortality, positive results indicate areas dominated by early mortality, and near-zero results indicate either low overall mortality or evenly spread mortality. Many areas saw substantially more mortality in the beginning of the decade, although the outbreaks have predominantly been in the latter half (inset histogram, Figure 5). Furthermore, if the cumulative mortality was dominated by deaths relatively early in the observation period, the observed trends in LAI were mainly neutral or even positive; if the converse, the observed trend was mainly negative (Figure 5). To investigate this relationship, a linear regression was run between the differenced values (inset histogram, Figure 6) and the mean and max. LAI values. Results were significant (mean LAI: $p \approx 0$, $r^2 = 0.09$; max. LAI: $p \approx 0$, $r^2 = 0.08$); however, predictive power was very low. This suggests that relative difference in the timing of mortality will contribute to, but does not drive, the decadal trend of this study (Figure 7). These trends are still significant even when the minimum severity criterion is increased to at least 10 trees killed/ha (TPH), and are also significant for max. LAI at 15 trees killed/ha. Due to the even lower correlations between phenology trends and insects, an analysis of mortality timing was not pursued for those metrics.

4. Discussion

We found that trends in phenological metrics were relatively insensitive to observed mortality. In contrast, both summer mean and max. LAI were significantly influenced by observed mortality, even after controlling for elevation and trends in precipitation and temperature. Predictive power for the latter relationships was low, but this may be a function of the short period for available MODIS data.
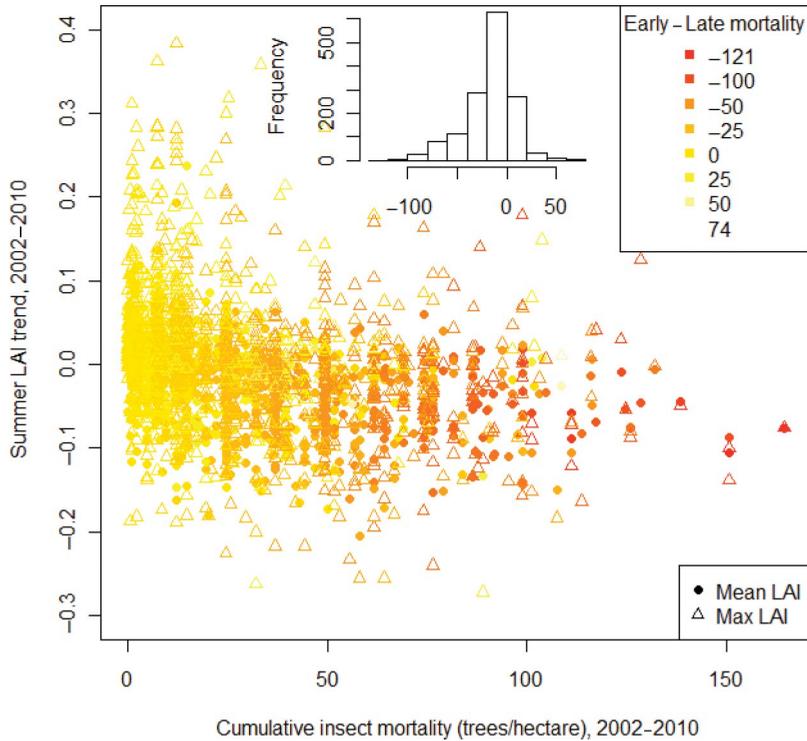
Figure 6. Effect of timing of tree mortality on observed mean and max. summer LAI trends ($n = 1458$). Cumulative mortality (trees/ha) from 2002 to 2004 minus cumulative mortality from 2007 to 2010 resulted in the distribution observed in the inset histogram: Areas where 2007–2010 mortality dominated are in the negative portion of the distribution, areas where the mortality was distributed more or less evenly are around zero, and areas dominated by early kill are in the positive section. A clear relationship between the timing of mortality and the magnitude and direction of the observed trend can be seen, with early-mortality areas being mainly low magnitude/positive. Late-mortality areas are mainly negative.

4.1. *MODIS versus ground estimates of LAI*

Ground LAI$^\circ$ and MODISLAI values were comparable, although the significance depended upon the stage of mortality and this indicates a shift in the LAI that MODIS is capturing – from reflecting LAI$^\circ$ at the green stage to the understory component in the later stages. In the green stage, in these forests, MODISLAI appears to be reflecting LAI$^\circ$. The significantly higher LAI estimates in grey-stage plots could correspond to increased opening of the canopy due to a loss of needles, allowing for a stronger influence of the understory on MODIS estimates. When the canopy is fuller, that influence would be less, and the observed differences less as well (Figure 4). Other studies have also seen differences between in situ or higher-resolution satellite modelling and MODISLAI estimates (e.g. De Kauwe et al. 2011 with Landsat, Jensen et al. 2011 with LIDAR, McColl et al. 2011 with LiCOR). Broadly speaking, there appears to be a convergence of studies showing under-prediction of LAI at high values (e.g. >4) and over-prediction at low values (e.g. <0.75), with good accuracy between them. This study falls into that range (~1–3). The ground values in this study did not include the understory, or consider branch clumping or woody material, which are considered in the MODIS algorithm. We are unaware of any
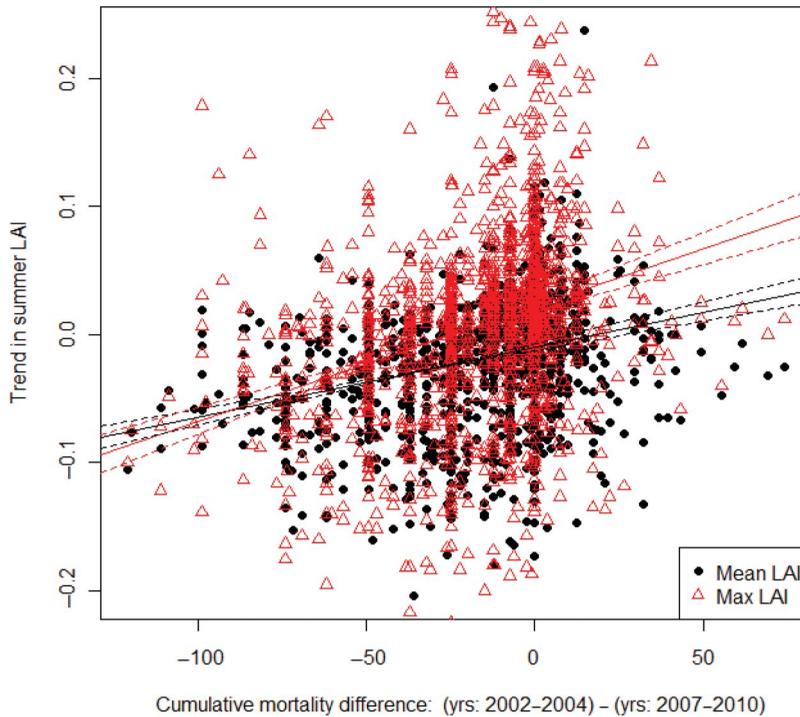
Figure 7. Cumulative mortality difference in relation to mean and max. summer LAI values. Trends are significant for both, with 95% confidence interval shown (mean LAI: $p \approx 0$, $r^2 = 0.09$/max. LAI: $p \approx 0$, $r^2 = 0.08$). Minimum severity shown is 1 tree/ha (2002–2010).

clumping factor studies in insect-killed plots. Inclusion of the understory or a clumping factor would increase the ground-truthed LAI estimates, although removing the woody plant component, which we were unable to do with the black/white hemispherical photographs, would decrease them. The grey-stage effective LAI values indicate that a substantial portion of the ground estimates may be non-photosynthetic, woody material, increasing the value of remote sensing-based estimates of LAI for modelling studies in these environments.

The late-season MODIS comparison with the ground estimates was an attempt to get as close to synchronous observations as possible while avoiding snow, excess mixing with understory (although this appears only partially successful), and isolating LAI contribution from the coniferous component. In addition, the inevitable pixel mixing with deciduous trees (primarily Quaking aspen, *Populus tremuloides*), water bodies, understory, and other cover types within the 1 km pixel are also responsible for some of the variation. Nonetheless, the increased LAI estimated by MODIS in grey-stage plots captures understory growth and recovery of LAI, suggesting that ground-based methods focused on overstory LAI will inaccurately assess the early stages of forest recovery.

4.2. LAI trends and timing

Both mean summer and max. summer LAI trends varied significantly with the level of insect infestation, even after taking the conservative step of removing the influence of

concurrent trends in precipitation and temperature and the influence of elevation. This is not unexpected, especially given the nature of the insects, whose effects result in tree mortality and the dropping of dead needles. Overall, the insect infestation, which at its core is a tree-scale phenomena (although it spreads at the landscape level), is represented in the much-larger scale LAI measurements (1 km) which include, in many cases, a substantial amount of cover-type mixing inside a given pixel. While unmixing techniques and other refinements would no doubt improve the results, it is reassuring to know that even 'off-the-shelf' usage of the MODISLAI product reflects the dynamics of an insect disturbance occurring at a variety of infestation intensities.

The relationship between the timing of outbreaks (early decade or late decade) and the direction and magnitude of the LAI trend is also interesting (Figure 6). It appears that areas which experienced peak disturbance in the early parts of the decades are already recovering in terms of LAI, with many showing positive trends; it is unknown whether this is due to understory seedling release, an increase in herbaceous or shrub cover, or other factors. However, results of the ground versus MODIS comparison hint that the understory is playing a major role (Figure 3). Further work should be done in this area. Locations which have recently experienced beetle kill (red stage) exhibit lower LAI values, as expected. But we should consider an alternative hypothesis: This relationship could also indicate that areas of declining LAI due to some other factor prior to infestation were more susceptible to attack, thereby leading to the temporal pattern observed (declining LAI and late-decadal attack). However, research by Mitchell, Waring, and Pitman (1983) and Landsat-based research by Coops et al. (2009) show the converse that beetle mortality was more intense at higher LAI values due to a reduction in individual tree vigour via competition (comparisons conducted in thinned vs. unthinned stands). Thus, it seems likely that the observed declines were caused by beetle mortality as opposed to the beetle mortality being driven by the changes in LAI due to other reasons. Pugh and Gordon (2012) found a similar magnitude of decline when comparing uninfested stands with those in an advanced state of mortality. This observation is tempered by the fact that the early-period mortality tended to be less severe and covered a smaller area, and so more observations are needed to truly assess resilience, the severity of outbreaks that can occur without long-term change to the ecosystem. These forests are quite resilient to insect disturbance according to Holling (1973). Both Aoki, Romme, and Rocca (2011) and Diskin et al. (2011) have observed ample tree recruitment in the understory with slight shifts in vegetation composition, and primary productivity recovering rapidly from severe infestations (Romme, Knight, and Yavitt 1986). This has implications for several fields, such as carbon (C) modelling. LAI is the interface for carbon fixation in plants and therefore an important driver of ecosystem C exchange and balance. In an eddy flux study in British Columbia, two stands with high mountain pine beetle mortality remained fairly C neutral, with the earlier-attacked stand remaining a slight C sink (Brown et al. 2010), likely due to increased uptake of C by the understory (Bowler et al. 2012). Further integration is needed to determine other effects of switching from primarily overstory to primarily understory leaf area, regardless of the net changes in total LAI.

4.3. *Phenology assessment and tradeoffs*

In some sense, the lack of a strong relationship between phenological variables and the ongoing insect disturbance is surprising. While the insects' preferential damage of mature

trees and the subsequent opening of the canopy would be expected to alter observed phenological trends, the fact that those alterations were not significant (at the 250 m pixel scale) lends credence to the idea that phenologic trends are somewhat insensitive to disturbances of this scale and type. Temporally, insect outbreaks are not discrete, as cumulative mortality plays out over several years, allowing for understory growth and expansion which likely offsets some of the expected changes in observed reflectance. The phenology is also strongly driven by variable onsets in snow-fall/snow-melt (for example, the snow-free date at the Lost Dog NRCS Snotel site in the Park Range of northern Colorado was 25 June in 2011, and 6 May in 2012, NRCS 2012), which affect a number of the phenological metrics via changes in season length. A correlation between season length and the other phenology variables shows much higher correlations than those seen between phenology and tree mortality (Table 3). This is unsurprising, since phenology variables are partially a function of the growing season length, but illustrates the difficulty of separating the effect of tree mortality and variation in weather from year to year in the relatively short time period of recording.

There are two potential reasons for the lack of significant trends which should be explored further: Either the effect is very minor for any given year, or too transient to be observed in this decadal investigation. If the effects of tree mortality on phenology are small enough, yearly differences in weather will overshadow their effect. Studies in areas with less year-to-year variation in snow onset may better resolve this difficulty. If the effect is simply very transient and recovery happens within a few years, further work could focus on variable temporal windows for the analysis to determine at what scale and severity insects do influence observed phenology. Because the outbreaks started at different times across the study region presented here, exploring the temporal nature of the effect would require a smaller scale of investigation. But in sum, at this scale (large region, decadal time period), the influence of tree mortality on phenology trends seems minor.

Certainly, this is only one type of disturbance, however common, and the phenology was only assessed via moderate-resolution NDVI phenology and LAI. Higher-resolution imagery (e.g. Landsat), which would contain less pixel mixing, would likely see more significant relationships. However, the space *versus* time tradeoff precludes this type of phenologic analysis due to decreased flyover opportunities in coarser-grained satellites, and methods which build detailed phenologies from multiple years of imagery are not suited to tracking disturbances over time (non-stationarity). Current work focuses on data fusion techniques which may be able to address some of these tradeoffs (e.g. Hilker et al. 2009). However, one of our stated goals was assessing the utility of these MODIS products to the end user, and so we wanted to limit this analysis to products easily obtainable and usable by a more general audience. Other disturbances with different scales and effects on forest structure and function (e.g. fire) may have stronger effects on phenology as well. Catastrophic, discrete disturbances, such as wildfire, which drastically alter structure and cause complete mortality, have stronger effects on phenology. For example, van Leeuwen (2008) found stronger results in correlating recovery after a severe wildfire. A study attempting to map the degree of insect defoliation in south-eastern Norway Scots pine (Eklundh, Johansson, and Solberg 2009) was less successful, and was only able to satisfactorily map the occurrence of mortality, not severity. While we did not test the ability of these metrics to classify disturbed/not disturbed, the general inability to use phenology to map continuous insect-mortality severity is shared with that study. It is certainly possible, however, that advances in curve fitting and spatial resolution may improve results.

4.4. Caveats

As in all remote-sensing studies of this type, several caveats exist. First, these data are taken from several different sources, collected for different reasons, and at different spatial scales. In one sense, this is problematic, as mixing scales and resolutions always introduces an error. However, the fact that significant relationships were found despite this handicap gives some reassurance that the phenomena are robust enough to be detectable despite these problems. We intentionally used the 'off-the-shelf' version of the MODIS LAI and NDVI products, with no post-processing, to test the utility of these products to the end user. While further processing and refinements may improve the correlations, it is also useful to assess the utility of these products from a purely end-user perspective.

Tree mortality prior to 2002 was ignored. This was considered a minor source of error since mortality was minimal prior to 2002. Any mortality prior to 2002 would only increase the observed trends, so this is a conservative move. In addition, coverage of the aerial surveys was also relatively low prior to the study period, which limits the availability of points for analysis because a trend analysis requires continuous revisits. Second, the analysis covers an expansive area. The inclusion of precipitation and temperature trends across the region was intended to address the fact that climate trends are likely variable across the region, although other, unconsidered variables may also exist which are non-randomly distributed across the study area. This is a caveat in all large-scale investigations which necessarily depend on simplifying assumptions. Cover type variance (such as grass patches) at the subpixel scale may also vary. Finally, this is a highly seasonal, subalpine environment dominated by snow coverage in the winter, and so conclusions here must be carefully applied to other ecosystems where the MODIS signals may be more or less clear, at least in terms of definite seasons.

5.   Conclusions

In this highly seasonal, snow-affected environment, and at the regional scale, both summer mean and summer max. LAI are influenced by tree mortality, even after controlling for elevation and concurrent trends in precipitation and temperature. However, it appears that LAI may recover quickly from the severity seen in the early period of observation, which comes likely from an increased contribution by the understory – this remains to be explored. Phenological variables were insensitive to tree mortality after controlling for elevation, temperature trends, and precipitation trends at this regional scale. Likely differences in the onset of the outbreaks, influence of the understory on reflectance, and year-to-year variability play a role in the lack of correlation at this scale. Higher temporal and spatial resolution climate data may be more successful at resolving phenological change. Similarly, smaller focal areas, such as watersheds, may see stronger effects due to decreased variability in the time of attack and seasonal weather patterns. More extensive phenology investigations, with a wider range of curve-fitting methods and response variables (e.g. EVI), are still needed. Longer-term studies are always desired, and this study covers only 9 years. While the indication is that areas which experienced early tree mortality are on the road to recovery, longer-term monitoring across a wider range of infestation severities is needed. However, this study begins to shed some light on changes and trends important for ecosystem functioning across a wide expanse of the southern Rocky Mountains.

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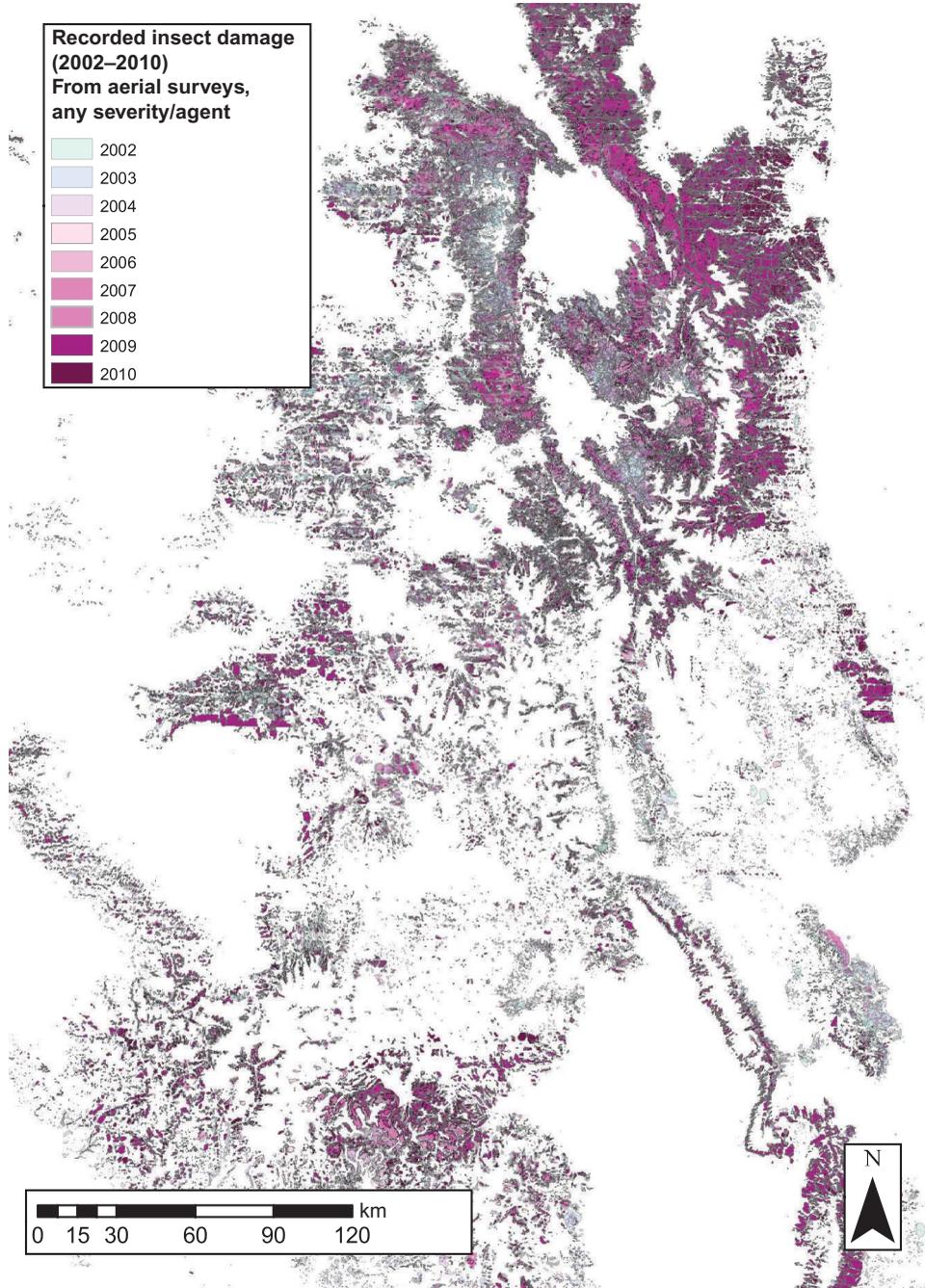
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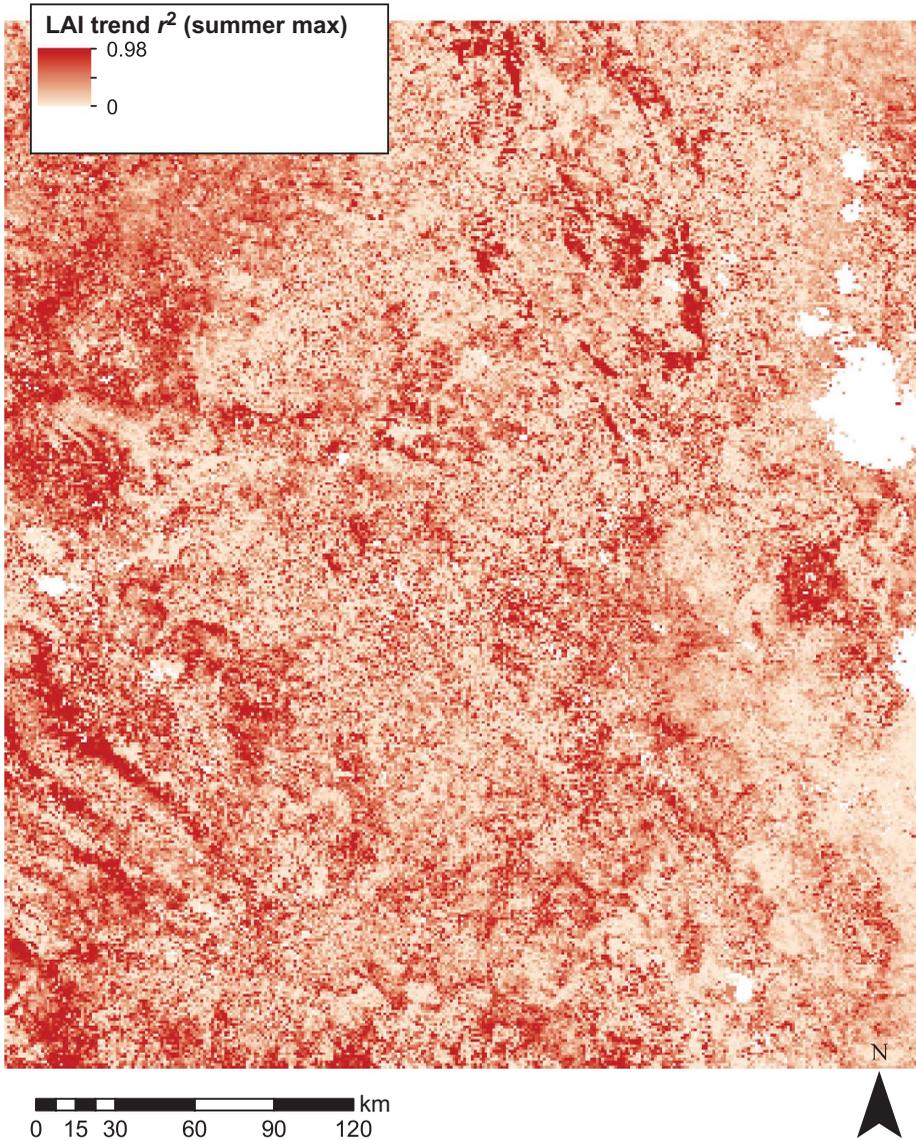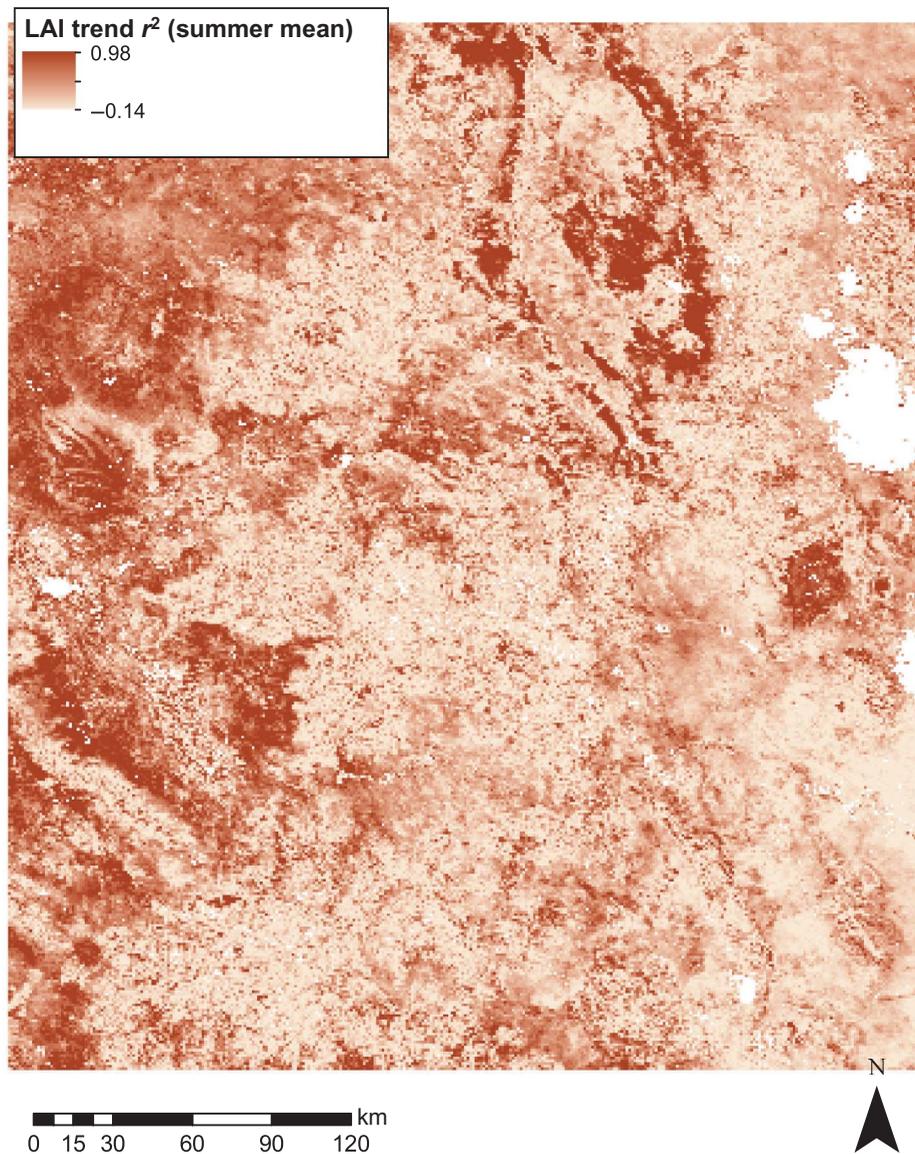
Appendix

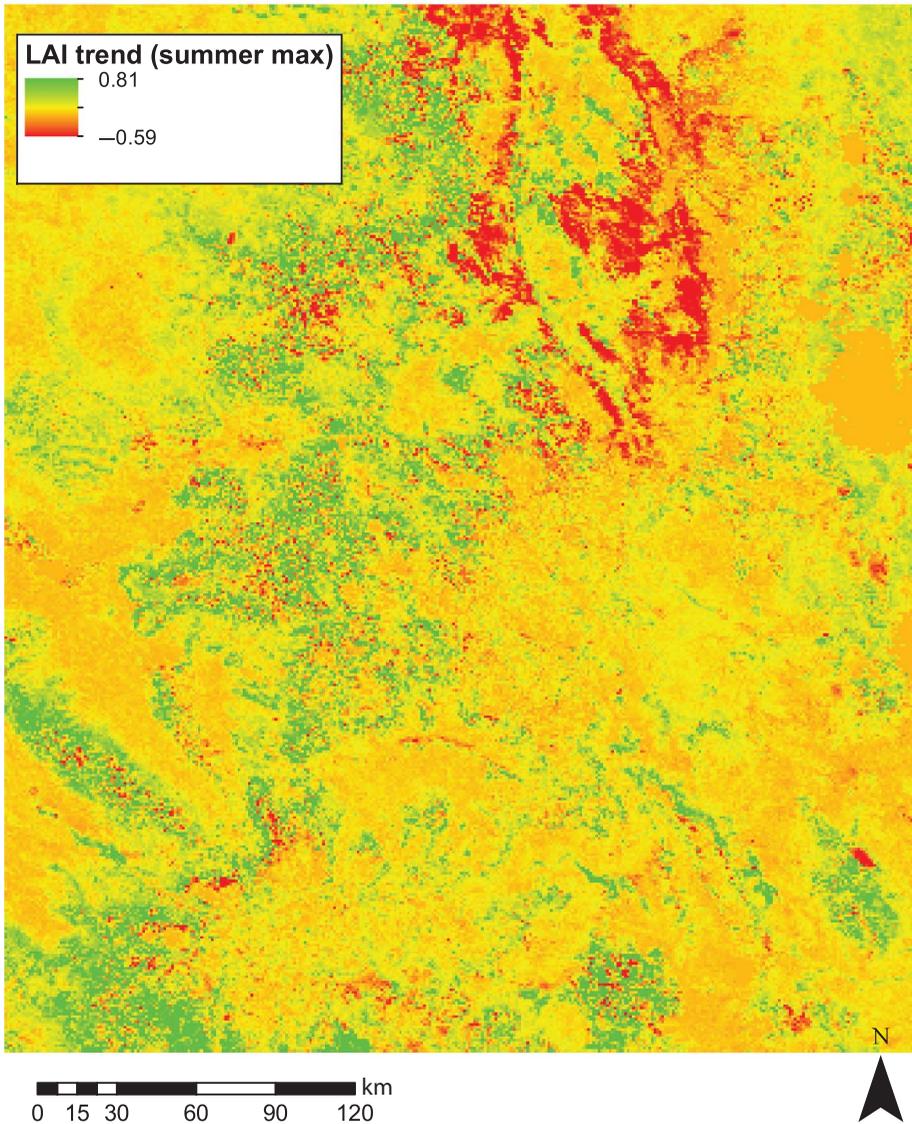### Higher-resolution aerial survey maps and complete LAI trend maps

What follows are a higher-resolution aerial survey (USDA) map (Ciesla 2006; see Johnson and Ross 2006 for accuracy information) and LAI trend maps (2002–2010). LAI data is from the MCD15A2 data set (∼1000 m resolution, 8 day temporal resolution, col. 5). The images were
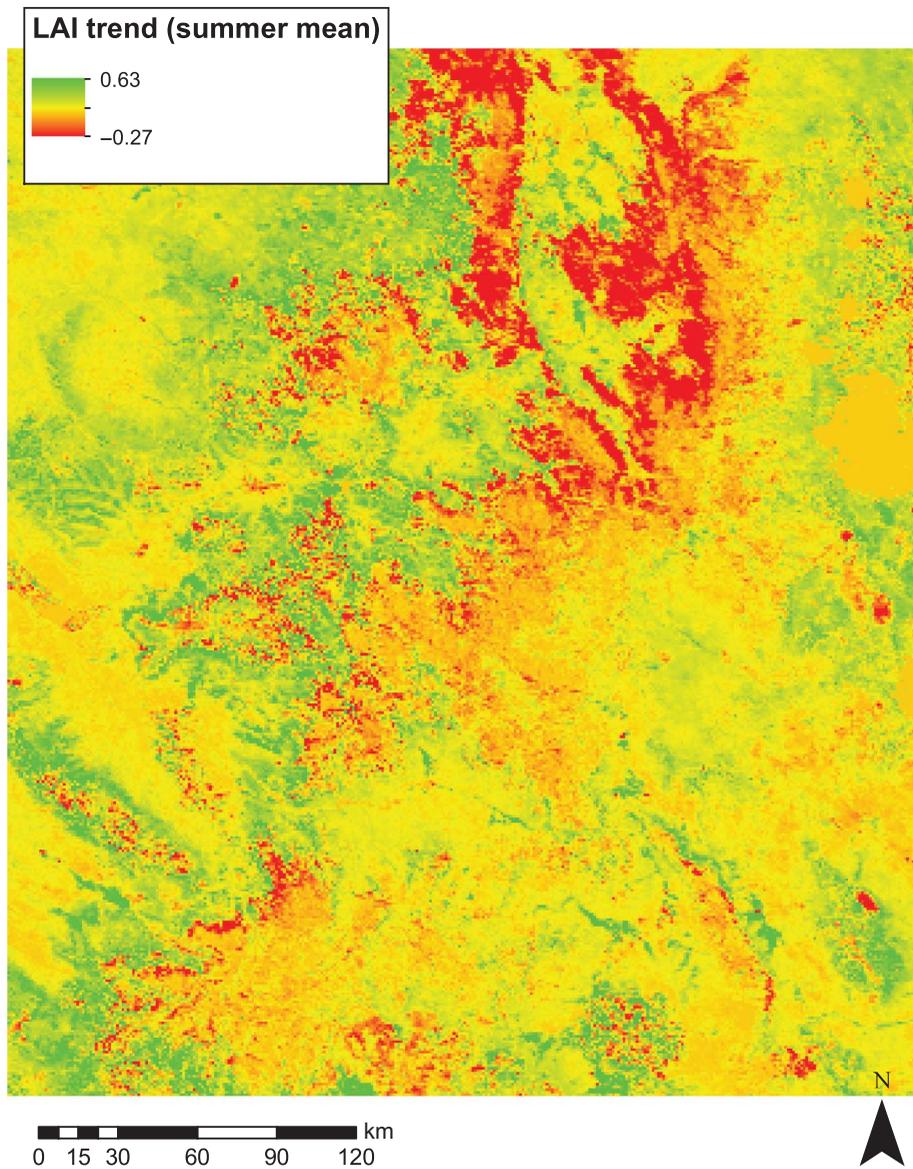
obtained at the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC). Maps were mosaicked and reprojected through the MODIS Reprojection Tool (https://lpdaac.usgs.gov/tools/modis_reprojection_tool). The trend is taken as the slope of a linear regression passing through each year at any given pixel; r^2 and p-values <0.05 are also shown. Note that only areas which experienced insect mortality were further analysed. The area covered is from $\sim$37° N 108° W (lower left; UTM 172897 4150354 zone 13, NAD83) to $\sim$41° N 105° W (upper right; UTM 517897 4545354), covering approximately 136,000 km^2.

Significant LAI trend (summer max)

▮ Significant (*p* < 0.05)

▯ Non-significant

km

0 15 30   60   90   120

N

Significant LAI trend (summer mean)