

AN INVESTIGATION OF RECENT SUDDEN MORTALITY
OF BALSAM FIR IN EASTERN NORTH AMERICA:
CLIMATE, STAND AND SITE DRIVERS OF MORTALITY

by

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Abstract

In 2018, a widespread, balsam fir mortality event occurred across the species southern range limit. The purpose of this thesis was to determine the role of climate and local factors as drivers of mortality in Atlantic Canada. A Random Forest model associated a combination of climate anomalies with mortality, notably a summer drought in the previous year. This model was able to predict a similar event that occurred in 1986 with a remarkable accuracy of 95% ($\kappa = 0.88$). Looking at local factors, I find that sites associated with elevated temperatures (i.e., lower elevations and south facing aspects), higher competition for water and taller trees display higher mortality risks. Mortality probability was also associated with low depth to water values with minimal influence observed for drainage and slope variables. This research highlights the vulnerability of balsam fir to drought induced mortality.

Dedication

My graduate degree was supported by the Canadian Memorial Foundation. This organization strives to strengthen the ties that exist between generations of Canadian and British citizens. This thesis seeks to honour the contribution that Canadian and British servicemen and women made to the First and Second World Wars.

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Chapter 1: General Introduction

1.1. Problem Statement

In the spring of 2018, a widespread balsam fir (*Abies balsamea* (L.) Mill.) mortality event was reported across its southern geographical range in New Brunswick (NBERD, 2018), northern areas of New Hampshire, Vermont, Maine (Maine Forest Service, 2018), and Wisconsin (Wisconsin DNR, 2019). Mortality appeared to be sudden with foliage remaining intact but turning bright red. The presence of intact but dead foliage confirmed that mortality was not directly caused by spruce budworm (*Choristoneura fumiferana*) as the insect consumes the current-year foliage, with partially defoliated foliage falling off after a few weeks (MacLean & MacKinnon, 1996) and at least 4-5 years of consistent defoliation is required to cause tree mortality (Houndode et al., 2021; MacLean, 1980). Given the wide-scale synchronicity of mortality that was observed, climate is hypothesized to be the primary driver with stand level vulnerability controlled by local conditions and tree characteristics.

1.2. Background

Balsam fir is the most prominent fir species in North America, and is a key economic softwood species used primarily for pulp and small dimension stud wood (Sinclair & Govett, 1983). It is a major component of the New England – Acadian Forest Region where forest management practices have increased its abundance across the landscape (Loo & Ives, 2011; Noseworthy & Beckley, 2020). It is also important for large herbivores, providing overwinter food for moose and shelter for deer (Bakuzis & Hansen, 1965). Balsam fir is a shade tolerant tree species that grows well in cold and moist conditions (Rowe, 1972; Sims et al., 1990). Climate change is predicted to increase

temperatures and change precipitation across its native range (Price et al., 2013; Wang et al., 2014). Future climate scenarios project a northward shift for balsam fir populations (Andrews et al., 2022; Bourque et al., 2020; Bourque & Hassan, 2008; Taylor et al., 2017), although these predictions often rely on annual climate variables that do not factor in the role of more acute climate anomalies. A climate anomaly is the departure from a long term average often given in units of standard deviation. Droughts are an important climate anomaly for forest health as they cause widespread tree mortality at the landscape scale (Allen et al., 2010). If tree mortality is combined with insufficient regeneration then it can lead to the extirpation of a species at the landscape scale (Turner et al., 1993).

Although climate change is increasing tree mortality across forests (Allen et al., 2015), determining the specific cause of individual tree mortality remains challenging because mortality is a complex process. Tree mortality is driven by different factors and can be viewed as a “death spiral” where a tree experiences a stressor which predisposes it to other stressors, which can eventually lead to mortality (Allen et al., 2015; Franklin et al., 1987). An example of this is the 1954-1955 dieback event of balsam fir in Ontario, where a combination of predisposing drought stress triggered a reduction in growth vigor and increased the impact of three fungi: *Thyronectria balsamea*, *Dermea balsamea* and *Valsa abietis* (Raymond & Reid, 1961). Initially this dieback was attributed to the fungi, but dieback symptoms were only observed in field experiments when combined with a reduction in growth vigor, so it was determined that the preceding anomalous hot, dry years had likely initiated the dieback rather than the fungi. Trees can also be predisposed to other stressors because of internal stand dynamics, including competition for resources

(Peet & Christensen, 1987; Yoda, 1963), or because of external drivers such as insect outbreaks (Anderegg et al., 2015).

To determine the drivers of tree mortality, its spatial occurrence must first be identified. Tree mortality can be recorded through intensive forest inventory data, such as permanent sample plots, but these are constrained to the area that contains those plots and display a low temporal resolution of three to five years (Taylor & MacLean, 2007). Aerial surveys provide widespread coverage and are historically widely used (Coleman et al., 2018). Satellite based remote sensing also provides broad coverage, but the spatial resolution can limit its ability to detect single tree mortality and cloud cover can limit its temporal coverage (Lausch et al., 2017).

Forest inventory data, aerial photography and satellite imagery have been combined with climate variables to build predictive models of tree mortality (Klein et al., 2019; Neumann et al., 2017). Lethal climate thresholds have also been used to predict tree mortality across a landscape based on climate data (Bourque et al., 2005). However, when a lethal climate threshold is unknown, dieback occurrence records combined with climatic and hydrological variables have been successfully used to predict the occurrence of tree mortality across a landscape (Brown et al., 2018).

1.2.1 Climate Drivers of Tree Mortality

Globally, forests are experiencing higher rates of tree mortality following increases in drought intensity and duration (Allen et al., 2010). A drought causes trees to experience a rise in internal water tension, which increases the risk of air entering vessels or tracheids (cavitation). This will reduce conductivity in the xylem with a 50% loss in hydraulic conductivity considered to cause lethal embolisms, where an air bubble can block the

xylem, which leads to hydraulic failure and mortality (Martínez-Vilalta et al., 2004; Sperry et al., 1998). Balsam fir is also more vulnerable to a loss of hydraulic conductance in response to increasing xylem pressure relative to many other eastern conifers that share its range such as red spruce (*Picea rubens*) (Sperry & Tyree, 1990), eastern white cedar (*Thuja occidentalis*), eastern hemlock (*Tsuga canadensis*) (Tyree & Dixon, 1986; Tyree & Sperry, 1989) and black spruce (*Picea mariana*) (Balducci et al., 2020). Stomatal closure will limit water loss and should limit the build-up of tension in the xylem (Hsiao, 1973). However, stomatal closure prevents photosynthesis stopping the production of sugars and reduces the potential for defence against other biotic agents such as insects (Anderegg et al., 2015). As respiration continues, consumption of non-structural carbohydrates continues, which can eventually lead to carbon starvation associated mortality (Dickman et al., 2015). This is a key issue for balsam fir because it has high stem maintenance respiration rates compared with other conifers (Hunt et al., 1999). Past warm summer temperatures have been linked to unusually high respiration rates and reductions in growth vigor in balsam fir, which preceded spruce budworm outbreaks (Grandpré et al., 2019).

The specific timing of a drought will affect the physiological response of balsam fir and is an important consideration when investigating its influence on a tree (Schwarz et al., 2020). At the start of the growing season, balsam fir goes through a stem rehydration phase that depends on soil water availability (Deslauriers et al., 2003), often driven by snowmelt (Zhang et al., 2019). As the growing season progresses the peak of cambial growth occurs in June and droughts at this point have a larger influence on radial growth compared to other months of the growing season (D'Orangeville et al., 2018).

Drought conditions also reduce fine root biomass production in balsam fir in the current growing season (Olesinski, Lavigne and Krasowski, 2011). Simulated drought conditions in the previous growing season also lead to a delay in the formation of xylem cells in balsam fir (D'Orangeville et al., 2013). A drought at the end of the growing season (August, September) has been shown to influence the following year's growth (D'Orangeville et al., 2018).

At latitudes with cold winters, freezing temperatures result in low water availability. If water is lost in overwintering foliage and there is no water to replace it, then tension builds in the xylem, which can lead to winter embolism (Mayr et al., 2003). Moisture is lost from foliage through either cuticular or stomatal transpiration. In winter when the ground is frozen, cuticular transpiration drives desiccation of needles and is known as frost-drought (Tranquillini, 1982). Balsam fir experiences a period of stem rehydration following winter desiccation (Deslauriers et al., 2003; Kozlowski & Winget, 1964). Higher snowfall and delayed spring melting lead to an increase in desiccation of subalpine fir (*Abies lasiocarpa*) needles (Cairns, 2001). Stomatal transpiration is a result of photosynthesis, but photosynthetic capacity is lowered in evergreen foliage during winter, which should limit photosynthesis related transpiration (Öquist & Huner, 2003). However, wintertime photosynthesis has been observed in red spruce (Schaberg et al., 1995) and Scots pine (*Pinus sylvestris*) (Sevanto et al., 2006). The earliest photosynthesis observed in balsam fir was in April and a lack of photosynthesis before this was attributed to frozen soil water (Goodine et al., 2008). There has been a warming trend of soils in spring (March, April, May) within the last 50 years (0.26-0.3°C a decade) across

balsam fir's native range (Qian et al., 2011) and, if this trend continues, there could be a future increase in early season photosynthesis in balsam fir.

Anomalous warm periods can cause early dehardening of overwinter foliage and, when followed by an abrupt cold period (freeze-thaw stress), can result in leaf damage (Perkins & Adams, 1995). Warm winter events are predicted to increase because of climate change (Vincent et al., 2018). Freeze-thaw stress has been found to increase embolism risk in winter (Mayr et al., 2006). Widespread winter injury to conifers, including balsam fir, was reported in Ontario (Buchan, 1958; Man et al., 2009, 2013), southern Manitoba and Saskatchewan (Cayford et al., 1959). A combination of anomalous high temperatures in March, followed by cold temperatures in April, led to foliage browning and needle drop, although complete tree mortality was only reported on young balsam fir in southeastern Manitoba (Cayford et al., 1959). In Ontario, snow cover was lost in March 2012, but returned in mid-April and appeared to correlate with the areas that experienced crown damage (Man et al., 2013). Although these historic events demonstrate how freeze-thaw stress can result in foliage damage, there does not appear to be a link with whole-tree mortality of mature balsam fir.

1.2.2 Stand and Site Level Drivers of Tree Mortality

Competition within stands is a key driver of mortality (Gleason et al., 2017; Ruiz-Benito et al., 2013; Zhang et al., 2020). Young, naturally regenerated forest stands have a high density of trees resulting in fierce competition for resources and high levels of mortality (Peet & Christensen, 1987). In balsam fir stands in Newfoundland, mortality was greatest in young stands, and lowest in 60 year old stands before increasing again in older stands (McCarthy & Weetman, 2007). Basal area is a widely used measure of competition

because it integrates the size and number of trees (Young et al., 2017). Basal area was the most influential variable explaining balsam fir mortality in New Brunswick permanent sample plots from 1990 to 2004 (Colford-Gilks et al., 2012).

Local site factors also influence the severity of a drought. Drainage characteristics will determine the rate at which precipitation moves through soil, with increased tree mortality risk associated with more rapidly drained soils (Rehschuh et al., 2017). The local topography and steepness of a site will also influence infiltration rates, with increased tree mortality observed on steeper slopes (Dietze & Moorcroft, 2011). The local groundwater depth (water table) is also influential in terms of water availability, with direct access to groundwater helping to alleviate drought stress in trees (David et al., 2013; Phillips et al., 2016). There are three distinct rooting habit groups of trees which are dictated by groundwater availability; 1) independence from groundwater; 2) roots that tap into capillary rise from groundwater; and 3) root growth that is restricted by groundwater (Fan et al., 2017; Roebroek et al., 2020). Across temperate and boreal forests, increased tree mortality is associated with warmer south-facing aspects (O'Brien et al., 2017). Higher elevation sites tend to be cooler than lower elevation sites during summer (Bourque et al., 2010) with lower temperatures reducing the severity of drought stress (Allen et al., 2015). Increased fir mortality has been linked with topographic features that cause increased vulnerability to water stress including steep, south facing slopes and sites with high soil drainage (Kharuk et al., 2017).

The different layers of a forest canopy are comprised of dominant, co-dominant, intermediate, and overtopped trees (Bechtold, 2003). As tree height increases, water must travel through a greater length of xylem, increasing the risk that an embolism may form

during drought conditions (Grote et al., 2016). Intermediate and overtopped trees have reduced growth compared with dominant and co-dominant trees (Assmann, 1970). Another measure of growth vigor is tree diameter. Larger tree diameters were observed in dead balsam fir compared with living (Taylor & MacLean, 2007) and in balsam fir that died as a result of spruce budworm defoliation (Yoga et al., 2017).

Growth vigor and the corresponding carbon reserves in trees are an important characteristic in determining survivability in response to stressors (Wiley, 2020). Live crown ratios are dictated by both stand density and a tree's relative position in the canopy, with internal stand competition creating differences in canopy structure as different trees establish dominance. There is a reported increase in radial increment for balsam fir trees with healthier crowns (Gagnon, 1963). Larger live crowns have also been observed to increase survivability in white fir (*Abies concolor*) during a drought (Pile et al., 2018). Smaller live crown ratios were found in dead balsam fir trees compared with living (Taylor & MacLean, 2005). A historic reduced growth increment and smaller live crown ratios were reported in balsam fir trees that experienced sudden mortality in 2018 (Zhou, 2021).

1.2.3 Historic Balsam Fir Mortality

The major exogenous driver of balsam fir mortality across its native range is defoliation from spruce budworm (MacLean, 1980). However, other causes of mortality have also been reported. In the 1970 Forest and Insect Disease Survey (FIDS) report from Ontario the “*reddening of balsam fir*” was observed (Hall et al., 1971). Then in 1971 “*Mortality of Balsam Fir*” was reported (Sippell et al., 1972), later referred to as “*Single Tree Mortality of Balsam Fir*” which occurred from 1972 – 1977 (Foster & Applejohn, 1976;

Foster & Lawrence, 1977; Howse et al., 1978; Sippell et al., 1973, 1974, 1975). Although widespread spruce budworm defoliation was occurring in Ontario during the 1970s, these reports of balsam fir mortality were considered novel enough to highlight separately in the FIDS reports.

In the Maritimes region, single tree mortality of balsam fir was initially attributed to secondary stem insects in association with spruce budworm defoliation (Magasi, 1981). Then in 1981, *Armillaria* root disease was highlighted as a key driver of single tree mortality of balsam fir (weakened by spruce budworm defoliation), with the presence of *Armillaria* confirmed on two thirds of dead trees and one third of living trees according to a small study undertaken on Cape Breton Island (Magasi, 1982). In 1982 a new definition emerged of “*Stillwell’s syndrome (sudden death of balsam fir trees)*” and was first noted in May with balsam fir, of varying levels of spruce budworm defoliation, suddenly turning bright red and dying (Magasi, 1983). Some years were more severe than others such as 1982 for New Brunswick and Nova Scotia (Magasi, 1983), 1986 for New Brunswick (Magasi, 1987) and 1990 for Prince Edward Island (Magasi, 1991). Similar reports were also noted in Maine in the mid 1980’s and were referred to as “*Red Fir*”, with around 1% of trees affected in 1990 (Dearborn & Granger, 1991). They associated it with *Armillaria* root disease and acknowledged that, once needles drop from affected trees, they are impossible to distinguish from mortality driven by spruce budworm.

Balsam fir mortality was also reported in Alberta from 1987 – 1992, with *Armillaria* root disease attributed as the main causal factor (Mallett & Langor, 1992). They acknowledged that drought may have been an inciting factor, but rule this out because no widespread mortality was observed in other tree species. However, the impact

of *Armillaria* in trees is often enhanced as a result of drought stress (Desprez-Loustau et al., 2006; Holuša et al., 2018). Single tree mortality of balsam fir was observed again in northeast Ontario in 1994, being most notable along major rivers and tributaries (Jones et al., 1995). No specific single causal organism could be linked to the mortality, but it was reported as an abiotic condition. Similar mortality was also reported in northwest Ontario in 1996 and was defined as Stillwell's Syndrome (Biggs et al., 1997). They link this type of mortality with spruce budworm defoliation but acknowledged that there was no specific causal organism. Reports continued in northwest Ontario in 1997 (Biggs et al., 1998), northeast Ontario in 1998 (Evans et al., 1999), and northwest Ontario in 1999 and 2000, but occurred at a reduced level (Biggs et al., 2001; Melbourne et al., 2000). Extensive balsam fir mortality was also observed in northern Alberta in 2015 (Whitehouse, 2016) with follow up aerial surveys confirming 144,693 hectares of balsam fir and subalpine fir mortality. No attempt to quantify the drivers of this mortality has been undertaken (Alberta Agriculture and Forestry, 2018).

The mortality of balsam fir observed in New Brunswick in 2018 appears comparable to the historic descriptions of Stillwell's syndrome in the Maritime FIDS reports in the 1980s. However, the Stillwell's syndrome name was used to honour the late M.A. Stillwell who noticed balsam fir trees in the Green River watershed of New Brunswick, that had survived spruce budworm defoliation, suddenly turning bright red and dying (Kondo & Moody, 1987). Due to this historic association of Stillwell's syndrome and spruce budworm defoliation, it is appropriate to define the 2018 event differently. We chose to refer to the 2018 balsam fir mortality as sudden balsam fir mortality because of the lack of connection to spruce budworm defoliation. Although the

historic reports of sudden balsam fir mortality occurred across many years in the Maritimes, there were some years when mortality was more severe. These annual spikes in mortality suggest an interaction with climate anomalies that justify further investigation (Anderegg et al., 2015).

1.3 Research Objectives

The overall objectives of this thesis were to: 1) investigate the climate anomalies associated with sudden balsam fir mortality across the Maritime region in eastern Canada; and 2) determine whether stand and site factors increased the probability of sudden balsam fir mortality.

The specific objectives of the first research chapter (Chapter 2) are to:

- 1) Investigate whether climate was a significant driver of the 2018 mortality event.
- 2) Use the 1986 event to validate the 2018 based modelling and investigate common climate drivers.

The specific objectives of the second research chapter (Chapter 3) are to:

- 1) Determine how mortality probability varies across site & stand variables.
- 2) Produce a landscape mortality probability prediction map.

1.4. Thesis Structure

This thesis is presented in four chapters. Following this introduction, Chapter 2, *Investigating climate anomalies associated with the sudden mortality of balsam fir trees*, explores the climate drivers associated with the 2018 sudden balsam fir mortality event across the Maritimes in eastern Canada. Chapter 3, *Integrating aerial imagery and*

random forest modelling to predict drought vulnerability of balsam fir, uses high resolution aerial imagery acquired in 2018 to detect sudden balsam fir mortality in New Brunswick and to determine how mortality probability varied across different stand and site factors. Chapter 4 outlines the primary results from Chapters 2 and 3, explores limitations of the research and outlines the implications and opportunities for the forestry industry.

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Chapter 2: Investigating climate anomalies associated with the sudden mortality of balsam fir trees

Abstract

Identifying which climate anomalies are associated with unexpected tree mortality across landscapes can help determine climate change vulnerability for specific tree species. In 2018, widespread, balsam fir mortality occurred with foliage remaining intact but turning bright red across the species southern range limit. We used a combination of air and field-based surveys of mortality as presence-absence data across the Maritimes in eastern Canada. We then fitted a Random Forest model using monthly climate data as explanatory variables with standardized values of precipitation, snow depth and maximum/minimum temperature. The Random Forest model identified a series of climate anomalies associated with mortality, including a drought in the previous growing season and high snow depth in the following spring. We also validated the model for a similar event that occurred in 1986 in the same region and predicted the spatial occurrence of mortality with an accuracy of 95% ($\kappa = 0.88$). Across the 2018 and 1986 balsam fir mortality events there were similar climate anomalies linked to mortality presence. Drier than usual conditions in March and August in the previous growing season and warmer than usual maximum temperatures in July were attributed to mortality occurrence. Deeper than usual spring snowpack in April and warmer than usual maximum temperatures in May of the same year that mortality was reported were also common anomalies between both events. This research demonstrates techniques that could be used to revisit mapped historic records of tree mortality to determine the influence of deviations from long term monthly climate averages.

2.1 Introduction

While mortality is an essential aspect of forest renewal, our capacity to determine specific causes is limited because of the many interacting factors that lead to tree mortality (Franklin et al., 1987). Nonetheless, improving our understanding of the drivers of tree mortality is important under a changing climate. Climate anomalies, such as lower than usual precipitation or higher than usual temperatures or a combination of both can lead to droughts which are continuing to increase the risk of tree mortality globally (Allen et al., 2010).

Tree mortality induced by drought is caused by carbon starvation and hydraulic failure. Carbon starvation occurs when drought induced closure of stomata leads to a sustained reduction in photosynthate (McDowell et al., 2008). Reduced conductance in the xylem of a tree can occur when water loss from transpiration is not matched by water uptake in the roots, which increases xylem tension and can lead to cavitation and hydraulic failure (McDowell et al., 2011). Both hydraulic failure and carbon starvation are relevant when investigating drought-induced tree mortality, with individual tree responses often being species specific (Adams et al., 2017).

Balsam fir (*Abies balsamea* (L.) Mill.) is a shade tolerant, North American, northern conifer species with optimal growth in moist conditions (Rowe, 1972; Sims et al., 1990). It is a key economic softwood species used primarily for pulp and small dimension stud wood (Sinclair & Govett, 1983). Historic logging practices, fire suppression and insecticide protection have led to an increased abundance of balsam fir across the Maritimes region in eastern Canada (Noseworthy & Beckley, 2020). A northward shift is predicted for these balsam fir populations under future climate change

scenarios (Bourque et al., 2010; Dombroskie et al., 2010; Taylor et al., 2017). This will have a significant impact on the forestry sector of the Maritimes region, as balsam fir comprises over 25% of operable wood volume (National Forest Inventory, 2022).

There has been recent extensive novel mortality of balsam fir observed with sudden reddening of foliage and whole tree crowns turning bright red. Reports were first observed in spring 2018 in Wisconsin (Wisconsin DNR, 2019), northern areas of New Hampshire, Vermont, Maine (Maine Forest Service, 2018) and New Brunswick (NBERD, 2018) (Figure 2.1). Mortality in New Brunswick was considered high enough to include recording locations of mortality within a province wide aerial survey. This mortality was unlikely to be caused by spruce budworm (*Choristoneura fumiferana*) because foliage had no evidence of defoliation. Mortality from spruce budworm is reported to take more than four consecutive years of severe defoliation (MacLean, 1980). Due to the synchronicity of observed mortality, it is likely that climate conditions played a major role. It is expected that local stand and site conditions influenced mortality frequency and extent as has been previously reported in fir (*Abies*) mortality (Harvey et al., 2021; Lalande et al., 2020).

Historic Canadian Forest Insect and Disease Survey (FIDS) reports from the Maritimes region of eastern Canada reveal similar balsam fir mortality events occurring in the 1980s, referred to as “*sudden death of balsam fir trees*” or “*Stillwell’s syndrome*” (Magasi, 1987). The FIDS reports are mostly anecdotal with mortality levels varying in intensity across different years. The only attempt to map this mortality was undertaken in 1986 due to the much higher severity reported in that year (Magasi, 1987).

Although sudden balsam fir mortality has been historically associated with biotic agents (Magasi, 1987), the rapid appearance of symptoms (bright red, intact crowns) also supports the hypothesis of hydraulic failure, likely linked to drought (Arend et al., 2021). Drought is known to decrease xylem tracheid size in balsam fir (D'Orangeville et al., 2013) and compared to other species in the region, it is relatively vulnerable to a loss of hydraulic conductance in response to increasing xylem pressure (Balducci et al., 2020; Tyree et al., 1994). Identifying the broad scale climate anomalies, such as a drought, associated with the reported sudden balsam fir mortality in 2018 could prove useful to determine the likelihood of future mortality in response to climate change (Bourque et al., 2005).

The modelling of dieback of blue oak (*Quercus douglasii*) in California was possible through the use of dieback occurrence record polygons combined with climatic variables (Brown et al., 2018). Here, we aim to apply a similar approach to balsam fir mortality data and standardized climate data so that climate anomalies associated with mortality in 2018 can be identified. We define a climate anomaly as the deviation from the local average and represented it in units of standard deviation. We also validate the modelling by predicting a mapped record of similar historical balsam fir mortality. We hypothesize that drought-related climate anomalies will be the strongest predictor of mortality because of balsam fir's relative vulnerability to hydraulic conductance loss in response to increasing xylem pressure (Martínez-Vilalta et al., 2004).

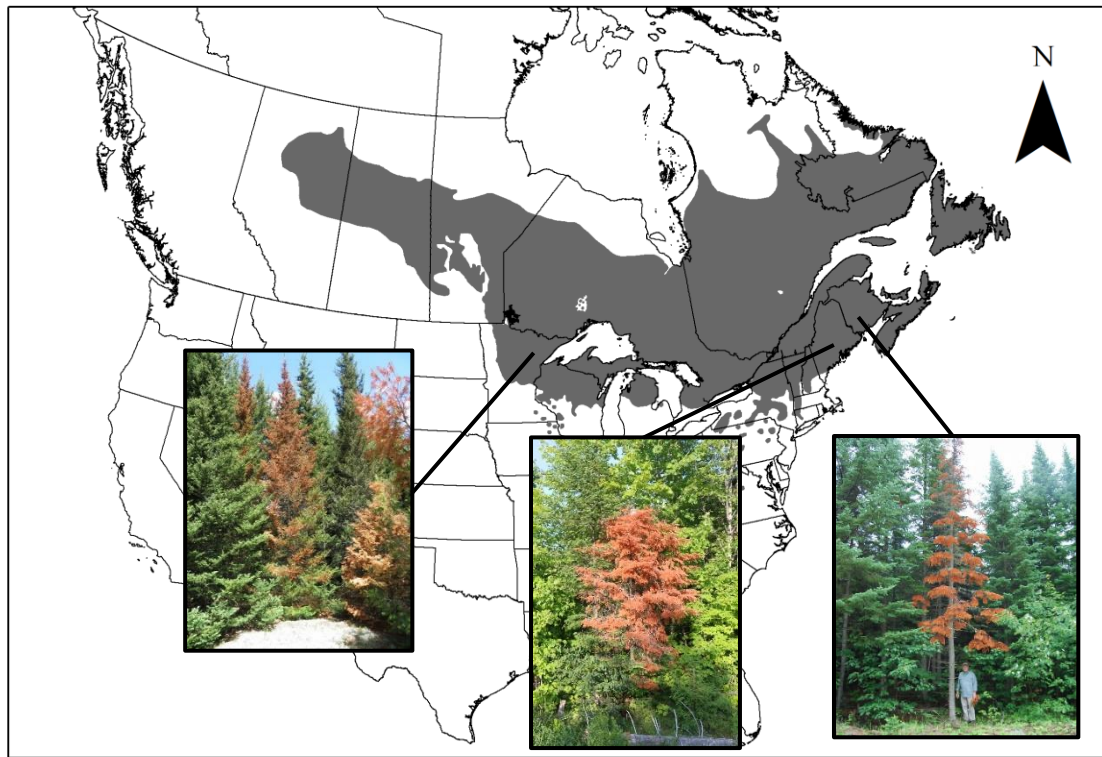


Figure 2.1 - the range of balsam fir is highlighted in grey (Natural Resources Canada, 2015) with pictures of the rapid reddening of intact foliage associated with sudden balsam fir mortality in 2018 reported in Wisconsin (Wisconsin DNR, 2019), northern areas of New Hampshire, Vermont, Maine (Maine Forest Service, 2018) and New Brunswick (NBERD, 2018).

2.2 Methods

2.2.1 Study Area

The provinces of New Brunswick (NB), Nova Scotia (NS) and Prince Edward Island (PEI) form the Maritime provinces of Canada. They are part of the Atlantic Maritime Ecozone, a region strongly influenced by the Atlantic Ocean resulting in a cool and moist environment. Annual precipitation is between 800 mm inland and over 1500 mm near the coast. In the upland regions, Humo-Ferric Podzols and glacial tills are the dominant soils

with underlying hard, crystalline rocks including granite and gneiss. In lowland areas nearer to the coast, deeper Luvisolic soils are formed from the underlying sedimentary bedrock (Ecological Stratification Working Group, 1996).

2.2.2 Response Variable

Following multiple public reports of sudden balsam fir mortality across NB in the spring of 2018, NB Department of Energy and Resource Development (NBERD) undertook a survey to identify and locate recently dead balsam fir – defined as balsam fir trees with complete crowns of bright red foliage – during their annual province-wide aerial survey in July 2018 (NBERD, 2018). Flight lines were conducted 5 km apart in northern NB and 11 km apart in the south. The survey recorded 115 point locations which indicated either single balsam fir trees or groups of balsam fir trees with symptoms of sudden mortality, which covered a large proportion of the province. However, the recorded mortality was likely underestimated due to the coarse resolution of the aerial survey data and difficulty for surveyors to record all cases of individual tree mortality. There were also additional reports of sudden balsam fir mortality after the aerial survey (Drew Carleton, pers. comm.). We therefore deemed the NB absence data to be unreliable and so locations in NB with no sudden balsam fir mortality recorded from the initial aerial survey were excluded from further analysis. Aerial surveys were not flown in the other Maritime provinces due to a lack of reported sudden balsam fir mortality, but we surveyed local foresters in neighbouring provinces and were able to confirm that the same extent of balsam fir mortality seen in NB was not reported in NS (Jeffrey Ogden, pers. comm.) and PEI (Mary Myers, pers comm). For the purpose of this study, both NS and PEI were

therefore defined as areas with no sudden balsam fir mortality (absence data) given no widespread reported cases in 2018 (Figure 2.2).

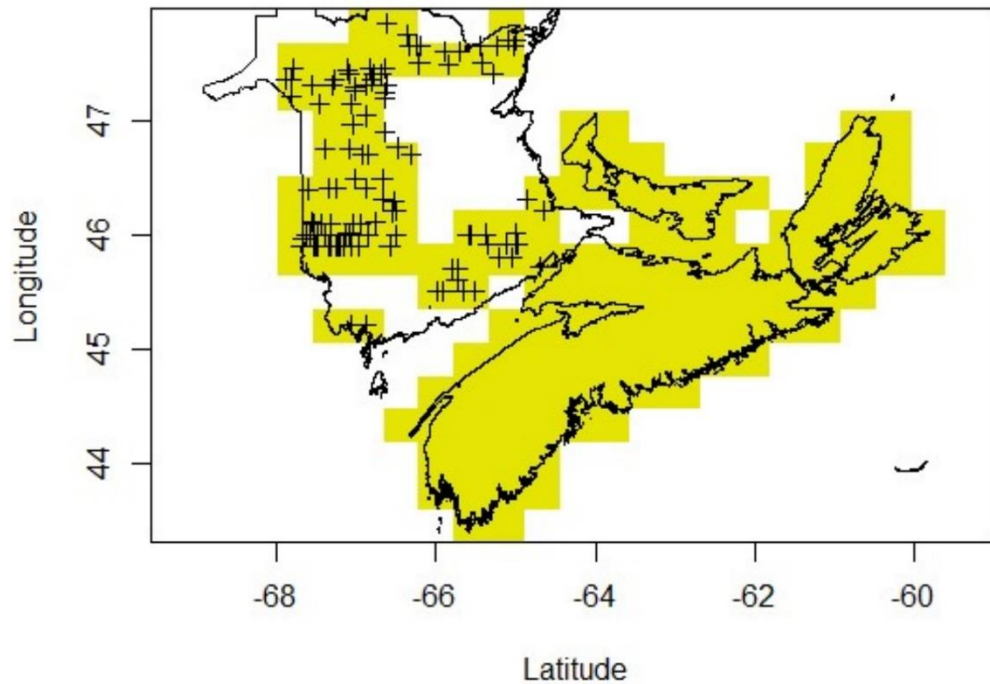


Figure 2.2 – Individual and groups of balsam fir trees with symptoms of sudden mortality were identified from a systematic aerial survey of New Brunswick (NB) indicated by ‘+’ symbols. Areas of NB with no reported mortality from the aerial survey were omitted to avoid false negatives. Nova Scotia and Prince Edward Island had no mortality reported, which was confirmed by local foresters and became absence data.

2.2.3 Climate Data

Temperature, precipitation and snow depth data were acquired for the study region.

Monthly averages of daily maximum temperature (T_{MAX}), minimum temperature (T_{MIN}) and the monthly sum of precipitation were interpolated at 2 km resolution from meteorological weather station data for the 1950-2018 period using thin-plate smoothing

splines, as implemented in the ANUSPLIN climate modeling software (McKenney et al., 2011). As deeper snow depths combined with earlier melting in spring have been positively correlated with balsam fir growth (Duchesne et al., 2012) and shown to influence crown health (Man et al., 2013), 1979-2018 monthly snow depth data were acquired from the National Center for Environmental Prediction North America Regional Reanalysis (Mesinger et al., 2006) at ~32 km resolution. Temperature and precipitation values were aggregated to a mean value that matched the coarser resolution of the snow depth data using the “raster” package in R (Hijmans et al., 2013).

To identify climate anomalies across the study area we developed standardized climate indices for each 32 km cell that reflected deviations from the local climate normal. Precipitation data was normalized using the Standardized Precipitation Index (SPI) (McKee et al., 1993). The 69 years of precipitation data (1950-2018) were fitted to a gamma distribution and then transformed into a normal distribution with SPI values that represent the standard deviation from the median (which is a SPI value of 0). Positive SPI values indicate higher than average precipitation with negative values indicating drier than usual conditions. We also used the same process to standardize the 40 years of snow depth data (1979-2018), which we refer to as the Standardized Snow Depth Index (SSDI). Periods without any snow can be common, so we fitted a gamma distribution to the data in the same way as the precipitation data (Skaugen & Melvold, 2019). The 69 years of temperature data (1950-2018) were also standardized in a similar method as the SPI, which is referred to as the Standardized Temperature Index (STI) (Zscheischler et al., 2014), but, as temperature was normally distributed we fitted the data to a log-logistic distribution. The SPI, SSDI and STI all have units of standard deviations from the long

term average. The “spei” package (Beguería et al., 2017) was used to standardize the climate data and the “raster” package (Hijmans et al., 2013) was used to convert the standardized climate data back to a spatial format in R.

2.2.4 Data preparation

The presence-absence of sudden balsam fir mortality was then scaled to the ~32 km grid cell resolution of the climate data using the gridRecords function in the “fuzzySim” package in R (Barbosa, 2016). If one or more point occurrences of sudden balsam fir mortality was in a ~32 km cell, then that cell was assigned as a presence cell. Only climate data from the previous 15 months prior to widespread sudden balsam fir mortality being reported was included, ranging from March 2017 to May 2018, which ensured a full growing season was investigated. This resulted in 15 monthly climate variables for T_{MAX} , T_{MIN} and precipitation respectively, and nine variables for snow depth (only winter and spring months were included). This gave a total of 54 monthly climate variables.

Three preliminary screening processes were used to reduce the large number of initial monthly climate variables to avoid overfitting when building our predictive model (Appendices Table AP2.1). First, each climate variable was averaged across presence and absence areas. Next, only the 32 climate variables that displayed a greater anomaly in presence areas were retained. Second, a simple logistic regression model was built for each climate variable and was used to predict the presence-absence data. A Cohen's kappa value was obtained from this prediction and only variables that had a significant logistic regression model ($p < 0.05$) were retained. The kappa value was chosen as the accuracy metric as it gives a more conservative measure of accuracy because it accounts for chance in a binary prediction (Cohen, 1960). Next, the collinearity between the

remaining 24 explanatory climate variables was determined through Pearson correlations and visualised through the “corrplot” package in R (Wei et al., 2017) (Appendices Figure AP2.1). Finally, each pair of climate variables was ordered by the strength of their correlation ($\geq \pm 0.7$) and the variable with a higher kappa value from its prediction of presence-absence data, through its logistic regression model, was retained. In the single situation where two explanatory variables had the same kappa value, then the variable in the growing season was retained due to its expected greater influence on tree mortality. These three preliminary screening processes resulted in 11 explanatory climate variables that were used in the modelling (Appendices Table AP2.2), which were all correlated under ± 0.7 (Appendices Figure AP2.2). There were also 8 cells across the study area that had to be removed because of a lack of snow depth data in May, with a final total of 126 cells across the study area with 42 classed as presence cells and 84 absence cells (~33% presence).

2.2.5 Random Forest modelling

To model the presence-absence of sudden balsam fir mortality based on our set of explanatory climate variables, we employed the machine learning algorithm Random Forest (RF; Breiman, 2001). RF analysis accommodates many of the violations of conventional, parametric statistics that are common for observational data, including departures from normality and homogeneity of variance, and are well suited for the analysis of ecological data (Elith, 2019). The probability of mortality reported through the random forest modelling is based on the count of the number of trees across the ensemble of decision trees that vote for a certain class. The default 0.5 threshold was set

to determine which class a data point falls within. The reported probability of mortality is the probability of one or more dead balsam fir trees occurring in a ~32 km grid cell.

Machine learning techniques usually require data to be split into a training dataset, which is used to build a model, and the model is then validated on a withheld testing dataset (on data unseen during the training process). However, when a dataset is relatively small, as in the current analysis, then the testing/training splitting procedure can omit potentially useful data when the model is being trained. RF modelling is useful in this situation as there is an internal training and testing procedure. For each individual decision tree, a new training set is sampled with replacement, where each unique data point can be randomly chosen multiple times. This is known as a bootstrap sample and typically includes $2/3$ of the original data observations (Efron & Tibshirani, 1997; Gareth et al., 2013). The remaining $1/3$ that was not selected then forms the out-of-bag dataset, which is used for testing purposes. The predicted class for a data point is then calculated by a majority vote from the decision trees that did not contain that specific data point (~32 km cell) in the respective bootstrap sample. The overall accuracy of the RF model is based on the proportion of out-of-bag samples that were incorrectly classified across the ensemble of decision trees and is referred to as the out-of-bag error.

Climate data is spatially autocorrelated (Dormann et al., 2007), which leads to spatially dependent testing and training datasets (Ploton et al., 2020). This limits the ability to properly evaluate the performance of the final RF model based on the out-of-bag error. Due to this spatial autocorrelation, we chose to use mapped records of a similar sudden balsam fir mortality event from 1986 to independently test the 2018 RF model. Areas of high, medium and low frequency of sudden balsam fir mortality were recorded

in 1986, as well as areas of mortality absence (Magasi, 1987). High and medium frequency areas were combined due to the small relative size of medium frequency areas and the subsequent overlap of climate data with high frequency areas. First, we used the 2018 RF model to predict areas of mortality from 1986 based on different combinations of frequency levels as the presence data (high/medium vs. absence; high/medium/low vs. absence; low vs. absence). Next, we fitted a separate RF model for 1986 using the same 11 monthly climate explanatory variables used in the 2018 RF model but limited the presence areas to the high and medium frequency areas only (excluding low frequency areas).

The “caret” package in R (Kuhn, 2009) was used to determine the optimum *mtry* hyperparameter, which defines the number of explanatory variables that are randomly sampled at each node split in each decision tree of the RF model. The *train* function used 25 bootstrap resamples (with replacement) of the data to evaluate how different *mtry* values (1:11) altered the predictive performance of the RF model. Once the optimum *mtry* value was determined, then a final RF model was run using the “randomForest” package in R (Liaw & Wiener, 2002). The *nree* (number of trees) parameter was set at the default (500) to determine when the out-of-bag error stabilized, and then rerun with the appropriate reduced number of trees (Elith, 2019). The node size, which specifies the minimum number of observations in a terminal node in each decision tree, was kept at the default for classification of 1.

The final step investigated the partial dependence plot (PDP) for each climate variable generated for both the 2018 and 1986 RF models. A PDP gives a graphical representation of how, across the range of values for a single climate variable, the

probability of the presence of sudden balsam fir mortality changes. The comparison of the PDPs meant that the level of agreement across the two RF models could be visually interpreted to determine if the effect of each climate variable on mortality probability was consistent for each mortality event. The variable importance for each RF model used the mean decrease in Gini Importance (also referred to as the Mean Decrease in Impurity). This is the average decrease in node impurity, based on each split in a decision tree for a specific variable, across all the individual decision trees that make up a random forest model (Liaw & Wiener, 2002). Inflated impurity-based variable importance related to a varied scale of measurement or number of categories was avoided because the climate explanatory variables were continuous and standardized (Strobl et al., 2007).

2.3 Results

2.3.1 Seasonal climate trends across March 2017 – May 2018

The following seasonal descriptions are based on the non-standardized mean averages for monthly climate variables across presence areas to aid interpretation (Appendices Table AP2.3). Spring 2017 was initially cold and dry in March with a reduced snow depth (Figure 2.3), then temperatures increased with April and May $T_{MIN} +2.0$ °C and $+1.2$ °C warmer than normal. Precipitation was also higher than the average in both April ($+11.1$ mm) and May ($+53.5$ mm). Summer 2017 T_{MAX} was warmer than normal with June, July and August $+0.5$, $+0.4$ and $+0.5$ °C above the average, respectively. This was combined with lower than average precipitation, dropping 43% to 42.6 mm and 38% to 34.7 mm in July and August, respectively. The warm wet spring and dry warm summer were followed by an exceptionally warm fall in 2017 with T_{MAX} in September and October

+3.2 and +4.7 °C above normal. T_{MIN} was also warmer than the average in September at +2.6 °C and October at +2.8 °C. Winter 2017-2018 tended to have higher precipitation rates than usual. The initial cold conditions in December, with T_{MAX} and T_{MIN} -2.0 °C and -1.6 °C below the average, were followed by warm conditions in February, with T_{MAX} and T_{MIN} +3.5 °C and +3.0 °C above the average, which resulted in a reduction in snow depth, 23% below normal. The 2018 spring leading up to widespread reports of sudden balsam fir mortality began with a warm March (+3.3 °C in T_{MIN}), followed by a cool April (-1.2 °C for both T_{MAX} and T_{MIN}). The combination of cool temperatures and high precipitation in April (+34.2 mm) led to an exceptionally high snow depth, 94% above normal. The cold April was then followed by a warm May, with T_{MAX} +2 °C higher than the average.

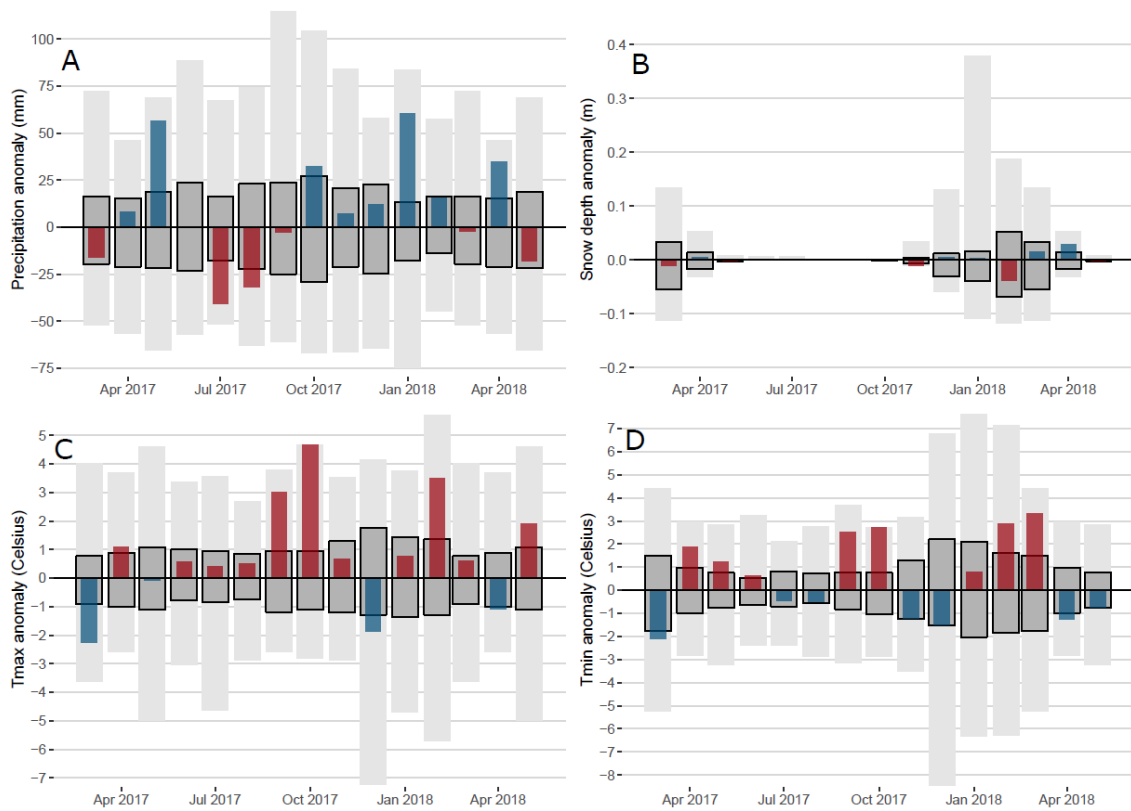


Figure 2.3 – The 2017-2018 precipitation (A), snow depth (B), T_{MAX} (C) and T_{MIN} (D) are colored (blue higher, red lower). The range of historic anomalies (maximum-minimum) is in light grey. The interquartile range of the historic time series is in dark grey. Climate data is limited to presence areas only.

2.3.2 2018 RF modelling and variable importance

The best performing 2018 RF model ($mtry = 3$, $ntree = 250$) was accurate with an out-of-bag error rate of 1.6%. The 2018 RF model identified a series of seasonal climate anomalies which can exacerbate water stress. According to the 2018 RF model variable importance scores, the 2017 summer drought was the best predictor of mortality, with low August precipitation ranked as the most important predictor of sudden balsam fir

mortality (Table 2.1). Dry conditions in March 2017 (63 mm) were also considered important in the 2018 RF model, ranking 3rd. The water deficit was likely exacerbated by unusually high summer temperatures in 2017, although only high temperatures in July were included in the RF model, which were ranked 5th. The thicker than usual snow depth in April 2018 was considered the second most important variable in the RF model with the warmer than usual T_{MAX} in May ranked 7th.

Table 2.1 – 2018 Random Forest (RF) model and 1986 RF model variable importance rankings for 11 climate explanatory variables used in RF modelling (Previous refers to 2017 for the 2018 event and 1985 for the 1986 event, while Current refers to 2018 and 1986, respectively).

<i>Variable</i>	2018		1986	
	<i>Rank</i>	<i>Mean Decrease Gini</i>	<i>Rank</i>	<i>Mean Decrease Gini</i>
PrecipPreviousAug	1	26.06	1	12.32
SnowDepthCurrentApr	2	7.89	7	1.02
PrecipPreviousMar	3	5.90	4	4.28
MinTempPreviousAug	4	5.11	5	2.10
MaxTempCurrentMay	5	2.25	6	1.48
PrecipCurrentApr	6	1.88	11	0.07
MaxTempPreviousJul	7	1.74	9	0.32
MaxTempCurrentApr	8	1.67	3	4.86
PrecipPreviousJun	9	1.28	2	9.94
MaxTempPreviousMar	10	0.96	10	0.08
SnowDepthCurrentMay	11	0.87	8	0.46

2.3.3 Model validation through the 1986 event

The 2018 RF model predicted the 1986 event with an accuracy of 95% (kappa 0.88) with 103 out of 108 raster cells correctly classified when the area tested was limited to absence, medium and highest frequency of mortality for 1986 (Table 2.2). When the model was applied across the whole province (including the low frequency areas as presence data) the accuracy dropped to 89% (kappa 0.77), with higher mortality probability in areas that matched the high and medium frequency regions (Figure 2.4). The lower predictive ability of the 2018 RF model with areas of low frequency included justified removing these areas from the final 1986 RF model. This was further confirmed when only low frequency areas formed the presence data with the accuracy further dropping to 87% (kappa 0.69).

2.3.3 Similarity between the 1986 and 2018 balsam fir mortality events

Five out of the 11 climate explanatory variables had similar mortality probability patterns across the separate PDP plots generated from the 2018 and 1986 RF models (Appendices Figure AP2.3 & AP2.4). The two most important climate variables in the 2018 RF model demonstrated similar effects on mortality probability for the 1986 RF model (Figure 2.5). The 1986 and 2018 RF model importance score rankings also displayed important similarities, notably, both models ranked below-average previous August precipitation first (Table 2.1) Drier conditions in March and August of the previous year increased mortality probability for both events (Appendices Figure AP2.3). Warmer than usual previous year July temperatures (T_{MAX}) also increased mortality probability for both events. In the current year that mortality was reported, both events demonstrated a higher

mortality probability for areas with a deeper than usual snowpack in April followed by a warmer than usual T_{MAX} in May.

Table 2.2 – Prediction accuracy and kappa scores when the 2018 Random Forest model was applied to different mortality severity combinations of 1986 presence and absence data.

	Accuracy	Kappa
1986 High/Medium frequency vs. 1986 Absence	95%	0.88
1986 High/Medium/Low frequency vs. 1986 Absence	89%	0.77
1986 Low frequency vs. 1986 Absence	87%	0.69

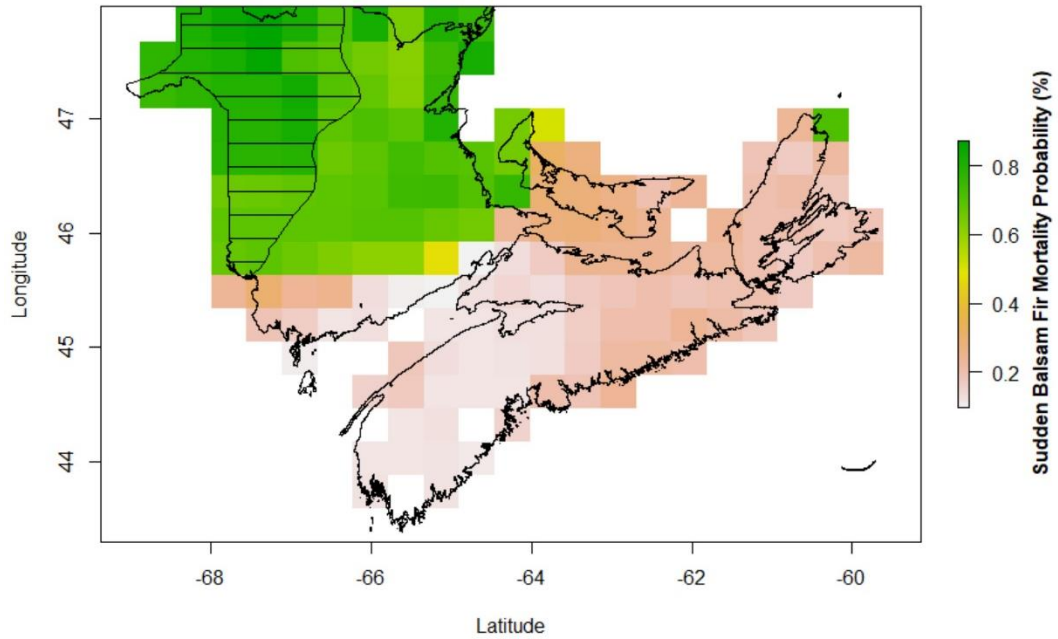


Figure 2.4 - Predicted probability of sudden balsam fir mortality (occurrence of one or more trees with sudden balsam fir mortality) in 1986 using the 2018 Random Forest (RF) model. The combined medium and high frequency areas (black horizontal lines - refer to Magasi, 1987) are associated with higher probabilities of mortality.

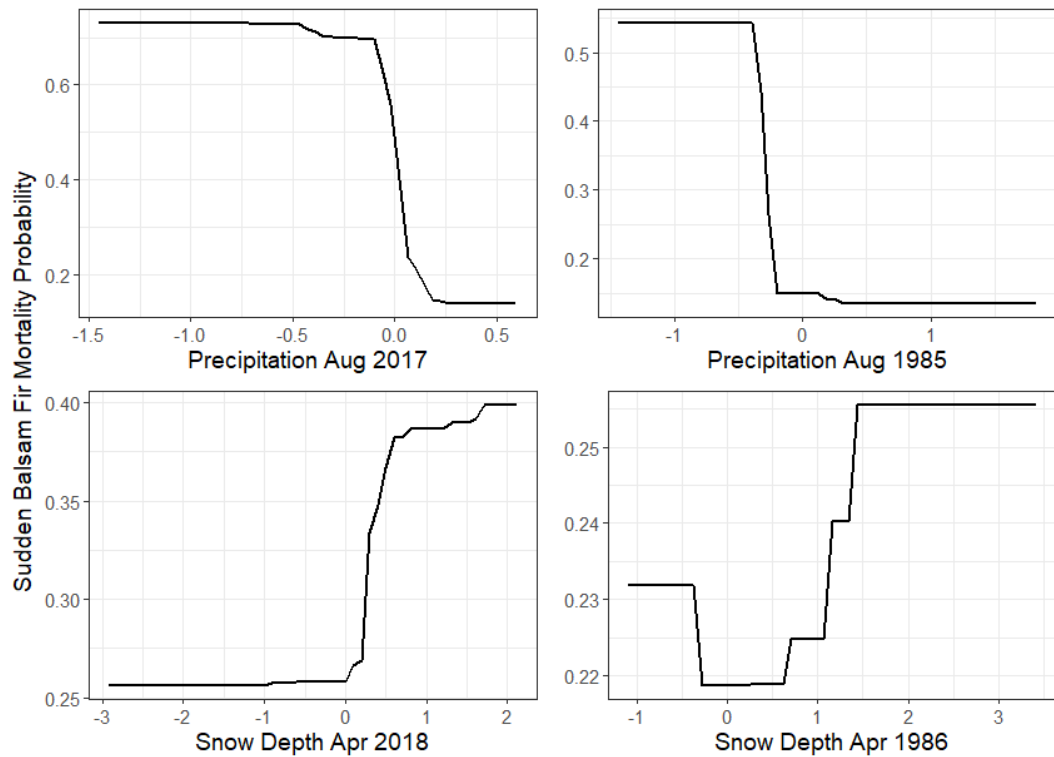


Figure 2.5 - The Partial Dependence Plot for the two most important climate variables in the 2018 Random Forest (RF) model demonstrated a similar mortality probability trend (occurrence of one or more trees with sudden balsam fir mortality) as those from the 1986 RF model. X axis values are the standard deviations from the long term climate average represented by 0.

2.4 Discussion

Lower than usual August precipitation in the previous growing season was identified as the most important variable for both the 2018 and 1986 RF models confirming the hypothesis that drought was a key driver of sudden balsam fir mortality. Intense water deficit leads to damage to a tree’s hydraulic transport system through cavitation (Sperry et al., 1998) and exhaustion of non-structural carbohydrates (McDowell et al., 2008). It can also be the combination of both these phenomena that leads to tree mortality (Sevanto

et al., 2014). Legacy effects from drought anomalies have been reported before for balsam fir (D'Orangeville et al., 2018). Compared to other coniferous tree species of the Maritime provinces, balsam fir displays higher respiration rates (Hunt et al., 1999) and a greater vulnerability to cavitation that is induced by xylem tension (Balducci et al., 2020; Sperry & Tyree, 1990; Tyree & Dixon, 1986; Tyree & Sperry, 1989). Such attributes, combined with the lower general drought adaptation of trees growing in regions with relatively high precipitation (Jump et al., 2017; Reich et al., 2016), support the high risk of balsam fir mortality observed from drought conditions.

The dry 2017 conditions would have been further exacerbated by the high T_{MAX} anomaly in June, July and August which would have amplified the evopotranspirative pull (Grossiord et al., 2020). Balsam fir is projected to display a strong decline across the Maritime provinces under future warming (Bourque et al., 2010; Dombroskie et al., 2010; Taylor et al., 2017). In both the 2018 and 1986 RF models, a higher probability of mortality was associated with warmer than usual T_{MAX} in July (Appendices Figure AP2.4). Warm conditions were also present in spring 2017 and likely induced an early start to the growing season, as it is cold temperatures that constrain the growth of balsam fir in spring (Rossi et al., 2008). Although cambial activity in the stem ceases at the end of August in balsam fir (Rossi et al., 2008), the warm temperature anomalies in September and October could have induced continued root growth, further using up carbohydrate reserves in already stressed trees (Olesinski et al., 2012). Warm September temperatures in the previous year were also observed for the 1986 mortality event, but this variable did not feature across the RF models due to collinearity (Appendices Table AP2.4).

The high snow depth in April 2018 would have maintained low soil temperatures while air temperatures would have been increasing. While frozen soil water has been observed to inhibit photosynthesis (Goodine et al., 2008), the decoupling between soil and air temperatures could have induced water stress, due to the higher viscosity of water in cold soils and low root temperatures (Kaufmann, 1975; Wang & Hoch, 2022) leading to insufficient replacement of the water lost through leaf cuticles (Tranquillini, 2012). The needles and twigs of cut Scots pine (*Pinus sylvestris*) maintained relatively consistent water content throughout the winter and it was only in spring that there was a sudden reduction compared to the uncut control trees (Havas & Hyvärinen, 1990). This could support the hypothesis that the balsam fir trees reported dead in 2018 could have experienced hydraulic failure in 2017, which then only became apparent in the following spring through the rapid drying and reddening of whole balsam fir crowns. Foliage desiccation has been shown to be more severe in years with higher snowfall and delayed melting (Cairns, 2001), and when coupled with the high photosynthetic active radiation at this time (Duchesne et al., 2012), would suggest that balsam fir is more vulnerable to needle desiccation in early spring. A later than usual snow pack has been previously associated with foliage damage in balsam fir in Ontario (Man et al., 2013). Higher than usual April snow depth was also observed in areas of high and medium mortality in the 1986 event. Interestingly, 1982 was another year with a late spring snowpack and higher than usual sudden balsam fir mortality reported across the Maritimes, but a lack of mapped occurrence data restricted our ability to test the RF model in this year (Magasi, 1983).

Although sudden balsam fir mortality was reported across large parts of New Brunswick, mortality was irregular with only certain individual trees affected. Individual tree mortality is a complicated process with many predisposing, inciting and contributing factors (Sinclair, 1965; Manion, 1981). It is likely that biotic factors at the individual tree level were responsible for the sporadic nature of mortality with the balsam fir bark weevil (*Pissodes dubius*) and *Armillaria* root disease being previously associated with sudden balsam fir mortality (Magasi, 1987). The position of individual trees in the canopy and corresponding live crown ratios will also of contributed to mortality rates with a reduction in growth vigor and smaller live crown ratios reported for balsam fir trees that experienced sudden mortality in 2018 (Zhou, 2021). There was also a heavy cone crop reported in balsam fir in 2013, 2015 and 2017 which will have also influenced carbohydrate reserves (Bouchard & Pernot, 2020). However, due to the large spatial scale of the climate data and the coarse quality of the presence data used in this study it was not possible to integrate the finer resolution tree level factors into the current analysis.

Our analysis was restricted to the 15 months prior to reported mortality and will have overlooked other historic climate stress, such as sequential multiyear droughts (Sánchez-Pinillos et al., 2021). The current analysis was also limited because only monthly climate variables were used, restricting the analysis of more acute climate stressors, such as high wind, which could have increased foliage desiccation in spring (Cairns, 2001). It is also important to acknowledge the error in climate data derived from both the North America Regional Reanalysis and ANUSPLIN climate modeling software (Bukovsky & Karoly, 2007; McKenney et al., 2011).

Assessing the relationship between climate data and tree mortality occurrence is a useful exercise for forest management (Law et al., 2018). This has been demonstrated through the 2018 RF model achieving a surprising prediction accuracy for the medium and highest frequency areas of balsam fir mortality in 1986. Modern thin-plate smoothing splines have enabled greater availability of widespread historic climate data (McKenney *et al.*, 2011) making the spatial techniques outlined in this paper a viable method to examine the climate drivers of other recent tree mortality (Kosiba et al., 2018).

The inclusion of the historic 1986 balsam fir mortality event was only possible because of the FIDS – a Canada-wide tree health monitoring programme that ceased in 1995 (Hurley & Magasi, 1996). With climate change likely to increase anomalous climate events, it is important to spatially record and report tree mortality so that analysis investigating extreme climatic events can be undertaken. With the current widespread availability of historic climate data, this research demonstrates techniques that could be applied to other historic tree mortality events. If we can improve our understanding of how climate anomalies influenced historic tree mortality events, then we can improve our understanding of species-specific vulnerabilities across forested landscapes. If vulnerable species are identified, then silvicultural responses to increasing climate stress can be better targeted.

2.5 References

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Chapter 3: Integrating aerial imagery and random forest modelling to predict drought induced mortality of balsam fir

Abstract

Increases in temperatures and droughts are elevating tree mortality risk worldwide. Identifying stand and site factors that increase mortality risk can help determine drought vulnerability and better inform forest management. In 2018, a widespread, balsam fir mortality event occurred across the species southern range limit. Mortality appeared to be sudden with foliage remaining intact but turning bright red. This research aims to identify local stand and site conditions that were controlling the probability of mortality. We first identified the presence of dead balsam fir individuals using high resolution aerial imagery. Next, we used these occurrences to create a presence-absence dataset at the 20 m cell scale of the site and stand explanatory variables. Then we used the Random Forest machine learning algorithm to understand how local site and stand conditions influenced mortality probability through partial dependence plots. Increases in mortality probability were all related to factors that would affect drought severity. Sites associated with elevated temperatures (lower elevations and south facing aspects) increased mortality probability. Increased forest stand competition (basal area) and tree height also elevated mortality risk. The effect of site factors that influence water availability and root adaptation were more complex with non-linear relationships observed for drainage and depth to water, but minimal influence observed for slope steepness. The modelling was also used to generate a landscape-level mortality probability map to assess regions of elevated drought risk associated with balsam fir mortality.

3.1 Introduction

Drought is increasing tree mortality events around the world (Allen et al., 2010). Drought induced single tree mortality is difficult to model accurately because of the complex interactions between drought, site factors and biotic agents (Trugman et al., 2021). Regardless of the difficulties of modelling tree mortality, it is a useful exercise because it can highlight specific tree species vulnerabilities across forested landscapes.

Balsam fir (*Abies balsamea* (L.) Mill.) is a northern affiliated North American conifer adapted to cool and moist site conditions (Rowe, 1972; Sims *et al.*, 1990). It forms a large component of the Acadian forest in eastern Canada, which is predominantly located across the Canadian Maritime provinces, and is an ecological transition zone linking the temperate deciduous forests to the south with the boreal forest to the north (Loo & Ives, 2003). The major exogenous driver of balsam fir mortality across its native range is defoliation by eastern spruce budworm (*Choristoneura fumiferana*) (MacLean, 1980). However, climate change is projected to drive a northward shift in balsam fir populations (Andrews et al., 2022; Bourque et al., 2010; Dombroskie et al., 2010; Taylor et al., 2017). With balsam fir comprising over 25% of operable wood volume in the Canadian Maritime provinces, the predicted decline in abundance, will have significant impacts on the forestry sector (National Forest Inventory, 2022).

Recent widespread balsam fir mortality was reported in spring 2018 across Wisconsin (Wisconsin DNR, 2019), New Brunswick (NBERD, 2018) and northern areas of New Hampshire, Vermont, Maine (Maine Forest Service, 2018). Full, intact crowns were observed suddenly turning bright red suggesting that mortality was rapid. This mortality is unlikely to be driven by spruce budworm as there was little evidence of

defoliation on the trees affected with at least 4-5 years of consistent defoliation required to cause mortality (Houndode et al., 2021; MacLean, 1980). A series of seasonal climate anomalies, including drier than usual conditions in the previous growing season, have been associated with sudden balsam fir mortality in 2018 and 1986 (Chapter 2).

Local site factors influence the severity of a drought. Higher elevation sites tend to be cooler than lower elevation sites during summer (Bourque et al., 2010), with lower temperatures likely to reduce the severity of a drought (Allen et al., 2015). Across boreal and temperate forests, increased tree mortality is linked to warmer south-facing aspects (O'Brien et al., 2017). Other local topographical characteristics that influence soil moisture and groundwater access also affect the risk of drought-associated tree mortality. The rate at which precipitation moves through soil is dictated by its drainage characteristics, with increased tree mortality risk observed on more rapidly drained soils (Rehshuh et al., 2017). The steepness of local topography will also influence how precipitation infiltrates into the soil, with increased tree mortality observed on steeper slopes (Dietze & Moorcroft, 2011). The local depth to groundwater (water table) is also influential, with direct access to groundwater helping to alleviate drought stress (David et al., 2013; Phillips et al., 2016). Groundwater depth dictates rooting habits in trees, which can be assigned to three distinct groups: 1) independence from groundwater, 2) roots that tap into capillary rise from groundwater, and 3) root growth that is restricted by groundwater (Fan et al., 2017; Roebroek et al., 2020).

Individual tree characteristics can further influence the risk of mortality from drought. As tree height increases, there is a longer period that water must travel through the xylem, increasing embolism risk during drought conditions (Grote et al., 2016). Stand

competition is also a key driver of tree mortality with basal area a widely used metric reflecting the size and number of trees (Bradford & Bell, 2017; Kershaw et al., 2016; Young et al., 2017).

Permanent sample plot networks can provide detailed stand information that can then be used to examine drivers of tree mortality (Bashir & MacLean, 2015; Colford-Gilks et al., 2012; Guan et al., 2021; Taylor & MacLean, 2005). However, the use of these is restricted if the analysis of a specific year of elevated tree mortality is required because resampling periods tend to be greater than one year. Remote sensing techniques, including aerial imagery, can facilitate the spatial delineation of tree mortality more frequently than traditional permanent sample plot networks (Huang et al., 2019). High resolution aerial imagery from 2018 was available in north and northwest New Brunswick and due to the bright red intact balsam fir crowns, it was possible to distinguish these from non-symptomatic balsam fir trees (Figure 3.1). Other remote sensing techniques, such as airborne laser scanning (LiDAR), have also improved our ability to measure forest stand and site attributes (White et al., 2016).

The objective of this paper was to use the spatial presence-absence of individual balsam fir mortality, identified from aerial imagery, to examine stand and site characteristics associated with mortality presence (one or more mortality occurrences) across 400 m² areas of balsam fir dominant stands. This will provide an analysis of sudden balsam fir mortality at a spatial scale not previously explored (Chapter 2). We hypothesized that increased mortality probability would occur in areas with taller trees (Grote et al., 2016) and greater basal area (Young et al., 2017), on sites at lower elevations (Bourque et al., 2010) and south-facing slopes (O'Brien et al., 2017) and on

sites with more rapid drainage (Rehshuh et al., 2017), steeper slopes (Dietze & Moorcroft, 2011) and a greater depth to water values (Phillips et al., 2016).

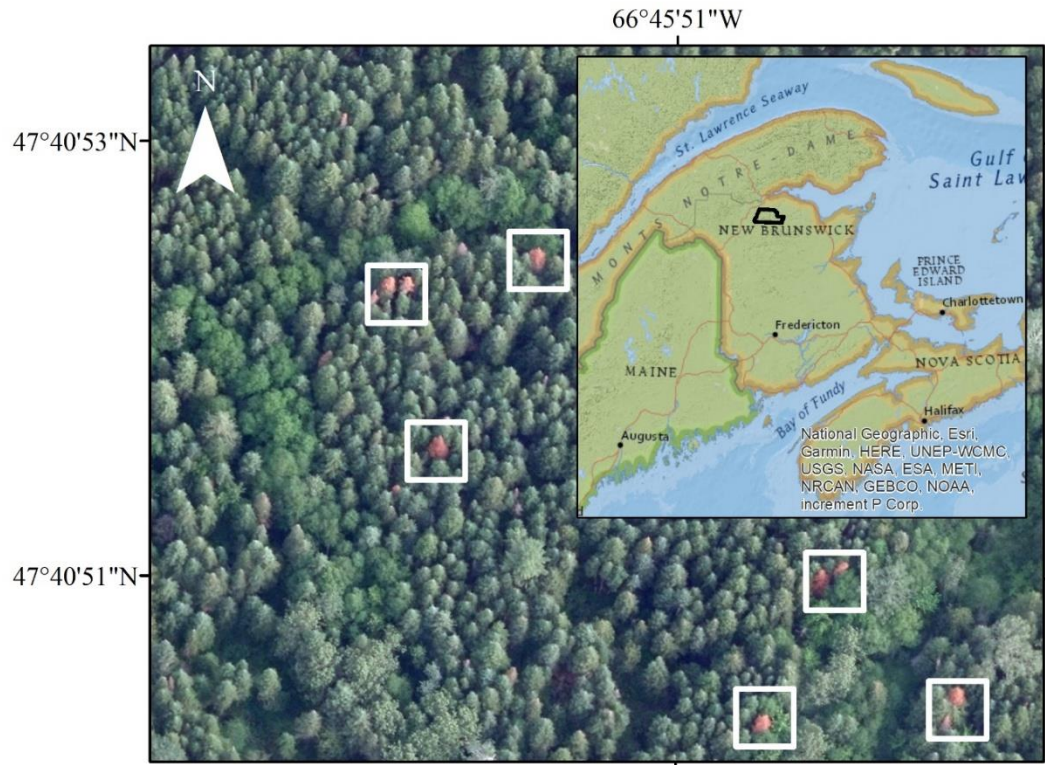


Figure 3.1 - Sudden balsam fir mortality was visible in aerial imagery from 2018 due to the bright red, intact tree crowns (indicated by white boxes). The study area can be seen on the inset location map noted by the black boundary.

3.2 Methods

Aerial imagery at 10 cm resolution was acquired in 2018 at ~1800-2000 m altitude across a large area (~17,680 km²) in the north and northwest of New Brunswick from June 11th to September 14th. To exclude the July peak of reddish-brown coloration of foliage due to spruce budworm defoliation (MacLean & MacKinnon, 1996), only aerial imagery taken in June was considered for further analysis. Also, to avoid variations in shading across

imagery and to maximize the number of stands to provide enough variation, we selected areas of the aerial imagery acquired on the same day which included at least 100 balsam fir stands. This resulted in four areas with three either partially or fully located in the highland regions of New Brunswick, an area of likely refuge for balsam fir as the climate changes (Bourque et al., 2020). The other area was fully located in the Northern Uplands Ecoregion and was chosen because there were relatively more occurrences reported in this region compared to the highland region from the provincial aerial survey (NBERD, 2018). Furthermore, by limiting the analysis to one geographic area the effect of variation in climate (including precipitation) across forest stands, which was not investigated in this study, was reduced.

3.2.1 Study Area

The study area was located primarily in the Upsalquitch Ecodistrict of the Northern Uplands Ecoregion (Figure 3.1). The geology consists of non-calcareous sedimentary bedrock in the west, with calcareous and highly calcareous sedimentary soils dominating in the middle and soils of mafic and felsic volcanic origin further east (Zelazny et al., 2007). Elevation in the Northern Uplands Ecoregion averages around 150 – 300 meters and it lies in the rain shadow of the Highlands Ecoregion. Balsam fir is dominant in the higher elevation regions on the poorer, volcanic derived soils. The Upsalquitch River runs through the centre of the study area and is a tributary of the larger Restigouche River to the north.

3.2.2 Forest Stand Selection

We first filtered the aerial imagery in the study area to select only forest stands composed of at least 60% balsam fir according to the most recent, 2007 aerial photo interpretation (NBERD, 2019a). This stand inventory data (forest stand shapefile) is provided as spatial vector files and includes forest attribute data including height and species composition. Some of the selected stands were likely to have been harvested since the 2007 photo interpretation. To exclude these areas, we first obtained a mean top height for each forest stand from the New Brunswick's Enhanced Forest Inventory (EFI) (NBERD, 2019b). The EFI is derived from LiDAR and available for the whole of New Brunswick at a spatial resolution of 400 m² (20 m cells). We excluded stands where the LiDAR derived height was lower than the height in the forest stand shapefile, as this was assumed to be indicative of stand disturbance. After the selection process, a total of 278 balsam fir dominant forest stands remained across the study area. Next, we randomly shuffled the 278 stands and assessed the aerial imagery of half (139) to check for stands with any partial cutting (which was not identified in the previous step) and non-forest structures being present, with these stands being removed from further analysis. This process reduced the number of stands down to 128 (Figure 3.2).

3.2.3 Response and Explanatory Variables

To derive the presence-absence response variable, we manually checked each of the 128 forest stands and added a point to the centre of each individual balsam fir tree with symptoms of sudden mortality (bright red intact crowns). A total of 1158 dead balsam fir trees were identified, being present across 108 of the 128 forest stands examined. Next, we scaled the 1158 points to the 20 m cell resolution of the top height EFI data across the

128 forest stands using the *gridRecords* function in the “fuzzySim” package in R (Barbosa, 2016). If one or multiple points were in an individual 20 m cell than it became a presence cell and if there were no points it became an absence cell. However, because 10–40% of each forest stand was made up of non-balsam fir tree species (Appendices Figure AP3.1) only 20 m cells with a top height between 12 – 18 m were included, as this is considered the normal height range for balsam fir (Frank, 1990).

To assess stand characteristics associated with mortality presence top height and basal area variables were derived from the EFI data (Appendices Figure AP3.7 & SD3.8) and were not correlated (Appendices Figure AP3.2). Height and basal area are the most accurate EFI variables (Northern Hardwoods Research Institute, 2020) with other EFI variables not included because of high general correlation with basal area (Appendices Figure AP3.4). Drainage was obtained from the Forest Soils shapefile, a province wide inventory of forest soil drainage conditions derived from climate, geomorphology, and soil parent material. The drainage variable was categorical (Appendices Table AP3.1) and ranged from rapidly drained to poorly drained (Appendices Figure AP3.12). Elevation data was obtained from a LiDAR derived Digital Elevation Surface (DEM) at 1 m cell resolution (Appendices Figure AP3.6). This was upscaled to match the coarser 20 m cell resolution using bilinear interpolation. Using the original 1 m DEM resolution the aspect of each cell was determined using the aspect tool in ArcGIS and cubic smoothing to identify the direction that a slope faces. The output raster included a value (based on compass degrees) which was converted into a categorical value of coldest NW-NE aspects (292.5-67.5), moderate SW- NW aspects (67.5-112.5/247.5-292.5) and warmest SE-SW aspects (112.5-247.5). This was then upscaled to match the 20 m cell size using

bilinear interpolation (Appendices Figure AP3.10). Slope was available at 1 m cell resolution and was upscaled to match the coarser 20 m cell size using bilinear interpolation (Appendices Figure AP3.11). Slope is defined as the incline of a surface with a slope of 45 degrees equaling 100 percent slope. Finally, depth to water data was available at 10 m cell resolution and was upscaled to match the coarser 20 m cell size using bilinear interpolation (Appendices Figure AP3.9). The depth to water variable identifies the distance (m) between the surface and the groundwater table. This process assumed a 4 ha threshold for delineating flow channels and the corresponding depth to water value reflected end of summer flow conditions (White et al., 2012). Site factors were obtained from GeoNB, the geographic data catalogue website of the province of New Brunswick (<https://gis-erd-der.gnb.ca/server/services>).

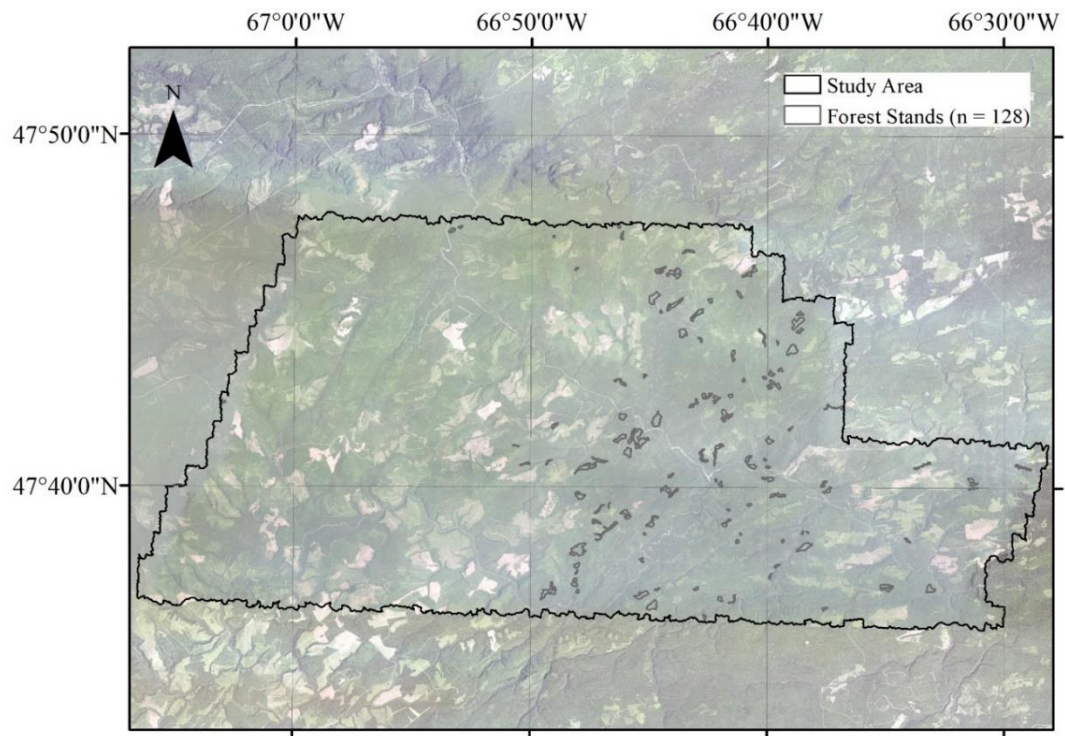


Figure 3.2 - 1158 balsam fir trees with sudden balsam fir mortality were identified, being present across 108 of the 128 balsam fir dominant ($\geq 60\%$) forest stands (grey outline) within the study area (black outline) located in the Northern Uplands Ecoregion of New Brunswick.

3.2.4 Data Analysis and Modelling

The 20 m cells of mortality presence-absence and explanatory variables were analyzed using an ensemble decision tree method. Ensemble decision trees accommodate many of the violations of conventional, parametric statistics that are common for observational data, including departures from normality and homogeneity of variance and are well suited for the analysis of ecological data (Elith, 2019). Ensemble decision trees can also identify nonlinear relationships (Brown et al., 2018; Elith et al., 2006).

We used the supervised machine learning algorithm, Random Forests (RF; (Breiman, 2001) and the “randomForest” package in R (Liaw & Wiener, 2002). The

number of explanatory variables to examine when forming each split in each decision tree was kept at the default square root of the number of explanatory variables (3) and the number of decision trees were kept at the default of 500. The node size, which specifies the minimum number of observations in a terminal node in each decision tree, was kept at the default for classification of 1. The probability of mortality reported throughout the random forest modelling is the probability of a presence cell defined as one or more sudden balsam fir mortality trees occurring within a 20 m cell.

For each continuous explanatory variable (elevation, slope, depth to water and basal area) values beyond the 5th and 95th percentiles were removed prior to modelling to improve the generalisation and interpretation of the models. This was not required for the height data because of the 12 – 18 m height restriction already implemented. The final number of 20 m cells was 4972 (198.88 ha) with ~6.5% presence cells that contained at least one balsam fir with symptoms of sudden mortality (bright red intact crown).

To correct for the imbalance between the underrepresented presence class and overrepresented absence class, we applied stratified random sampling in the RF modelling. Due to the under sampling of the absence class, the RF modelling process was repeated 100 times to capture the variation omitted across the absence class. For each model run, data was first randomly split into 75% training and 25% testing sets. Next, for the training and testing sets the absence class cells were randomly sampled to match the number of presence class cells.

The accuracy of each RF model was determined through the Area Under the Receiver Operating Characteristic curve (AUC) metric on each withheld testing dataset, where the true positive rate is plotted against the false positive rate using various

threshold values to determine the allocation to each class. An AUC of 0.5 indicates a model that cannot predict classes better than a random guess and 1 represents a perfect model prediction of each class.

For each RF model run the explanatory variable importance was determined using the mean decrease in accuracy metric, where after constructing the RF model and generating an idea of accuracy on the out-of-bag data (OOB) a specific explanatory variable is then randomly permuted. Then the RF model is tested again on the withheld OOB data and how the random permutation affects the accuracy of the RF model determines the mean decrease in accuracy metric. This was chosen over the alternative Gini impurity variable importance measure because the explanatory variables varied in cardinality. The Gini impurity variable importance measure would have inflated variable importance for the continuous explanatory variables that had greater cardinality (Strobl et al., 2007).

An assessment of how each explanatory variable influenced balsam fir mortality probability across the 100 RF models was made through the interpretation of Partial Dependence Plots (PDP). A PDP gives a graphical representation of how, across the range of values for a single explanatory variable, the probability of balsam fir mortality changes (with the other explanatory variables used in the model kept at a constant). A PDP was constructed for each of the 100 separate RF models for each explanatory variable using the “pdp” package in R (Greenwell, 2017). The mortality probability values and corresponding explanatory variable values were extracted from each PDP and then combined onto a single graph with a loess smoothing line added using the “ggplot2” package in R (Wickham et al., 2016).

The strength of the interaction effects between the explanatory variables were computed using Friedman's H-statistic, which ranges between 0 and 1, with larger values indicating a greater interaction (Friedman & Popescu, 2008). The unnormalized version of the H-statistic was extracted for each RF model run through the "Vivid" package in R which used all the rows of data and the default grid size of 50 (Inglis et al., 2022). The mean average of the H-statistic was then calculated across the 100 RF models for all the different pairs of explanatory variables and plotted using the "plotly" package in R (Sievert, 2020).

Although PDP's can help interpret complex black-box models in machine learning, it is still difficult to translate these models into a useable tool for forest management. To make the models more translatable for active forest management we also created a functional landscape map of mortality probability. The probability of mortality reported in the landscape map is based on the count of the number of trees across the random forest ensemble of decision trees that assigned a data cell as presence. The default 0.5 threshold was used to determine which class a cell falls within, with anything above 0.5 considered as presence. First, we generated the explanatory variables for the entire study area and used a combination of winsorization and removal of cells to provide a landscape prediction that covered the majority of the study area. We used values denoting the 5th and 95th percentiles to set the values beyond these for elevation, slope, depth to water, and basal area. Cells with drainage classes of 6 or heights <12 m were removed because these were not included in the original modelling. Cells with heights > 18 m were reduced to 18 m. Finally, we generated a landscape prediction map for each individual RF model run and then produced a landscape map of mortality

probability from the mean average of the 100 RF model spatial predictions within the “raster” package in R (Hijmans et al., 2013).

3.3 Results

The 100 RF models displayed an average AUC of 0.70 (± 0.04) which demonstrated an acceptable ability to distinguish the presence and absence of tree mortality (Hülsmann et al., 2017). Elevation was identified as the most important explanatory variable across the 100 RF models (Figure 3.3).

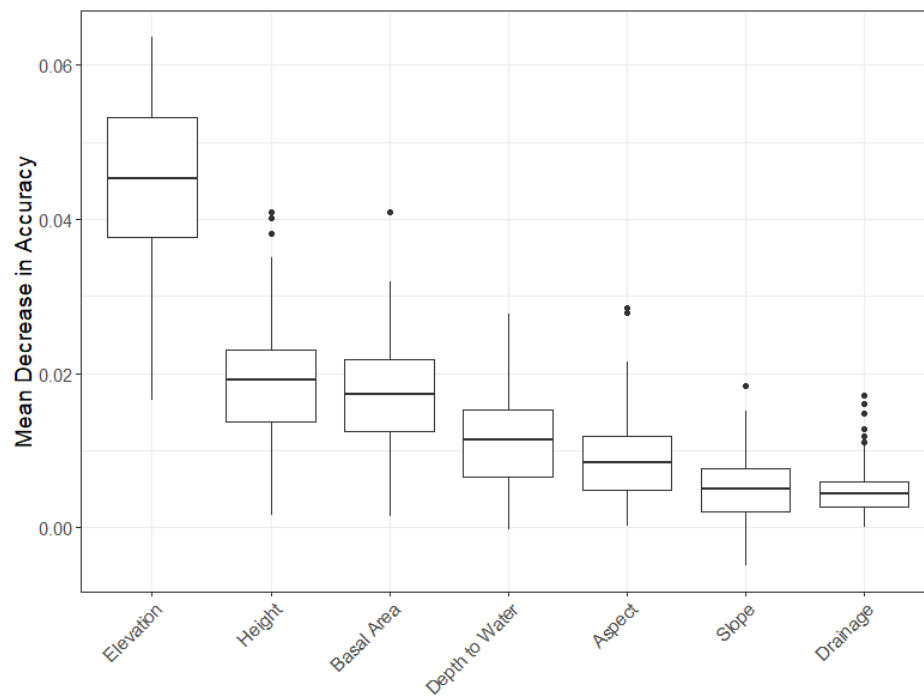


Figure 3.3 - Boxplots for each explanatory variable showing the mean decrease in accuracy importance metric across the 100 RF models. The y values represent the percentage decrease in prediction performance of the RF model when the values for that explanatory variable were randomly permuted (negative values indicate when a variable actually improved prediction accuracy when its values were randomly permuted).

3.3.1 Stand Factors

The two EFI variables included in the RF modelling, top height and basal area, were relatively important being ranked 2nd and 3rd respectively. There was a relatively linear relationship between mortality probability and tree height (Figure 3.4). 20 m cells that contained shorter trees had a lower mortality probability than cells with taller trees.

However, mortality probability became less certain beyond 17.5 m with greater variation around the trendline. There was also an increase in mortality probability up to a basal area of ~30 m²/ha which then plateaued at a consistently higher probability for cells with > 30 m²/ha values.

3.3.2 Site Factors

Mortality probability tended to be higher at lower elevations and when elevation reached ~275 m there was a rapid decrease in mortality probability. Depth to water was the 4th most important variable across the RF models with mortality probability showing a non-linear trend. Mortality probability was elevated for sites with shallow depth-to-water values (< 4m). Then mortality probability reduced to ~17 m values before then increasing for values up to ~35m where variation then increased, and mortality probability began to reduce again. The 5th most important variable was aspect with a clear increase in mortality probability for the warmest SE-SW aspects. Slope was the 6th most important variable across the RF models, but there were no distinct trends in mortality probability with a relatively flat trendline. Drainage was considered the least important variable across the RF models with a general linear trend with mortality probability decreasing as drainage became poorer across classes 2, 3 4 and 5. However, the most rapidly drained class 1 displayed the lowest mortality probability.

3.3.3 Interactions and Landscape Prediction

All explanatory variables interacted to some degree with a range of H-statistic values (Figure 3.5). The two EFI variables, height and basal area, had an H-statistic of 0.13 and demonstrated a similar effect on mortality probability (Figure 3.6). However, this pattern became irrelevant at the highest elevations, which explained the strong interaction with elevation for both height (H-statistic = 0.22) and basal area (H-statistic = 0.19). Depth to water also had a similar effect with low mortality probabilities at depth to water values of ~11 – 15 m regardless of height or basal area values, with height having the strongest interaction (H-statistic = 0.13) (Figure 3.7). Although slope and aspect had a relatively low interaction strength (H-statistic = 0.09) there were some interesting effects observed (Figure 3.8). Mortality probability was elevated for the coldest aspects (NW-NE) on flat terrain, but as slope increased mortality probability decreased suggesting the cooling effect of north facing aspects led to reduced mortality probability. In contrast, the warmest aspects (SE-SW) had a slight decrease in mortality probability on flatter sites which then plateaued with little effect of slope observed. Drainage interacted the least with other variables.

The landscape prediction map demonstrates how the probability of sudden balsam fir mortality varied across the study area (Figure 3.9). This gives forest managers a tool to help determine appropriate management of balsam fir in terms of drought vulnerability. The effect of the stand and site explanatory variables reflected the same trends represented in the PDP plots (Figure 3.4). At the broader landscape scale, the effect of higher elevation on reducing mortality was the most distinct. Other variables, including height and basal area, were less distinct at the scale of the map presented, but when

observed at finer resolutions, the varied probability at the stand level becomes clearer. For example, the map demonstrates areas of the landscape that have received minimal forest management (taller trees and higher basal areas) which are associated with higher drought induced mortality risk for balsam fir.

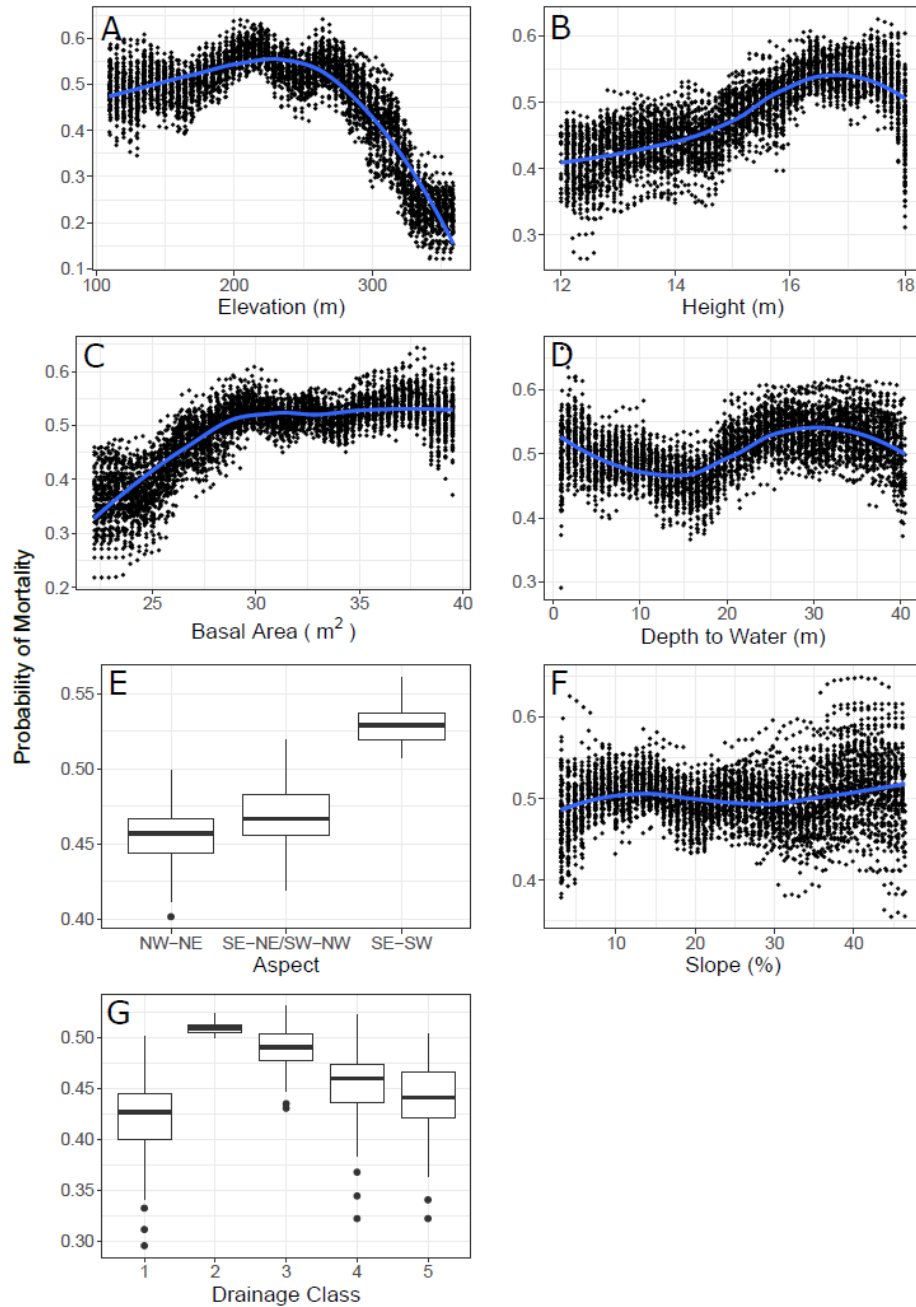


Figure 3.4 - Partial dependence plots for each explanatory variable which display all the mortality probabilities across the 100 RF models. For continuous variables, each RF

model run is represented by a single point for sequential steps in the x axis with a blue LOESS smoothing line. Drainage classes, where dominantly is 60-100% of area and significant is 0-40% of area, are:

- 1 = Dominantly Rapidly drained with significant well drained.
- 2 = Dominantly Well drained with significant rapidly or moderately well drained.
- 3 = Dominantly Moderately Well drained with significant well or imperfectly drained.
- 4 = Dominantly Imperfectly drained with significant moderately well or poorly drained.
- 5 = Dominantly Poorly drained with significant imperfectly or very poorly drained.

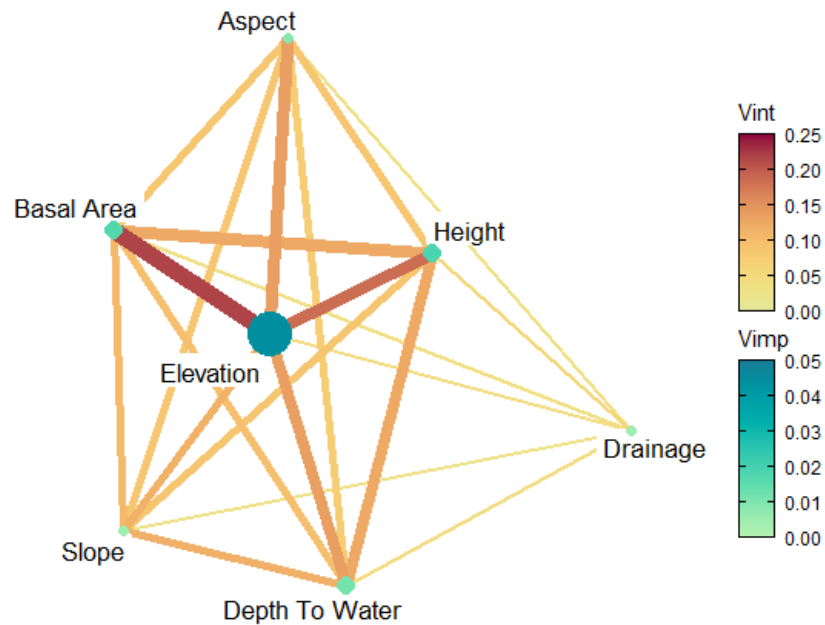


Figure 3.5. - Interaction network plot between the explanatory variables. *Vint* refers to the unnormalized Friedman's H-statistic with thicker lines demonstrating higher values (red). *Vimp* refers to the mean decrease in accuracy variable importance metric with larger circles indicating higher values (darker blue).

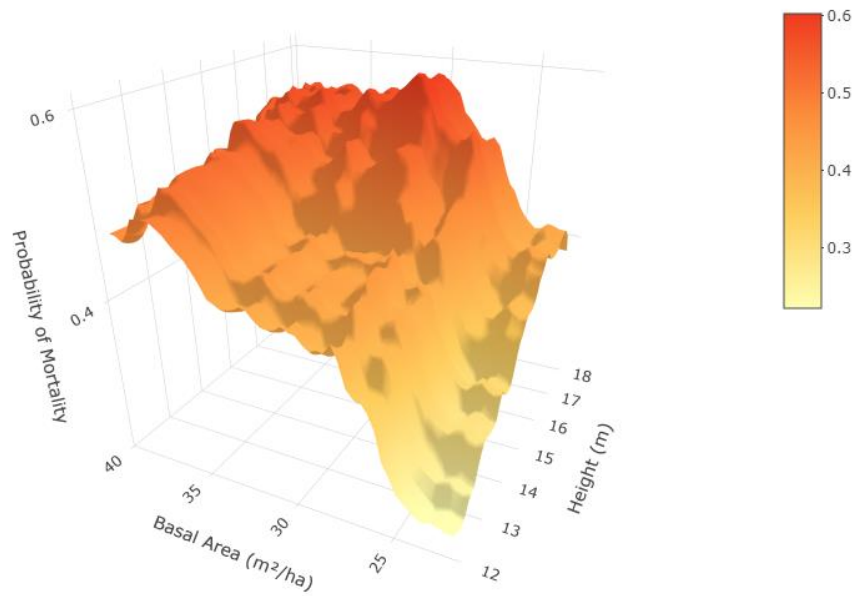


Figure 3.6 – Interaction plot showing mean values of mortality probability (z axis) across the 100 RF models across height and basal area values.

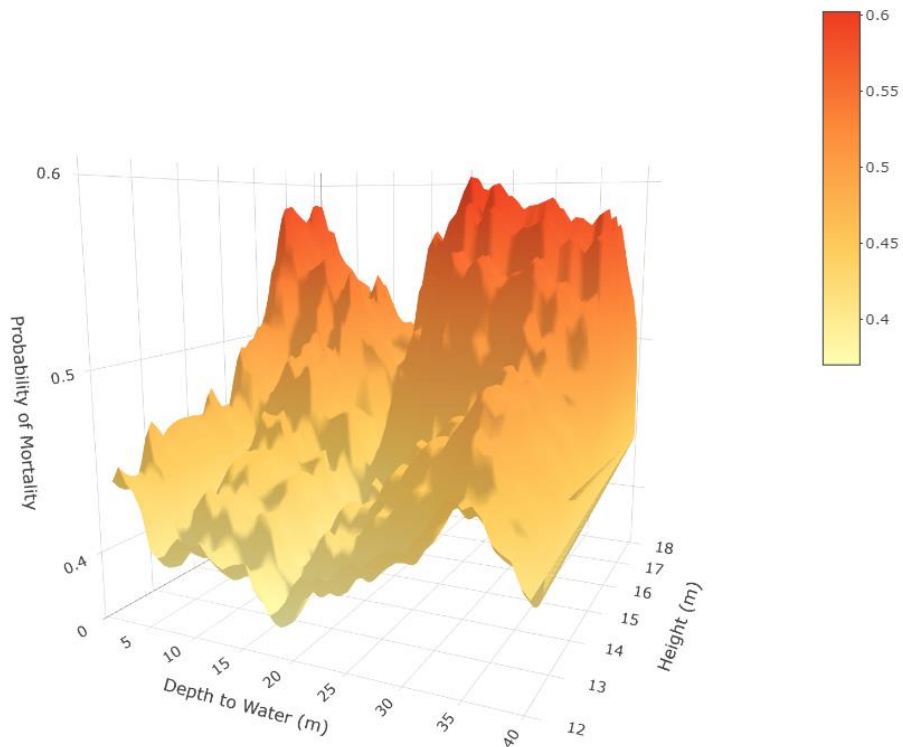


Figure 3.7 – Interaction plot showing mean values of mortality probability (z axis) across the 100 RF models across height and depth to water values.

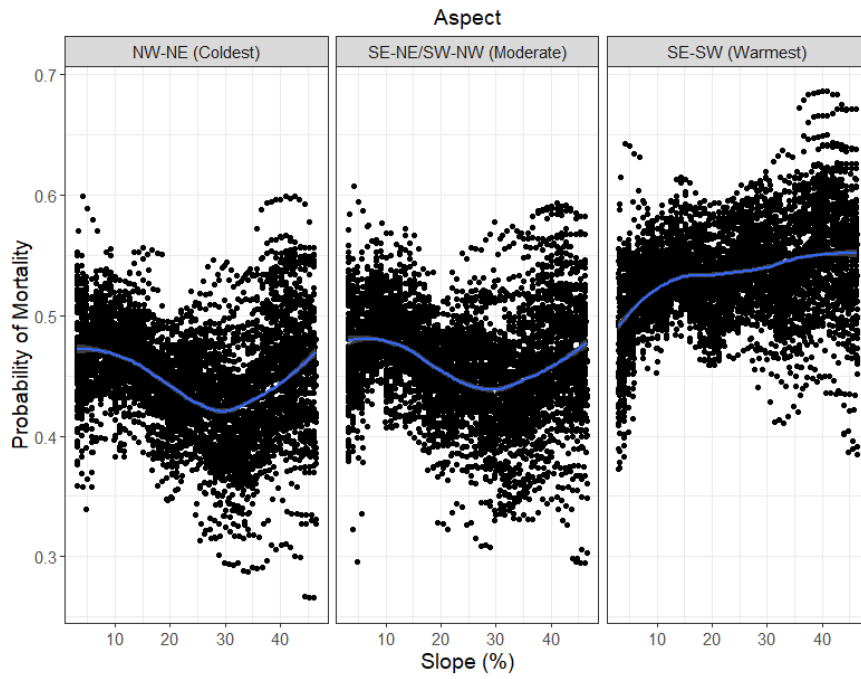


Figure 3.8 – Interaction plot showing values of mortality probability (y axis) across the 100 RF models for each categorical aspect across slope values.

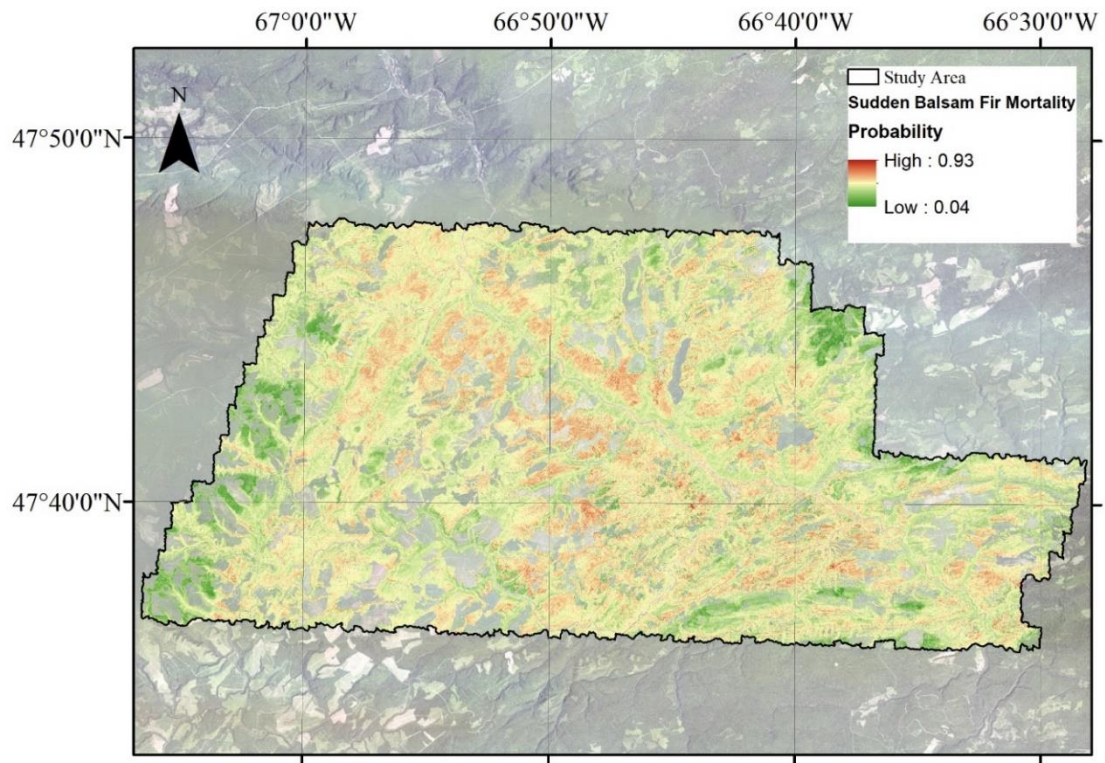


Figure 3.9 – The probability of at least one balsam fir tree being present with symptoms of sudden mortality (bright red, intact crown) in each 20 m cell across the study area. This is derived from the mean average probability of the 100 RF model predictions. Areas with no prediction values contained cells that included a drainage class of 6 or were < 12 m in height and were not included in the RF model predictions.

3.4 Discussion

The stand and site factors conducive to greater drought stress increased mortality probability and support the hypothesis that drought was a major contributor to the widespread balsam fir mortality observed in 2018 (Chapter 2). Balsam fir is adapted to cold and moist conditions (Rowe, 1972; Sims *et al.*, 1990) with an elevated risk of hydraulic failure compared with other Acadian Forest tree species (Balducci *et al.*, 2020; Sperry & Tyree, 1990; Tyree & Dixon, 1986; Tyree & Sperry, 1989).

A northward shift is predicted for balsam fir populations as they seek cooler, more suitable areas under future climate change scenarios (Andrews *et al.*, 2022; Bourque & Hassan, 2008; Dombroskie *et al.*, 2010; Taylor *et al.*, 2017). Areas associated with elevated temperatures (e.g., SE-SW aspects and lower elevations) had the highest probability of sudden balsam fir mortality. An elevational shift to cooler areas in response to climate change has also been observed for other fir species (Shao *et al.*, 2017), with increased mortality observed at lower elevations (Harvey *et al.*, 2021). Increasing temperatures are also predicted to cause range shifts for other fir species in Europe (Takolander *et al.*, 2019) and Asia (Liao *et al.*, 2020; Tanaka *et al.*, 2012). Higher temperatures amplify the evapotranspirative pull which increases the risk of hydraulic failure during a drought (Arend *et al.*, 2021; Grossiord *et al.*, 2020). Trees that grow in regions with high precipitation are generally less adapted to drought conditions (Jump *et al.*, 2017; Reich *et al.*, 2016). This is confirmed in balsam fir through its relatively high respiration rates and lack of transpiration reduction in response to drought (Hunt *et al.*, 1999; Oogathoo *et al.*, 2020). Defoliation-driven balsam fir mortality tends to be associated with higher elevation sites, which contrasts with the mortality observed in this

study (Chen et al., 2019). However, similar to our observations, an increase in defoliation driven mortality risk has been observed for warmer, south facing slopes (Amos-Binks et al., 2010; Guan et al., 2021; Osawa et al., 1986).

Cells with taller trees experienced an increased mortality probability. Taller trees have been observed to be more vulnerable to drought induced single tree mortality, including for *Abies* species (Stovall et al., 2019, 2020). As tree height increases there is a longer period that water must travel through the xylem, resulting in more potential that an embolism may form, especially during a drought. Taller balsam fir trees tend to have a greater likelihood of mortality (Mailly et al., 2009) with heights > 15 m unlikely to be driven by normal self-thinning (McCarthy & Weetman, 2007). The elevated mortality probability observed for higher basal area values has been previously confirmed for balsam fir within permanent sample plots from 1990 to 2004 in New Brunswick (Colford-Gilks et al., 2012).

The effect of depth-to-water on mortality probability showed a greater complexity with a non-linear relationship demonstrated. Balsam fir is considered a shallow rooting species but roots have been observed to depths of 1.3 m (Bakuzis & Hansen, 1965; Frank, 1990; Strong & Roi, 1983). Therefore, it was unexpected that the lowest mortality probability would be at depth to water values of ~11 – 15 m. The low precipitation across the study area in summer 2017 (Chapter 2) caused a 14.3% decline in the Upsalquitch River level in August 2017 (compared to the 2011 – 2020 mean average) (Environment Canada, 2022). Low precipitation would cause a reduction in the water table, increasing the depth to water across the study area beyond that which roots are adapted to (Kibler et al., 2021; Skiadaresis et al., 2021). The balsam fir growing on areas with high water

tables (low depth to water values) had an elevated risk of mortality. High water tables will reduce rooting depth (Krause & Lemay, 2022; Lieffers & Rothwell, 1987), which is linked to reduced productivity and defoliation recovery in balsam fir (Hennigar et al., 2017; Hix et al., 1987). High water tables have been previously associated with increased balsam fir mortality in Michigan (Lynch & Witter, 1985). Increased single tree mortality of balsam fir has also been observed along major rivers and tributaries in northeast Ontario (Jones et al., 1995) and on river deltas in eastern Labrador (Raske et al., 1992).

Increasing slope steepness has been linked to elevated tree mortality risk (Dietze & Moorcroft, 2011), but this was not observed in our study with a relatively minor effect of slope on the probability of sudden balsam fir mortality. The effect of slope steepness on infiltration rates is complicated by many factors, including vegetation cover, microtopography and soil texture (Morbidelli et al., 2018). Sites were generally not that steep across the forest stands used in the modelling which could explain its minimal influence (Appendices Figure AP3.3).

The effect of drainage was minimal in the modelling, but there was a general reduction in mortality probability as drainage worsened, although the most rapidly drained class 1 was an outlier. Although poor drainage can be associated with a lack of soil aeration restricting root development (Puhe, 2003; Xu et al., 1997) there may be a benefit to trees on these sites as the greater water retention, due to the poor drainage, could provide some buffer effects from drought conditions. However, the unknown accuracy of the drainage classes used in the study (due to limited on the ground validation) and much larger spatial scale compared to the 20 m cell size could be a factor

responsible for the minimal influence seen across the modelling (Furze & Arp, 2021; Yang et al., 2011; Zhao et al., 2013).

The current analysis investigated multiple forest stands at a 20 m cell spatial resolution, which could not account for other finer resolution tree level factors that influence mortality such as live crown ratios (Zhou, 2021) or biotic agents previously associated with sudden balsam fir mortality, such as the balsam fir bark weevil (*Pissodes dubius*) and *Armillaria* root disease (Magasi, 1987). However, it would have been difficult to integrate these finer resolution tree level factors into the current analysis due to the spatial scale of the stand and site variables investigated. The missing tree level factors may explain the acceptable but relatively low AUC scores of the RF models. The variability of mortality across the 128 forest stands varied considerably. There was a mean of 1.5 dead balsam fir trees per hectare (SD = 2.0) although the worst effected stand had a rate of 16 dead balsam fir trees per hectare. The study would have benefitted from additional exploration of the specific stand and site drivers in these worst affected stands.

The landscape prediction map is a useful aid for forest management because it provides insight on landscape vulnerability to drought induced tree mortality. However, due to the RF model inaccuracies, we suggest that the landscape prediction map should be used as a guide for silvicultural management decisions rather than dictating thinning or felling decisions directly. It is also important to highlight the possible inaccuracies associated with the LiDAR derived forest stand attributes used in the study, although height and basal area have been shown to be accurate, when validated with on the ground data (Northern Hardwoods Research Institute, 2020).

Climate change is continuing to shift global tree species ranges due to increased climate stress driving an increase in global tree mortality events (Allen et al., 2015). It is crucial to have techniques to monitor and examine unusual pulses of tree mortality across landscapes. We have successfully demonstrated the use of ensemble decision trees models to assess the stand and site factors associated with increased mortality probability using the presence-absence of single tree mortality. With these drought vulnerable areas of the landscape identified, silvicultural responses to increasing climate stress can now be better targeted (Achim et al., 2021; Bradford et al., 2022).

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Chapter 4: General Discussion

The purpose of this thesis was to determine the climate, stand and site drivers of sudden balsam fir mortality. The second thesis chapter identified monthly climate anomalies associated with the presence of sudden balsam fir mortality at a spatial resolution of ~32 km. The third chapter built predictive models that used higher resolution mortality presence-absence data, identified through the detection of single tree sudden balsam fir mortality from aerial photography, with stand and site explanatory variables at a 20 m cell resolution.

The objectives of this final chapter are to: 1) briefly summarize the main results from Chapters 2 and 3; 2) explore the limitations and identify improvements for each research chapter; and 3) outline the implications of the research and potential opportunities for the forestry industry.

4.2 Summary of Results

4.2.1 Investigating climate anomalies associated with the sudden mortality of balsam fir trees

We first created a presence-absence dataset of sudden balsam fir mortality observed in 2018 based on an aerial survey in New Brunswick and on the ground observations from local forest managers in Nova Scotia and Prince Edward Island. We then identified monthly climate anomalies more severe in presence areas based on long term averages for precipitation, snow depth, maximum and minimum temperature. Next, we used the ensemble decision tree machine learning algorithm Random Forest to build a predictive model that could successfully predict the presence-absence of sudden balsam fir

mortality. We then validated this model on a historic balsam fir mortality event by using climate data from 1986 to predict the spatial presence-absence of mortality. The model was able to predict areas with recorded high and moderate mortality with a surprisingly high accuracy of 95% (Kappa = 0.88). This suggested that similar climate anomalies were associated with balsam fir mortality across these two distinct mortality events. To determine which monthly climate variables had the same effect on mortality probability, we utilized partial dependence plots to compare the 2018 and 1986 event. There were five monthly climate variables that demonstrated a similar trend of mortality probability across the 1986 and 2018 RF models. Areas with drier than usual conditions in March and August of the previous year had an increased mortality probability across both events and confirms the vulnerability of balsam fir to drought induced mortality. Warmer than usual previous year July maximum temperatures also increased mortality probability across both events. In the current year that mortality was reported, both events demonstrated higher mortality probability for areas with a deeper snowpack in April followed by warmer than usual maximum temperature in May. We hypothesise that this unusual spring weather pattern likely drove the rapid drying and reddening of whole balsam fir crowns of trees that were already dead or in the process of dying because of hydraulic failure related to drier than usual conditions in the previous growing season.

4.2.2 Integrating aerial imagery and random forest modelling to predict drought vulnerability of balsam fir

We first identified individual balsam fir trees with symptoms of sudden mortality (bright red intact crowns) from aerial imagery across balsam fir dominant (>60%) forest stands in the Northern Uplands Ecoregion in New Brunswick. Next, we derived various stand

and site explanatory variables at a 20 m cell resolution and merged these with the mortality presence-absence data. We then used the ensemble decision tree machine learning algorithm Random Forest to build models that could predict the presence-absence of sudden balsam fir mortality. To determine how the stand and site variables influenced mortality probability we utilized partial dependence plots. There was an increase in mortality probability for 20 m cells that contained taller trees and higher basal area values. Mortality probability was also higher for areas of the landscape that would be hotter during a drought (low elevation areas and south facing aspects). There was elevated mortality probability for sites with both shallow and deep depth to water values, with the lowest mortality probability at ~17 m. There were no distinct trends in mortality probability observed for slope, which was attributed to the terrain across the forest stands being relatively flat. Mortality probability decreased as drainage became poorer (across classes 2, 3, 4, and 5), however, the most rapidly drained class 1 displayed the lowest mortality probability. Finally, the Random Forest models were used to generate a landscape map of sudden balsam fir mortality probability that covered a much larger area than the forest stands that the models were originally built from. This map provides the forestry industry with a modelled drought induced mortality risk for balsam fir at a 20 m cell resolution and can help influence silvicultural and management decisions.

4.3 Study Limitations

4.3.1 Investigating climate anomalies associated with the sudden mortality of balsam fir trees

A limitation of the study was not having access to quantitative presence-absence data for Nova Scotia and Prince Edward Island. Instead, we had to rely on qualitative

observations from local forest managers to confirm the lack of widespread sudden balsam fir mortality. It would have been preferable to have confirmation of the lack of widespread sudden balsam fir mortality through an aerial survey as was undertaken in New Brunswick in 2018.

Increasing reports reveal the importance of multi-year lagged climate effects on the health of trees (Sánchez-Pinillos et al., 2021). However, in my thesis, I did not account for the effects of historic climate stress earlier than spring 2017. Further, by focusing only on monthly climate variables, the analysis of more acute climate stressors, such as wind, were not explored. Also, the continued reporting of sudden balsam fir mortality throughout 2018 (Drew Carleton, pers. Comm.) would indicate that climate anomalies beyond May 2018, which were not examined, could have influenced mortality.

The necessary screening processes used to reduce the initial number of 54 climate predictors may have removed some influential climate anomalies from the study. An example of this was the lower than usual July 2017 precipitation, which will have influenced balsam fir mortality observed in 2018 but was omitted from the modelling process due to collinearity (with low August precipitation). It would have been possible to integrate July and August precipitation through a two-month Standard Precipitation Index (SPI). However, there was not a dry July across high and medium frequency mortality areas in 1986. Therefore, if a two-month drought metric had been used then the 1986 RF model prediction would have been less accurate. Other drought indices beyond the SPI were also not explored which could have been useful to add to the analysis. An example is the Standardised Precipitation-Evapotranspiration Index which factors in evapotranspiration (Vicente-Serrano et al., 2010; Zargar et al., 2011).

Temperature variables tended to display a greater similarity across presence and absence areas compared with precipitation and snow depth values. The random forest model was therefore biased to non-temperature related climate variables. Also, some variables may have been overlooked that were important to balsam fir mortality regardless of whether they occurred across both presence and absence areas. For example, warm February winter temperatures, experienced in both presence and absence areas, may have stimulated *Armillaria* rhizomorph growth (La Porta et al., 2008), but mortality was only observed in presence areas because of the preceding August dry conditions (confined to presence areas).

4.3.2 Integrating aerial imagery and random forest modelling to predict drought vulnerability of balsam fir

A major limitation of the study was not having access to up-to-date high resolution species composition data. The 12 – 18 m height restriction of 20 m cells removed a lot of area across the 128 forest stands and could have removed both balsam fir trees and retained non-balsam fir trees. However, it was essential to find a way to remove some of the 10 – 40% of each forest stand that was made up of non-balsam fir tree species. If this had not been implemented, then the partial dependence plots may have shown the probability of balsam fir presence itself rather than being specific to mortality probability.

A further limitation was that the initial forest stand species composition data was only assessed from aerial imagery so may have had initial inaccuracies. An improvement could have been to use remote sensing methods to delineate balsam fir dominant areas which has been previously demonstrated in New Brunswick (Bhattarai et al., 2021).

Although the majority of the 1158 trees with bright red intact crowns identified were likely to be balsam fir, there could have been some other, likely spruces (*Picea*), wrongly identified. It is also important to highlight the inaccuracies associated with airborne laser scanning (LiDAR) derived forest stand attributes, although height and basal area are the most accurate with on the ground data (Northern Hardwoods Research Institute, 2020).

Single tree mortality is difficult to model accurately because it is a complex process driven by multiple interacting factors (Franklin et al., 1987). The current analysis investigated multiple forest stands at a spatial resolution that did not account for tree level factors which will have influenced tree mortality, such as live crown ratios (Zhou, 2021). It could have been possible to investigate tree level characteristics, such as height and crowns from unprocessed LiDAR point cloud data and the 1 m canopy height model. The effect of microtopography could also have been examined using the available 1 m resolution digital elevation model. However, even with an investigation of these tree-level factors, the study would still be limited by the omission of biotic agents such as the balsam fir bark weevil (*Pissodes dubius*) and *Armillaria* root disease, previously associated with sudden balsam fir mortality (Magasi, 1987). *Armillaria* was observed on 50 out of 56 (89%) balsam fir trees with symptoms of sudden mortality sampled in 2019 (Broom & Costanza, *unpublished data*), although non-symptomatic balsam fir trees were not sampled, which can still have *Armillaria* presence (Magasi, 1982). Although spruce budworm defoliated foliage would have fallen off in the preceding year of mortality (MacLean & MacKinnon, 1996) the 1158 dead trees identified may have still experienced historic defoliation stress that was not accounted for in the study.

The depth-to-water values used in this study were a static measure of ground water depth and could not account for the dynamic nature of ground water in response to drought conditions (Bloomfield et al., 2019). Also, the influence of soil type, including fertility, coarseness and sand/silt/clay content, were not included in the analysis. However, there were 5224 unique soil polygons within the study area from the GeoNB Forest Soils shapefile with an average size of 14.6 ha and maximum size of 532 ha. It was likely that these soil polygons did not truly reflect the soil at the 20 m cell resolution being investigated. Furthermore, the drainage explanatory variable categories contained an unknown mixture of dominantly (60-100%) and significant (0-40%) areas with adjacent classes mixed based on these definitions. For example, a class 1 with 60% dominantly rapidly drained and 40% significant well drained and a class 2 of 60% dominantly well drained and 40% significant rapidly drained could occur. So, although these drainage classes are considered different, the level of difference could vary dramatically, and the extent of this variability is unknown. The study would have benefitted from having manually validated soil and drainage data with a high spatial resolution that better matched the 20 m cell scale investigated.

4.4 Implications and potential to the forest industry

Remote sensing provides an opportunity to spatially delineate tree mortality at a more frequent rate than permanent sample plots (Huang et al., 2019). The balsam fir mortality presence data for both chapters in this thesis used remote sensing (aerial survey and aerial photography). Aerial surveying and aerial photography are both forms of remote sensing that are currently extensively used across Canada. With the increasing availability of LiDAR derived stand and site attributes (White et al., 2016) there is an opportunity to

combine these two different data sources for other species tree mortality through the techniques described in this thesis. Remote sensing gives the forestry industry a more dynamic method of examining tree mortality compared with using PSP networks.

A limitation of PSP networks is the restricted definitions for tree mortality and include an other/unknown category (Bashir & MacLean, 2015; Colford-Gilks et al., 2012). Trees could have been dead prior to the PSP remeasurement but are assigned to a category that doesn't truly reflect the actual cause of mortality, with two of the categories linked to wind likely to increase if a tree has already died standing (stem breakages and broken tops). Balsam fir is more prone to stem breakage than uprooting compared to other tree species (Wilson & MacLean, 2015). There is a potential that this observed vulnerability to stem breakage could be attributed to the greater likelihood of balsam fir to die standing due to its relative vulnerability to hydraulic failure compared with other tree species (Martínez-Vilalta et al., 2004). Therefore, there is a chance that historic sudden balsam fir mortality may have been underestimated, as mortality occurring in the years prior to a PSP remeasurement could have been misidentified as wind-related mortality.

Looking beyond the sudden balsam fir mortality observed in 2018, there is other evidence of increasing climate stress affecting balsam fir populations at the south of its range. In the Northeastern USA from 2000 to 2016 balsam woolly adelgid affected 29% of the total forest area (Kosiba et al., 2018). Mortality from the balsam woolly adelgid is initiated from drought conditions (Puritch, 1973; Puritch & L'Arme, 1971) with widespread drought in Vermont acknowledged to predispose balsam fir to mortality (Wilmot et al., 2015). Maine experienced its most significant drought for 50 years during

1999-2002 (Lombard, 2004) and in 2006 there was 965,585 ha of mortality categorised as balsam woolly adelgid mortality compared with just 2575 ha in 2005 – a 66,827% increase in mortality in a single year (Duncan et al., 2021). Although an invasive insect, the balsam woolly adelgid was introduced into Maine from Europe in the early 1900's so this population explosion (represented by the increase in damage levels) is not from a recent introduction (Felt, 1910). Indeed, it is suggested that drought only affected 5% of the total forest areas in the Northeastern USA from 2000 to 2016 (Kosiba et al., 2018) but the interaction between drought and the balsam woolly adelgid is often not quantitatively examined (Davis et al., 2022; Hrinkevich et al., 2016). The availability of high resolution (~2 km) historic climate data for the whole of North America ensures it is possible to include climate data in the analysis of tree mortality (McKenney et al., 2011).

The assessment of historic balsam fir mortality in this thesis relied on the work of the historic Canadian Forest Insect and Disease Survey (FIDS). The historic FIDS reports rarely investigated the direct influence of climate anomalies and this could be a future research opportunity considering the now widespread availability of historic climate data (McKenney et al., 2011). Forest insect surveys first began in eastern Canada in 1936 before expanding across the rest of the country through an annual national survey by the mid-1940s (Sterner, 2001). The separate tree disease surveys (i.e. not insects) began in 1951 and from 1962 the insect and disease surveys were combined across each province in the FIDS reports (provinces could also be combined geographically, i.e. Maritimes Canada). A federal government review in 1994-95 deemed these surveys to be a provincial matter and they ceased to be undertaken by the Canadian Forest Service by 1995. With the cessation of the FIDS programme Canada lost a vital pest and disease

monitoring resource in the context of climate change. There is now only a varied quality and availability of provincial tree health reports and using New Brunswick as an example, since the cessation of the FIDS only 2013, 2018 and 2021 are readily available online (Government of New Brunswick, 2022). It is important that the Canadian forestry industry finds a suitable replacement that can distribute adequate tree health monitoring data as the FIDS programme did in the past. This looks to have been achieved in the Northeastern USA with the Northeastern Forest Health Atlas (Kosiba et al., 2018) and this approach should be encouraged in Canada.

One aspect of forest health monitoring that has not declined in eastern Canada is the active recording of spruce budworm defoliation and overwintering second-instar spruce budworm larvae (L2). This data continues to get extensive use for both research purposes and forest management and demonstrates the usefulness of readily available forest health monitoring data (Donovan et al., 2021; Li et al., 2020; MacLean et al., 2019; Rahimzadeh-Bajgiran et al., 2018). The methods described in this thesis could be used to explore the possible influence of spring conditions in 2018, beyond growing degree days (Li et al., 2020), that led to the unexpected decline in L2 populations in New Brunswick sampled in fall/winter 2018 (MacLean et al., 2019). Using standardized climate data, we identified warmer than usual February and March temperatures which were followed by colder than usual April temperatures. This pattern of warming followed by cooling has been hypothesised to have reduced L2 populations in Quebec in 2018 (Delisle & others, 2019).

With a changing climate it is important for foresters to not become complacent to tree mortality (Pauly, 1995). Most analysis of balsam fir landscape suitability currently

uses annual precipitation or temperature variables which overlooks the mortality risk from shorter term droughts (Andrews et al., 2022; Bourque & Hassan, 2008; Chang & Bourque, 2020; Dombroskie et al., 2010; Taylor et al., 2017). The techniques demonstrated in this thesis could be applied to other tree species in any region if adequate tree mortality presence data is available. Although the accurate modelling of single tree mortality is complex, this thesis has demonstrated techniques that can produce a useful analysis of tree mortality including identifying drought vulnerability across a forested landscape.

4.5 References

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Appendices

Table AP2.1. Preliminary screening processes for 54 initial explanatory variables. Bold values indicate more severe anomaly. P-values with * denote ≤ 0.05 .

Variable	Presence Mean	Absence Mean	Univariate Logistic Regression		
			<i>P-value</i>	<i>Accuracy</i>	<i>Kappa</i>
MaxTempPreviousMar	-1.455	-1.381	0.045*	0.667	0.000
MaxTempPreviousApr	0.871	1.136	-	-	-
MaxTempPreviousMay	-0.053	0.079	-	-	-
MaxTempPreviousJun	0.412	0.973	-	-	-
MaxTempPreviousJul	0.251	0.037	0.000*	0.714	0.280
MaxTempPreviousAug	0.403	0.401	0.923	0.667	0.000
MaxTempPreviousSep	1.814	1.369	0.000*	0.944	0.870
MaxTempPreviousOct	2.491	2.346	0.000*	0.810	0.571
MaxTempPreviousNov	0.447	0.892	-	-	-
MaxTempPreviousDec	-0.924	-0.336	0.016*	0.976	0.946
MaxTempCurrentJan	0.279	0.732	-	-	-
MaxTempCurrentFeb	1.630	1.872	-	-	-
MaxTempCurrentMar	0.369	0.321	0.534	0.667	0.000
MaxTempCurrentApr	-0.907	-0.582	0.001*	0.683	0.189
MaxTempCurrentMay	1.132	0.931	0.001*	0.746	0.351
MinTempPreviousMar	-0.945	-0.697	0.000*	0.683	0.250
MinTempPreviousApr	1.459	0.971	0.000*	0.952	0.890
MinTempPreviousMay	1.070	0.788	0.000*	0.802	0.528
MinTempPreviousJun	0.668	0.831	-	-	-
MinTempPreviousJul	-0.373	-0.388	-	-	-
MinTempPreviousAug	-0.431	-0.051	0.000*	0.722	0.331
MinTempPreviousSep	1.784	1.687	0.100	0.667	0.000
MinTempPreviousOct	1.843	1.559	0.000*	0.865	0.687
MinTempPreviousNov	-0.776	-0.625	0.000*	0.683	0.178
MinTempPreviousDec	-0.620	-0.271	0.000*	0.833	0.623
MinTempCurrentJan	0.324	0.298	0.191	0.667	0.000
MinTempCurrentFeb	1.102	1.138	-	-	-
MinTempCurrentMar	1.342	1.643	-	-	-
MinTempCurrentApr	-0.931	-0.534	0.000*	0.651	0.132
MinTempCurrentMay	-0.561	-0.458	0.115	0.635	-0.062
PrecipPreviousMar	-0.536	0.043	0.000*	0.730	0.400
PrecipPreviousApr	0.424	-1.576	-	-	-
PrecipPreviousMay	1.326	1.273	0.217	0.659	-0.016
PrecipPreviousJun	0.124	-0.005	0.020*	0.659	0.030
PrecipPreviousJul	-1.440	-0.294	0.000*	0.865	0.691
PrecipPreviousAug	-0.974	0.366	0.026*	0.976	0.946
PrecipPreviousSep	0.086	0.184	-	-	-
PrecipPreviousOct	0.879	-1.494	-	-	-
PrecipPreviousNov	0.324	-0.411	-	-	-
PrecipPreviousDec	0.508	0.428	0.177	0.667	0.000
PrecipCurrentJan	1.716	0.326	0.000*	0.952	0.892
PrecipCurrentFeb	0.634	0.727	-	-	-
PrecipCurrentMar	0.075	-0.163	-	-	-
PrecipCurrentApr	1.197	0.927	0.000*	0.730	0.338
PrecipCurrentMay	-0.384	-0.281	0.073	0.667	0.000
SnowDepthPreviousMar	-0.018	-0.071	-	-	-

SnowDepthPreviousApr	0.452	0.097	0.025*	0.611	-0.105
SnowDepthPreviousMay	-0.045	0.057	-	-	-
SnowDepthPreviousDec	0.145	-0.879	-	-	-
SnowDepthCurrentJan	0.097	-0.269	-	-	-
SnowDepthCurrentFeb	-0.402	-1.320	-	-	-
SnowDepthCurrentMar	0.224	-0.670	-	-	-
SnowDepthCurrentApr	0.888	-0.147	0.000*	0.802	0.528
SnowDepthCurrentMay	0.517	0.057	0.002*	0.690	0.146

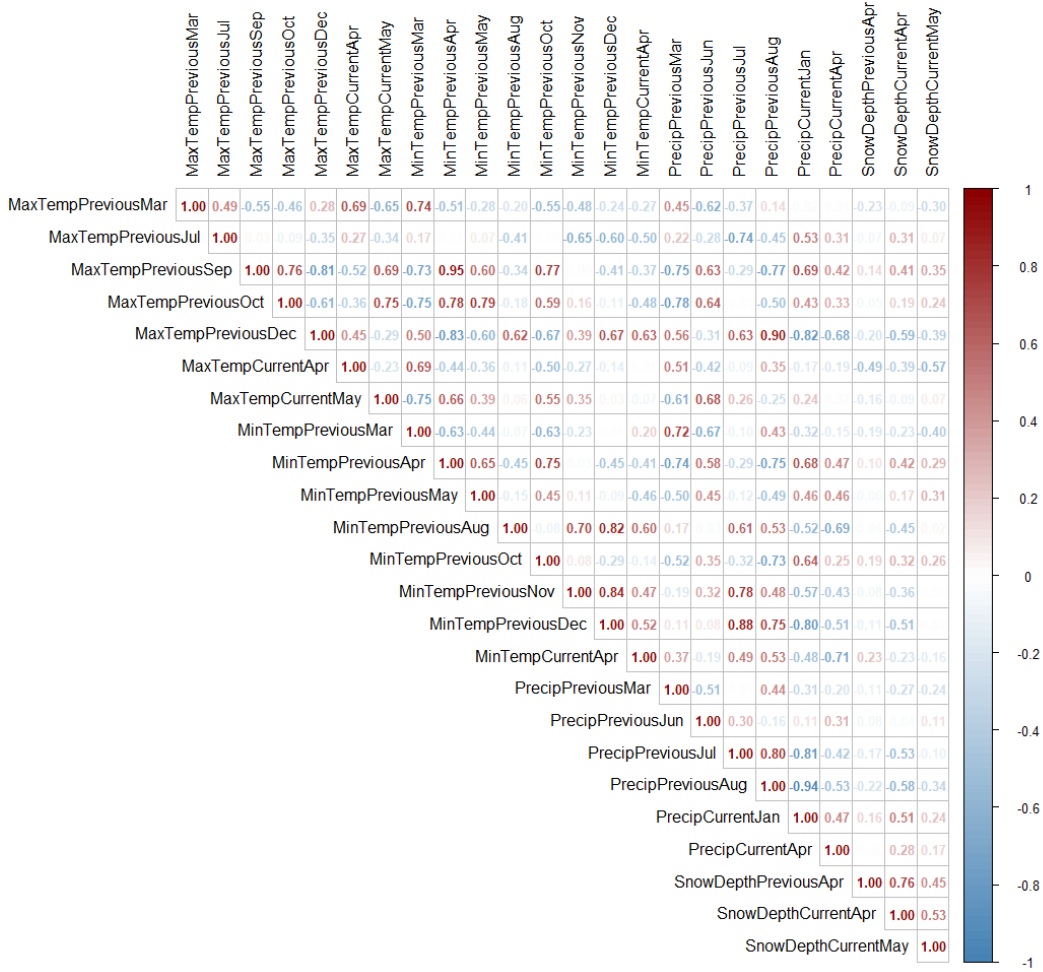


Figure AP2.1. Testing correlation between the 24 climate explanatory variables. The numbers refer to the Pearson correlations with red values positively correlated and blue values negatively correlated.

Table AP2.2. Identification of the additional 13 variables to remove due to collinearity ($\geq \pm 0.7$). Removal of collinear variable was done in correlation coefficient order with the highest (\pm) first. Underlined variables and values indicate higher kappa scores for each individual logistic regression.

Var1	Var1 Kappa	Var2	Var2 Kappa	coef	pvalue	Removed
MaxTempPreviousSep	0.870	<u>MinTempPreviousApr</u>	<u>0.890</u>	0.95	<0.001	(1) MaxTempPreviousSep
<u>PrecipPreviousAug</u>	<u>0.946</u>	PrecipCurrentJan	0.892	-0.94	<0.001	(2) PrecipCurrentJan
<u>MaxTempPreviousDec</u>	<u>0.946</u>	PrecipPreviousAug	<u>0.946</u>	0.9	<0.001	(3) MaxTempPreviousDec ¹
MinTempPreviousDec	0.623	<u>PrecipPreviousJul</u>	<u>0.691</u>	0.88	<0.001	(4) MinTempPreviousDec
MinTempPreviousNov	0.178	<u>MinTempPreviousDec</u> ²	<u>0.623</u>	0.84	<0.001	N/A
<u>MaxTempPreviousDec</u> ²	<u>0.946</u>	MinTempPreviousApr	0.890	-0.83	<0.001	N/A
MinTempPreviousAug	0.331	<u>MinTempPreviousDec</u> ²	<u>0.623</u>	0.82	<0.001	N/A
<u>MaxTempPreviousDec</u> ²	<u>0.946</u>	PrecipCurrentJan ²	0.892	-0.82	<0.001	N/A
MaxTempPreviousSep ²	0.870	<u>MaxTempPreviousDec</u> ²	<u>0.946</u>	-0.81	<0.001	N/A
PrecipPreviousJul	0.691	<u>PrecipCurrentJan</u> ²	<u>0.892</u>	-0.81	<0.001	N/A
PrecipPreviousJul	0.691	<u>PrecipPreviousAug</u>	<u>0.946</u>	0.8	<0.001	(5) PrecipPreviousJul
MinTempPreviousDec ²	0.623	<u>PrecipCurrentJan</u> ²	<u>0.892</u>	-0.8	<0.001	N/A
<u>MaxTempPreviousOct</u>	<u>0.571</u>	MinTempPreviousMay	0.528	0.79	<0.001	(6) MinTempPreviousMay
MaxTempPreviousOct	0.571	<u>MinTempPreviousApr</u>	<u>0.890</u>	0.78	<0.001	(7) MaxTempPreviousOct
MinTempPreviousNov	0.178	<u>PrecipPreviousJul</u> ²	<u>0.691</u>	0.78	<0.001	N/A
<u>MaxTempPreviousOct</u> ²	<u>0.571</u>	PrecipPreviousMar	0.400	-0.78	<0.001	N/A
<u>MaxTempPreviousSep</u> ²	<u>0.870</u>	MinTempPreviousOct	0.687	0.77	<0.001	N/A
MaxTempPreviousSep ²	0.870	<u>PrecipPreviousAug</u>	<u>0.946</u>	-0.77	<0.001	N/A
<u>MaxTempPreviousSep</u> ²	<u>0.870</u>	MaxTempPreviousOct ²	0.571	0.76	<0.001	N/A
SnowDepthPreviousApr	-0.105	<u>SnowDepthCurrentApr</u>	<u>0.528</u>	0.76	<0.001	(8) SnowDepthPreviousApr
<u>MaxTempPreviousOct</u> ²	<u>0.571</u>	MaxTempCurrentMay	0.351	0.75	<0.001	N/A
<u>MinTempPreviousApr</u>	<u>0.890</u>	MinTempPreviousOct	0.687	0.75	<0.001	(9) MinTempPreviousOct
MinTempPreviousDec ²	0.623	<u>PrecipPreviousAug</u>	<u>0.946</u>	0.75	<0.001	N/A
<u>MaxTempCurrentMay</u>	<u>0.351</u>	MinTempPreviousMar	0.250	-0.75	<0.001	(10) MinTempPreviousMar
<u>MaxTempPreviousOct</u> ²	<u>0.571</u>	MinTempPreviousMar ²	0.250	-0.75	<0.001	N/A
MinTempPreviousApr	0.890	<u>PrecipPreviousAug</u>	<u>0.946</u>	-0.75	<0.001	(11) MinTempPreviousApr
<u>MaxTempPreviousSep</u> ²	<u>0.870</u>	PrecipPreviousMar	0.400	-0.75	<0.001	N/A
MaxTempPreviousMar	0.000	<u>MinTempPreviousMar</u> ²	<u>0.250</u>	0.74	<0.001	N/A
MaxTempPreviousJul	0.280	<u>PrecipPreviousJul</u> ²	<u>0.691</u>	-0.74	<0.001	N/A
<u>MinTempPreviousApr</u> ²	<u>0.890</u>	PrecipPreviousMar	0.400	-0.74	<0.001	N/A
<u>MaxTempPreviousSep</u> ²	<u>0.870</u>	MinTempPreviousMar ²	0.250	-0.73	<0.001	N/A
MinTempPreviousOct ²	0.687	<u>PrecipPreviousAug</u>	<u>0.946</u>	-0.73	<0.001	N/A
MinTempPreviousMar ²	0.250	<u>PrecipPreviousMar</u>	<u>0.400</u>	0.72	<0.001	N/A

¹ the climate variable from the growing season was preferred due to its likely greater influence on balsam fir.

² indicates a variable that had been removed in a previous paired correlation.

<u>MinTempCurrentApr</u>	0.132	<u>PrecipCurrentApr</u>	<u>0.338</u>	-0.71	<0.001	(12) MinTempCurrentApr
<u>MinTempPreviousAug</u>	<u>0.331</u>	MinTempPreviousNov	0.178	0.7	<0.001	(13) MinTempPreviousNov

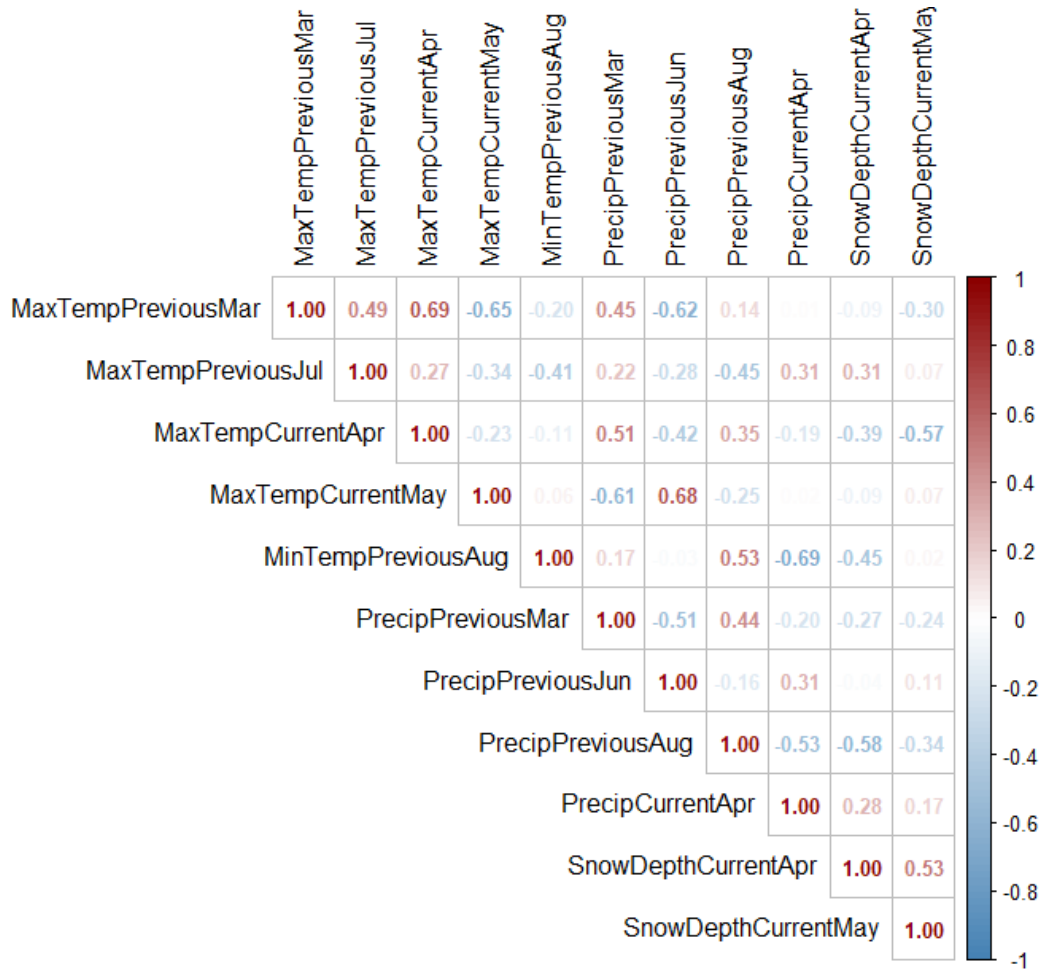


Figure AP2.2. Testing correlation between the 11 climate explanatory variables used in the 2018 RF model. The numbers refer to the Pearson correlations with red values positive correlated and blue values negative correlated.

Table AP2.3. Monthly climate means across presence areas in the Maritime provinces (March 2017 – May 2018) with long term averages and the difference between this average and the 2018 event. Bold values indicate the 11 variables that were included in the RF modelling.

	Precipitation (mm)			T _{MAX} (°C)			T _{MIN} (°C)			Snow Depth (cm)		
	1950-2018 mean	2018 Event	Diff.	1950-2018 mean	2018 Event	Diff.	1950-2018 mean	2018 Event	Diff.	1979-2018 mean	2018 Event	Diff.
Mar 2017	81.5	63.3	-18.3	1.6	-0.8	-2.3	-9.0	-11.3 ³	-2.2	14.4	12.9 ¹	-1.4
Apr 2017	79.9	90.9 ¹	+11.1	8.2	9.3 ¹	+1.1	-2.2	-0.2 ³	+2.0	3.2	3.8 ³	+0.6
May 2017	90.0	143.5 ²	+53.5	16.0	15.9 ¹	-0.1	3.7	4.9 ³	+1.2	0.2	0.0 ¹	-0.2
Jun 2017	94.8	95.6	+0.8	21.2	21.7 ¹	+0.5	9.0	9.6 ¹	+0.6	-	-	-
Jul 2017	99.2	56.6 ³	-42.6	24.3	24.7	+0.4	12.4	12.0 ¹	-0.4	-	-	-
Aug 2017	91.3	56.5	-34.7	23.4	23.9 ²	+0.5	11.5	11.0	-0.5	-	-	-
Sep 2017	91.6	89.6 ¹	-2.0	18.6	21.8 ³	+3.2	7.0	9.6 ²	+2.6	-	-	-
Oct 2017	101.6	145.5 ¹	+43.9	11.7	16.5 ³	+4.7	1.8	4.6 ³	+2.8	-	-	-
Nov 2017	104.2	111.1 ¹	+6.9	4.7	5.3 ¹	+0.7	-3.4	-4.6 ³	-1.2	-	-	-
Dec 2017	103.3	117.0 ²	+13.7	-2.2	-4.2 ³	-2.0	-11.3	-12.9 ³	-1.6	8.0	8.5 ¹	+0.5
Jan 2018	91.8	156.6 ³	+64.9	-5.1	-4.4 ¹	+0.7	-15.5	-14.7 ²	+0.8	17.9	17.4 ¹	-0.5
Feb 2018	75.2	90.5 ¹	+15.4	-3.5	0.0 ¹	+3.5	-14.9	-11.8 ¹	+3.0	20.8	16.1 ¹	-4.7
Mar 2018	81.5	79.9 ¹	-1.6	1.6	2.1 ²	+0.5	-9.0	-5.8 ¹	+3.3	14.4	15.2 ¹	+0.8
Apr 2018	79.9	114.0	+34.2	8.2	7.0	-1.2	-2.2	-3.4 ³	-1.2	3.2	6.2	+3.0
May 2018	90.0	71.5 ²	-18.4	16.0	18.0	+2.0	3.7	3.0 ²	-0.7	0.2	0.2	+0.0

¹ Climate anomaly worse in absence areas

² Univariate logistic regression between presence and absence areas not significant (p<0.05)

³ Removed due to collinearity

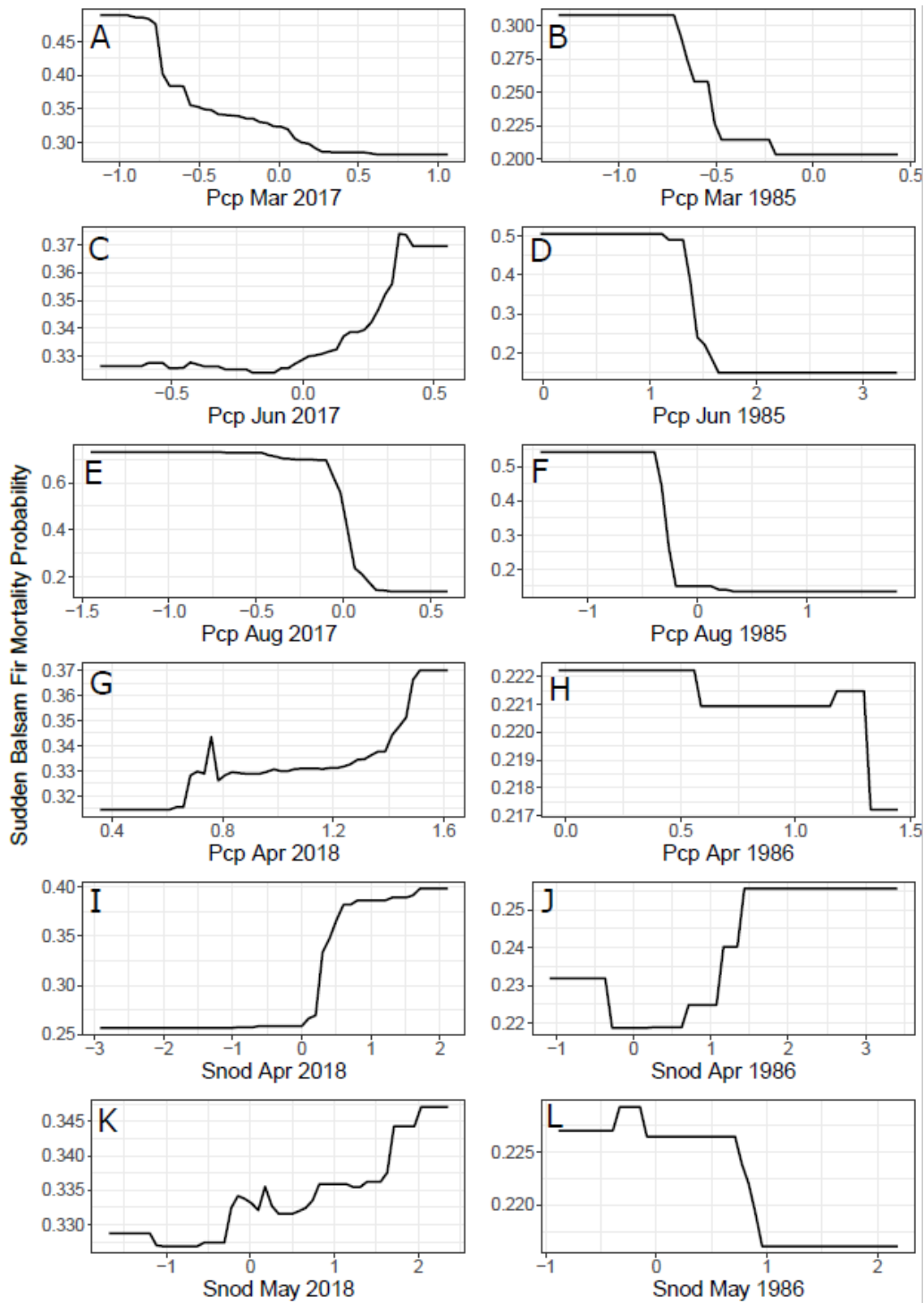


Figure AP2.3. Partial Dependence Plots (PDP) for precipitation (Pcp) and snow depth (Snod) (A – L) variables used in the 2018 and 1986 event Random Forest (RF) models.

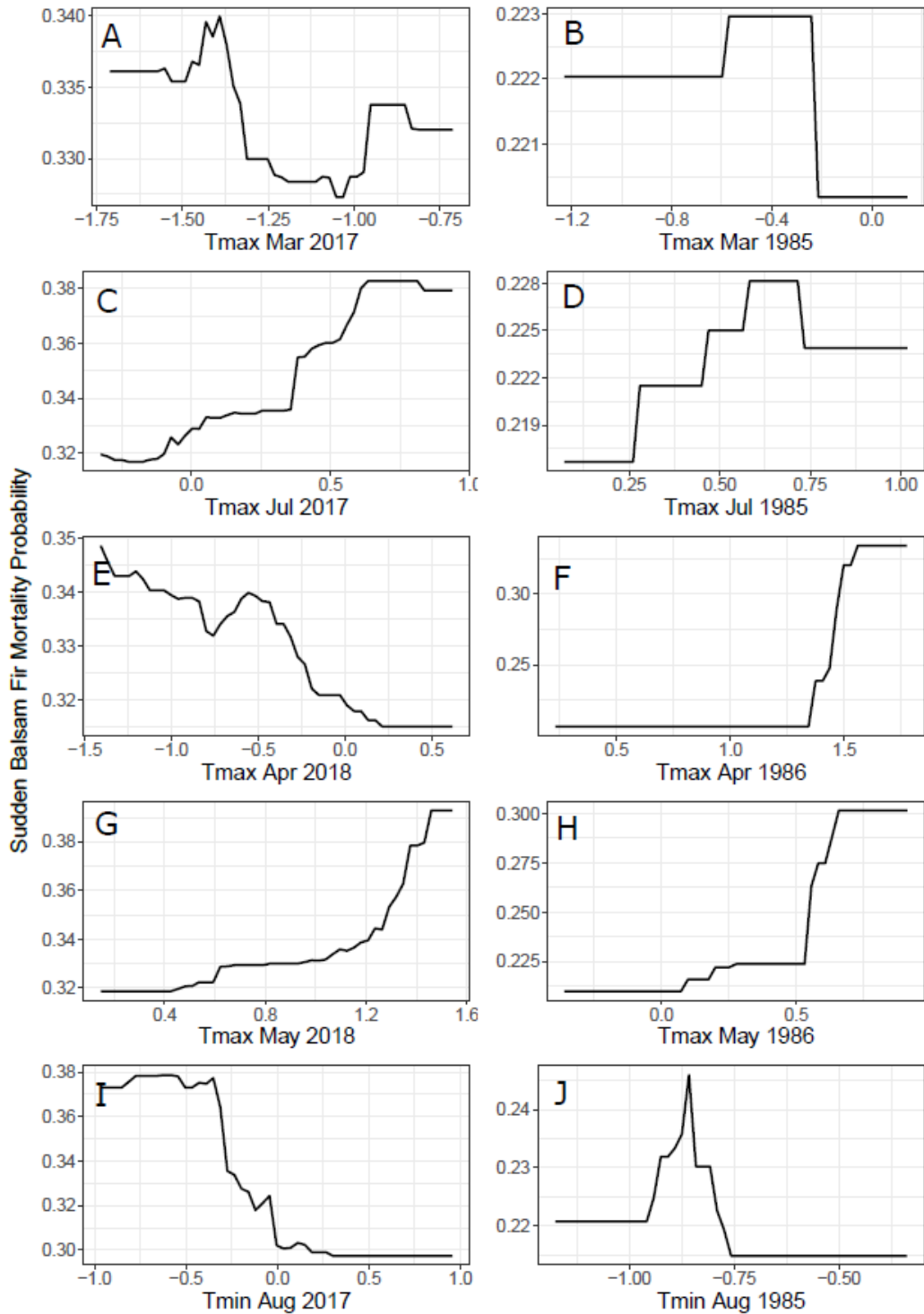


Figure AP2.4. Partial Dependence Plots (PDP) for T_{MAX} and T_{MIN} (A – J) variables used in the 2018 and 1986 event Random Forest (RF) models.

Table AP2.4. Monthly climate means for 2018 presence and absence areas and high/medium frequency, low frequency and absence areas in 1986

Variable	2018 Presence	2018 Absence	1986 High/Medium	1986 Low	1986 Absence
MaxTempPreviousMar	-1.455	-1.381	-0.25	-0.16	-0.56
MaxTempPreviousApr	0.871	1.136	-0.35	0.20	-0.73
MaxTempPreviousMay	-0.053	0.079	-0.31	-0.17	-0.22
MaxTempPreviousJun	0.412	0.973	-1.30	-1.41	-1.43
MaxTempPreviousJul	0.251	0.037	0.42	0.53	0.58
MaxTempPreviousAug	0.403	0.401	-0.32	-0.41	-0.79
MaxTempPreviousSep	1.814	1.369	0.50	0.84	0.52
MaxTempPreviousOct	2.491	2.346	0.00	0.08	-0.57
MaxTempPreviousNov	0.447	0.892	-1.24	-1.37	-1.35
MaxTempPreviousDec	-0.924	-0.336	-1.01	-1.09	-1.13
MaxTempCurrentJan	0.279	0.732	0.59	0.77	1.04
MaxTempCurrentFeb	1.630	1.872	-0.19	-0.46	-0.84
MaxTempCurrentMar	0.369	0.321	0.16	0.17	0.36
MaxTempCurrentApr	-0.907	-0.582	1.56	0.92	1.00
MaxTempCurrentMay	1.132	0.931	0.50	0.08	0.20
MinTempPreviousMar	-0.945	-0.697	-0.13	-0.19	-0.73
MinTempPreviousApr	1.459	0.971	-1.46	-1.22	-1.13
MinTempPreviousMay	1.070	0.788	-0.95	-0.52	-0.75
MinTempPreviousJun	0.668	0.831	-0.39	-0.08	0.03
MinTempPreviousJul	-0.373	-0.388	0.14	-0.11	0.24
MinTempPreviousAug	-0.431	-0.051	-0.84	-0.73	-0.71
MinTempPreviousSep	1.784	1.687	0.38	0.12	-0.27
MinTempPreviousOct	1.843	1.559	0.01	-0.19	-0.32
MinTempPreviousNov	-0.776	-0.625	-0.93	-0.71	-0.62
MinTempPreviousDec	-0.620	-0.271	-1.35	-1.51	-1.53
MinTempCurrentJan	0.324	0.298	0.11	0.22	0.32
MinTempCurrentFeb	1.102	1.138	-0.18	-0.24	-0.51
MinTempCurrentMar	1.342	1.643	-0.58	-0.78	-0.93
MinTempCurrentApr	-0.931	-0.534	1.29	1.06	1.26
MinTempCurrentMay	-0.561	-0.458	0.16	-0.06	-0.10
PrecipPreviousMar	-0.536	0.043	-0.79	-0.51	-0.09
PrecipPreviousApr	0.424	-1.576	-1.45	-1.99	-1.15
PrecipPreviousMay	1.326	1.273	0.35	0.89	0.96
PrecipPreviousJun	0.124	-0.005	0.72	1.53	2.55
PrecipPreviousJul	-1.440	-0.294	1.38	-0.32	-0.51
PrecipPreviousAug	-0.974	0.366	-0.86	-0.24	0.76
PrecipPreviousSep	0.086	0.184	-0.48	-1.40	-2.14
PrecipPreviousOct	0.879	-1.494	-0.96	-0.89	-0.62
PrecipPreviousNov	0.324	-0.411	-0.15	0.15	-0.19
PrecipPreviousDec	0.508	0.428	-1.05	-0.82	-0.95
PrecipCurrentJan	1.716	0.326	1.22	0.84	0.49
PrecipCurrentFeb	0.634	0.727	-1.88	-1.47	-0.40
PrecipCurrentMar	0.075	-0.163	-0.38	0.47	0.43
PrecipCurrentApr	1.197	0.927	0.67	0.91	0.67

PrecipCurrentMay	-0.384	-0.281	-0.37	-0.36	-0.69
SnowDepthPreviousMar	-0.018	-0.071	-0.69	-0.68	0.36
SnowDepthPreviousApr	0.452	0.097	-0.14	-0.02	0.62
SnowDepthPreviousMay	-0.045	0.057	1.74	1.09	0.79
SnowDepthPreviousDec	0.145	-0.879	0.61	0.15	-0.05
SnowDepthCurrentJan	0.097	-0.269	0.99	0.05	-0.36
SnowDepthCurrentFeb	-0.402	-1.320	-1.07	-1.12	0.08
SnowDepthCurrentMar	0.224	-0.670	0.33	-0.11	0.77
SnowDepthCurrentApr	0.888	-0.147	1.28	-0.22	0.25
SnowDepthCurrentMay	0.517	0.057	0.51	0.38	0.41

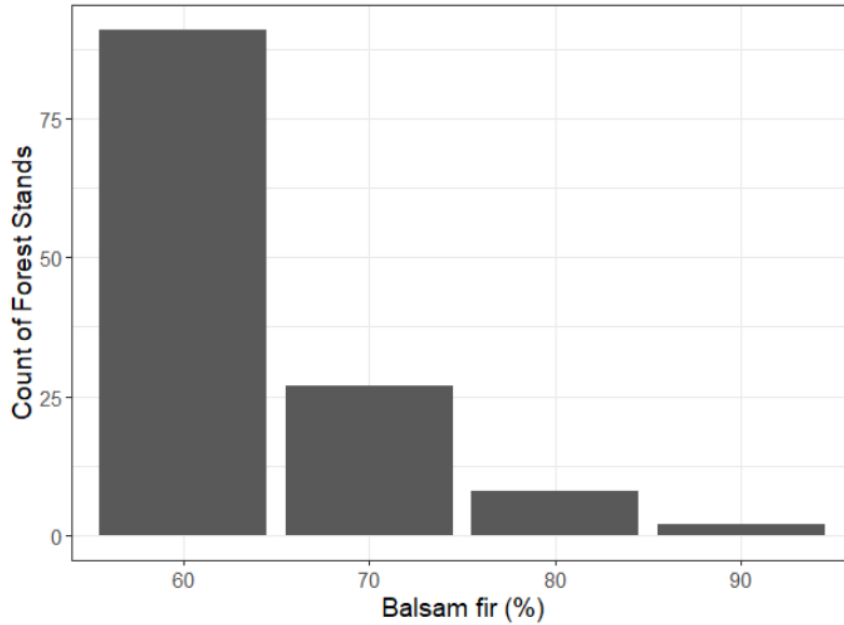


Figure AP3.1. Balsam fir proportion across the 128 forest stands used in the Random Forest modelling

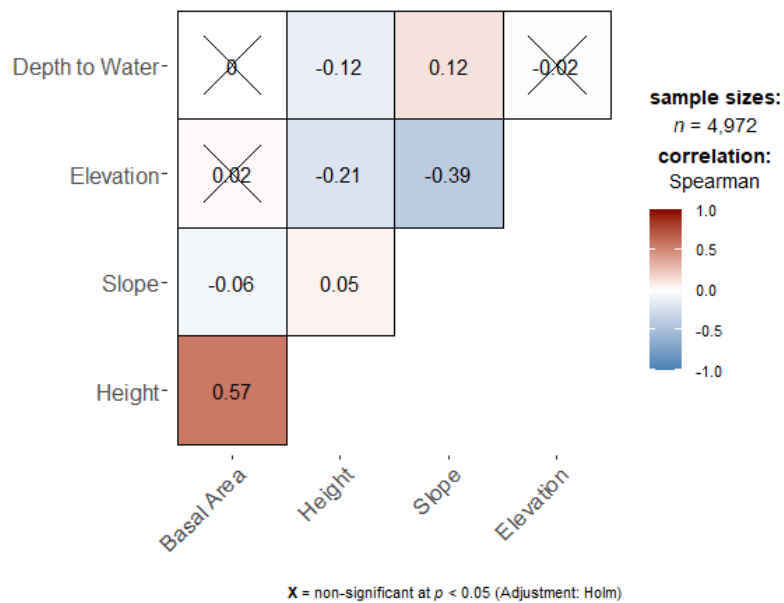


Figure AP3.2. Correlation between continuous explanatory variables used in the Random Forest modelling

Table AP3.1. Drainage Class Full Descriptions

Drainage Class Code and Name ⁶	Description (Canada Soil Information System Description) – applicable to dominant area of polygon
1 = Dominantly Rapidly drained with significant well drained.	Water is removed from the soil rapidly in relation to supply. Excess water flows downward if underlying material is pervious. Subsurface flow may occur on steep gradients during heavy rainfall. Soils have low available water storage capacity (2.5-4 cm) within the control section, and are usually coarse textured, or shallow, or both. Water source is precipitation.
2 = Dominantly Well drained with significant rapidly or moderately well drained.	Water is removed from the soil readily but not rapidly. Excess water flows downward readily into underlying pervious material or laterally as subsurface flow. Soils have intermediate available water storage capacity (4-5 cm) within the control section and are generally intermediate in texture and depth. Water source is precipitation. On slopes subsurface flow may occur for short durations but additions are, equaled by losses.
3 = Dominantly Moderately Well drained with significant well or imperfectly drained.	Water is removed from the soil somewhat slowly in relation to supply. Excess water is removed somewhat slowly due to low perviousness, shallow water table, lack of gradient, or some combination of these. Soils have intermediate to high water storage capacity (5-6 cm) within the control section and are usually medium to fine textured. Precipitation is the dominant water source in medium to fine textured soils; precipitation and significant additions by subsurface flow are necessary in coarse textured soils.
4 = Dominantly Imperfectly drained with significant moderately well or poorly drained.	Water is removed from the soil sufficiently slowly in relation, to supply to keep the soil wet for a significant part of the growing season. Excess water moves slowly downward if precipitation is the major supply. If subsurface water or groundwater, or both, is the main source, the flow rate may vary but the soil remains wet for a significant part of the growing season. Precipitation is the main source if available water storage capacity is high; contribution by subsurface flow or groundwater flow, or both, increases as available water storage capacity decreases. Soils have a wide range in available water supply, texture, and depth, and are gleyed phases of well drained subgroups.
5 = Dominantly Poorly drained with significant imperfectly or very poorly drained.	Water is removed so slowly in relation to supply that the soil remains wet for a comparatively large part of the time the soil is not frozen. Excess water is evident in the soil for a large part of the time. Subsurface flow or groundwater flow, or both, in addition to precipitation are the main water sources; there may also be a perched water table, with precipitation exceeding evapotranspiration. Soils have a wide range in available water storage capacity, texture, and depth, and are gleyed subgroups, Gleysols, and Organic soils.
6 = Dominantly Very Poorly drained with significant poorly drained and organic soils.	Water is removed from the soil so slowly that the water table remains at or on the surface for the greater part of the time the soil is not frozen. Excess water is present in the soil for the greater part of the time. Groundwater flow and subsurface flow are the major water sources. Precipitation is less important except where there is a perched water table with precipitation exceeding evapotranspiration. Soils have a wide range in available water storage capacity, texture, and depth, and are either Gleysolic or Organic.

⁶ dominantly is 60-100% of the area and significant is 0-40% of the area

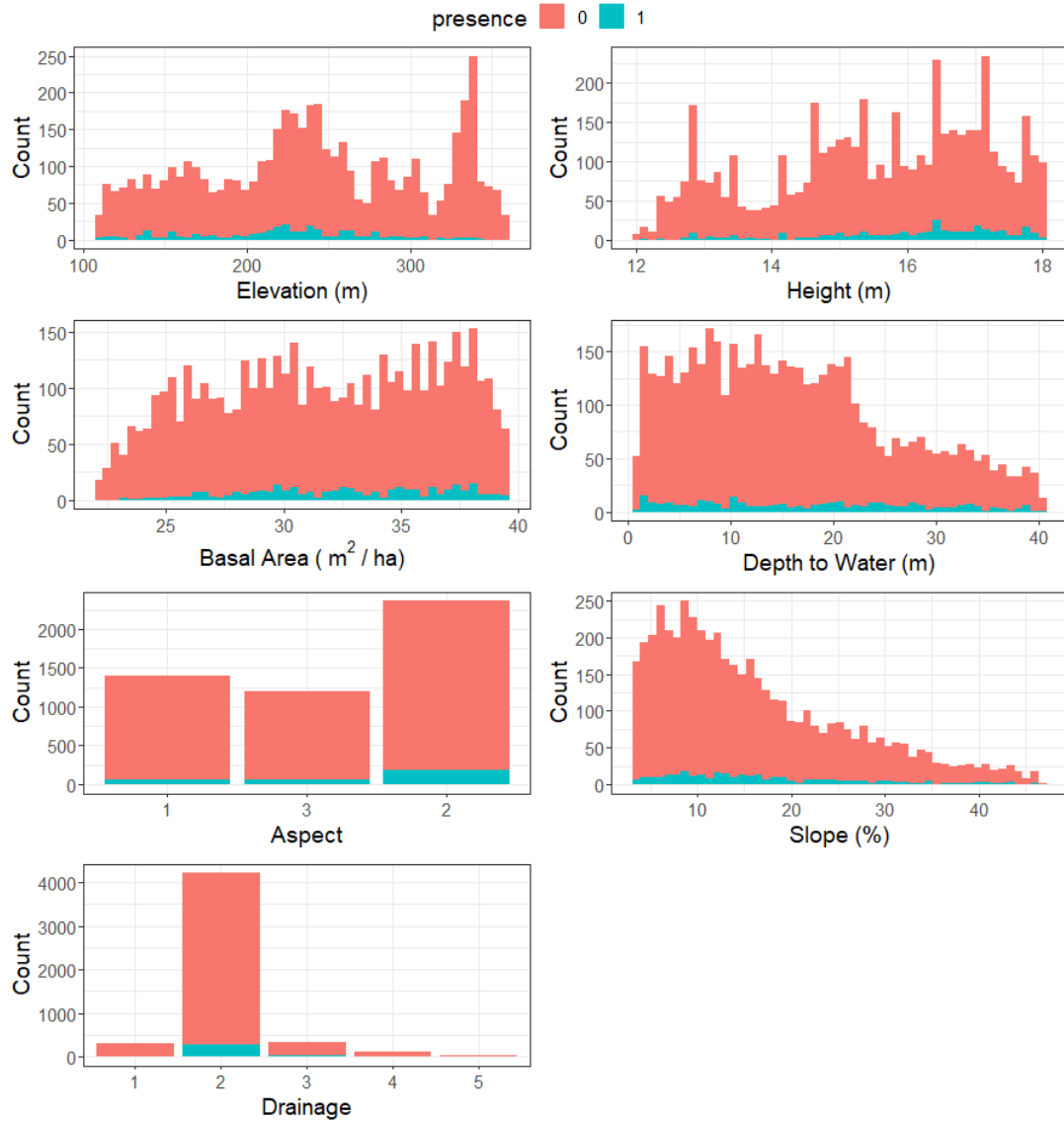


Figure AP3.3. Histograms of explanatory variable values across the 20 m cells used in the Random Forest modelling (0 = absence, 1 = presence)

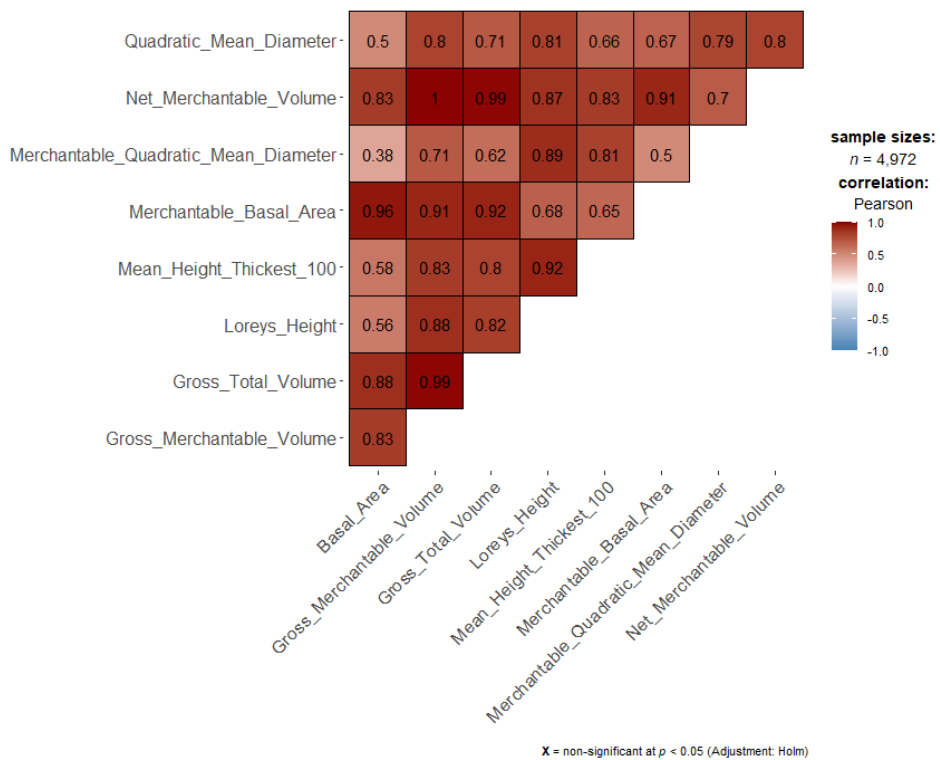


Figure AP3.4 Enhanced Forest Inventory Variable Correlation

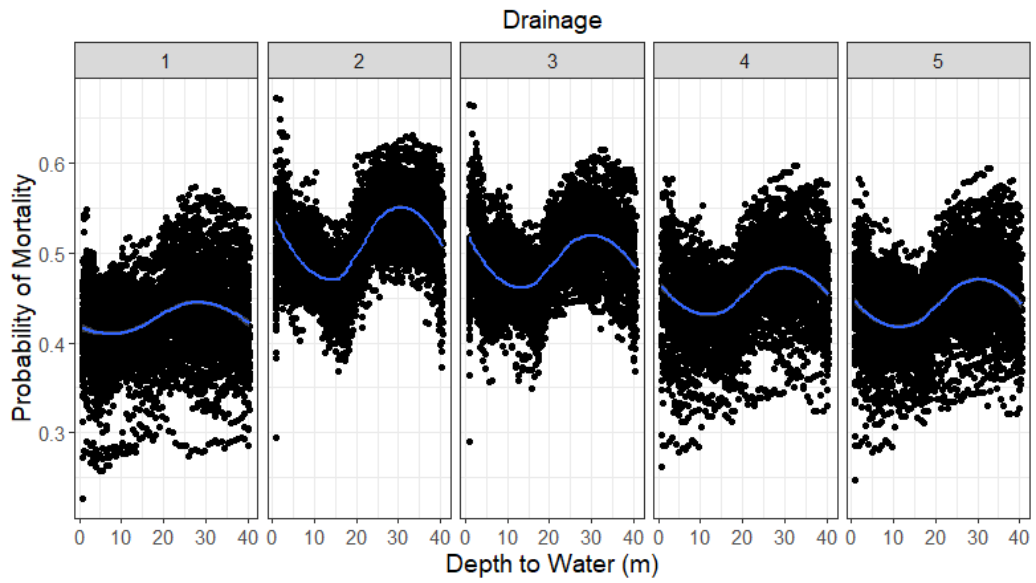


Figure AP3.5. Drainage and Water Table Interaction Partial Dependence Plot

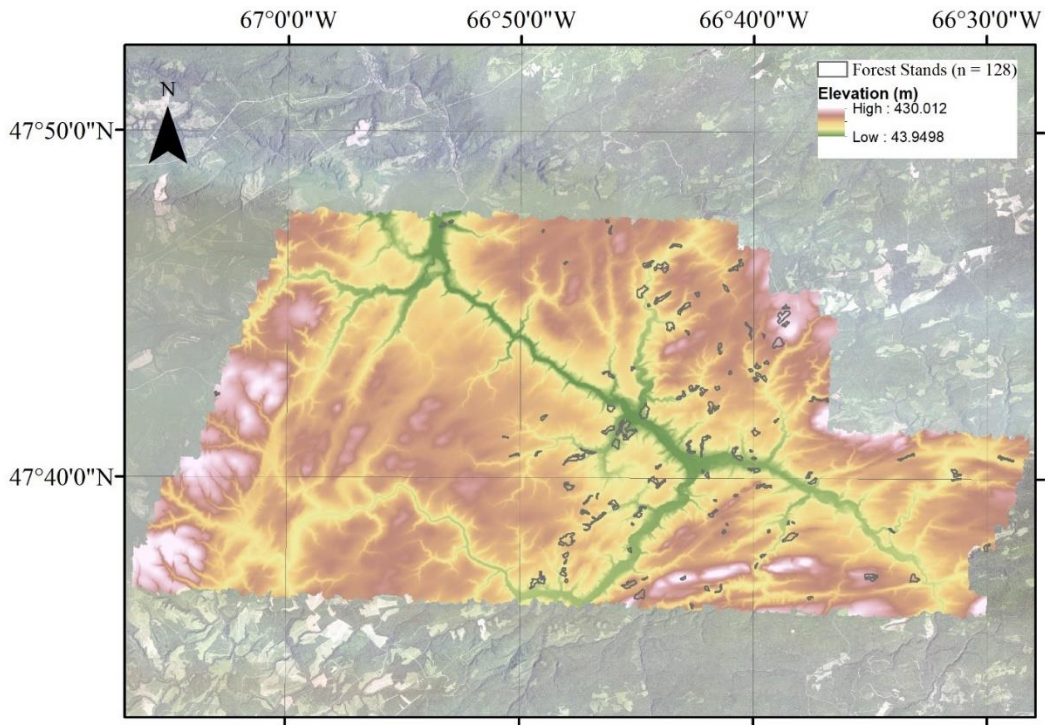


Figure AP3.6. Elevation (Study Area)

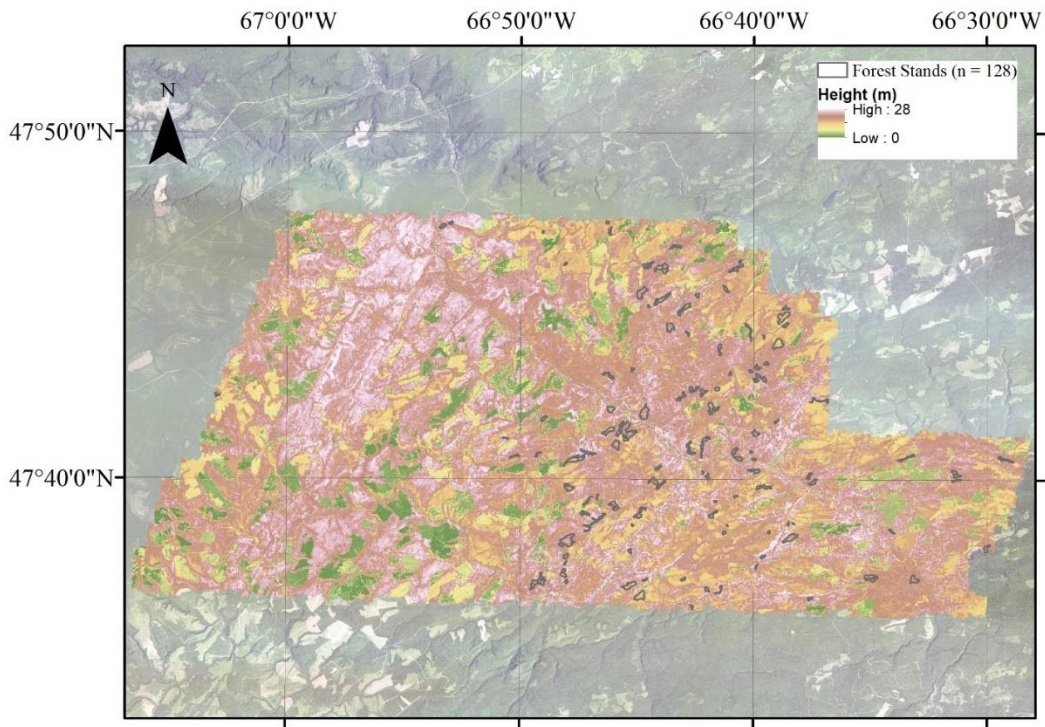


Figure AP3.7. Enhanced Forest Inventory Height (Study Area)

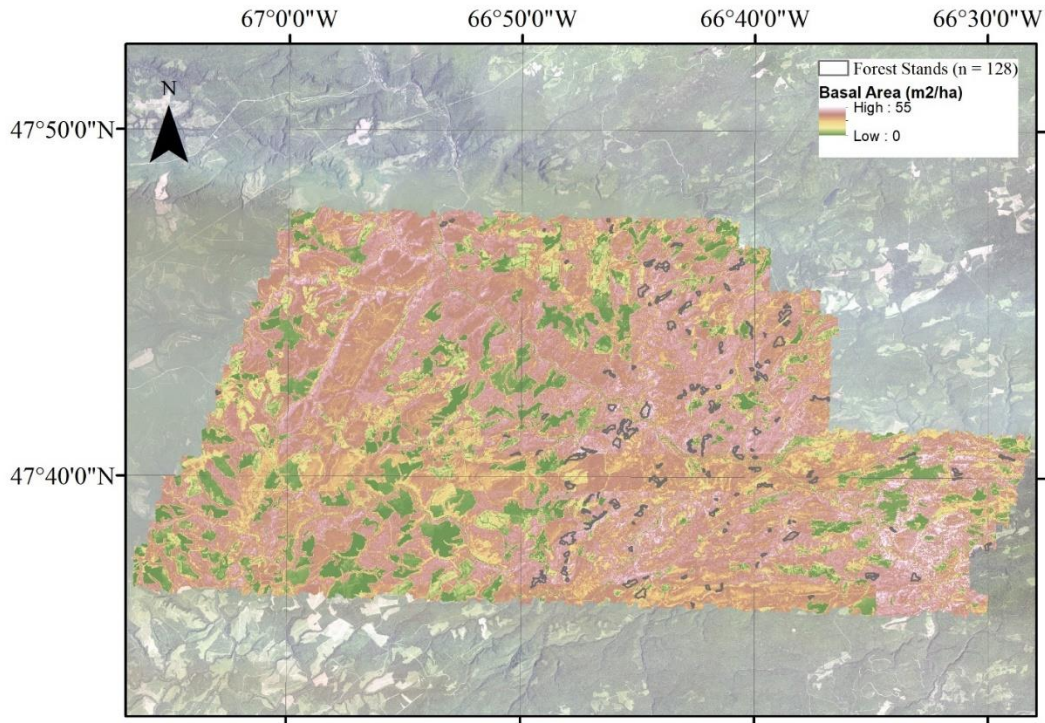


Figure AP3.8. Enhanced Forest Inventory Basal Area (Study Area)

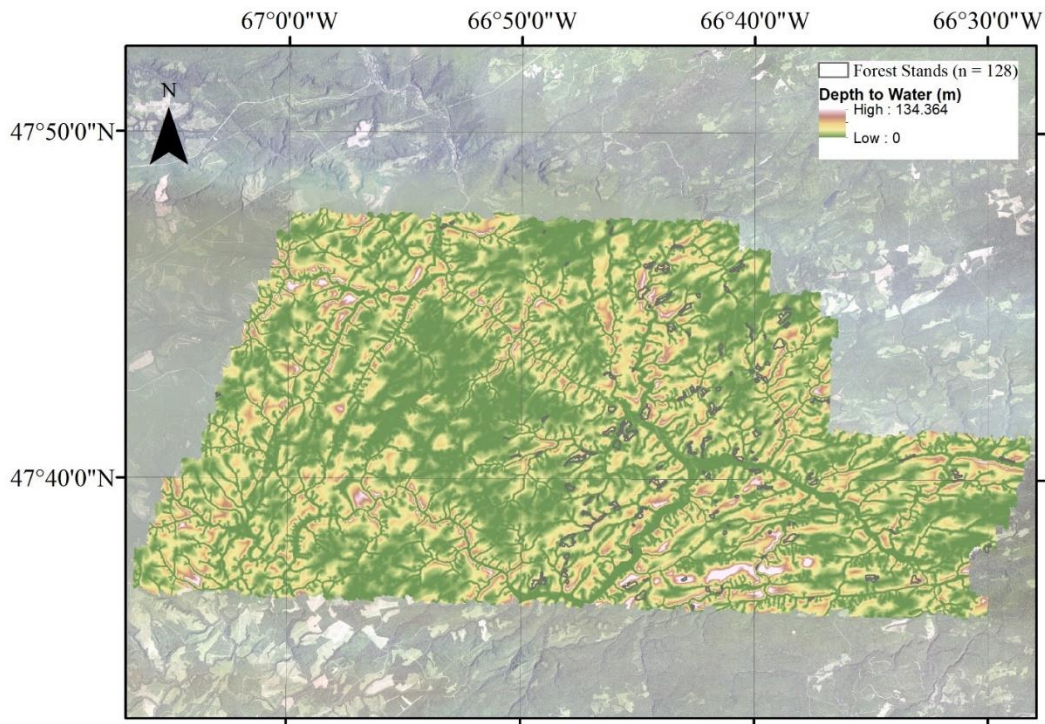


Figure AP3.9. Depth to water (Study Area)

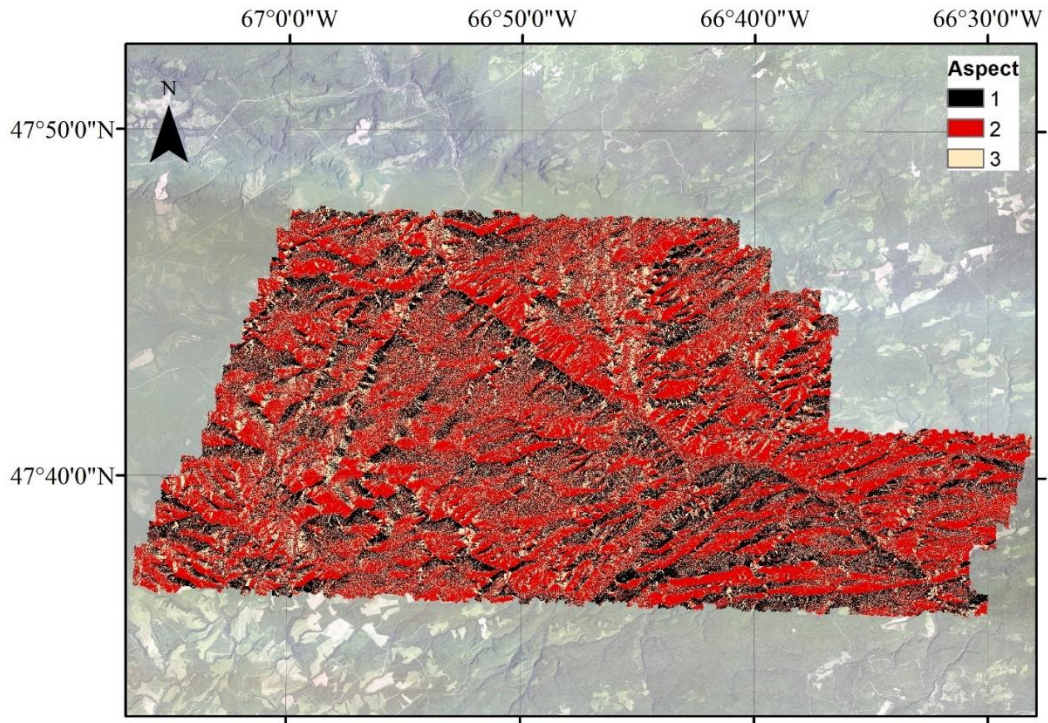


Figure AP3.10. Aspect (Study Area): coldest NW-NE aspects (292.5-67.5); warmest SE-SW aspects (112.5-247.5); moderate SW- NW aspects (67.5-112.5/247.5-292.5)

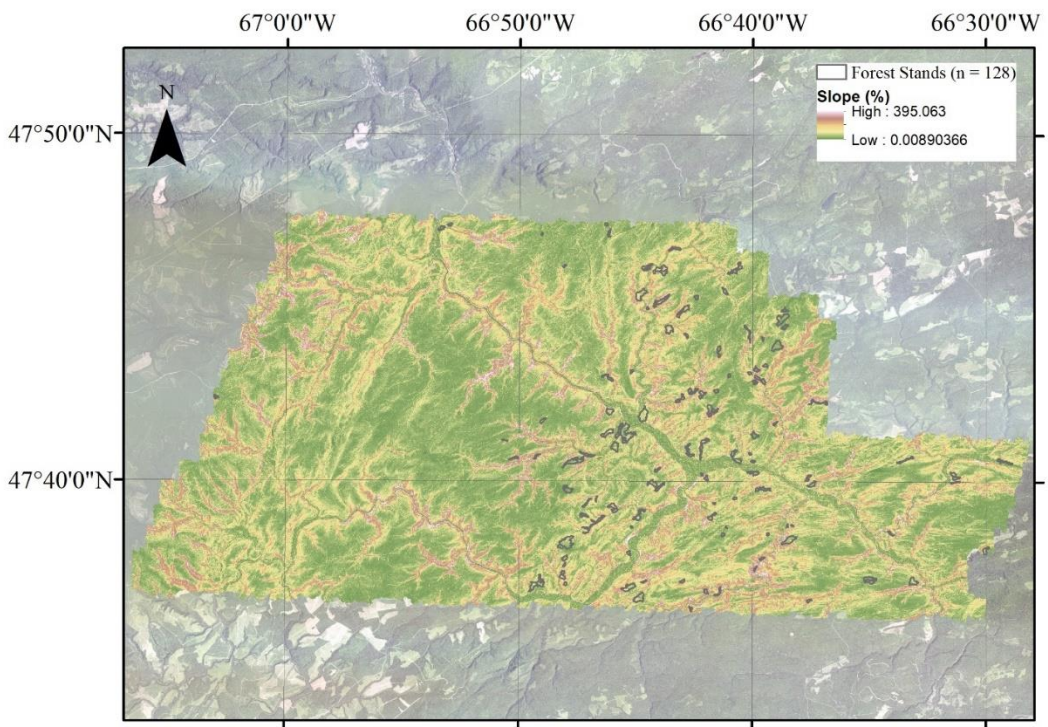


Figure AP3.11. Slope (Study Area)

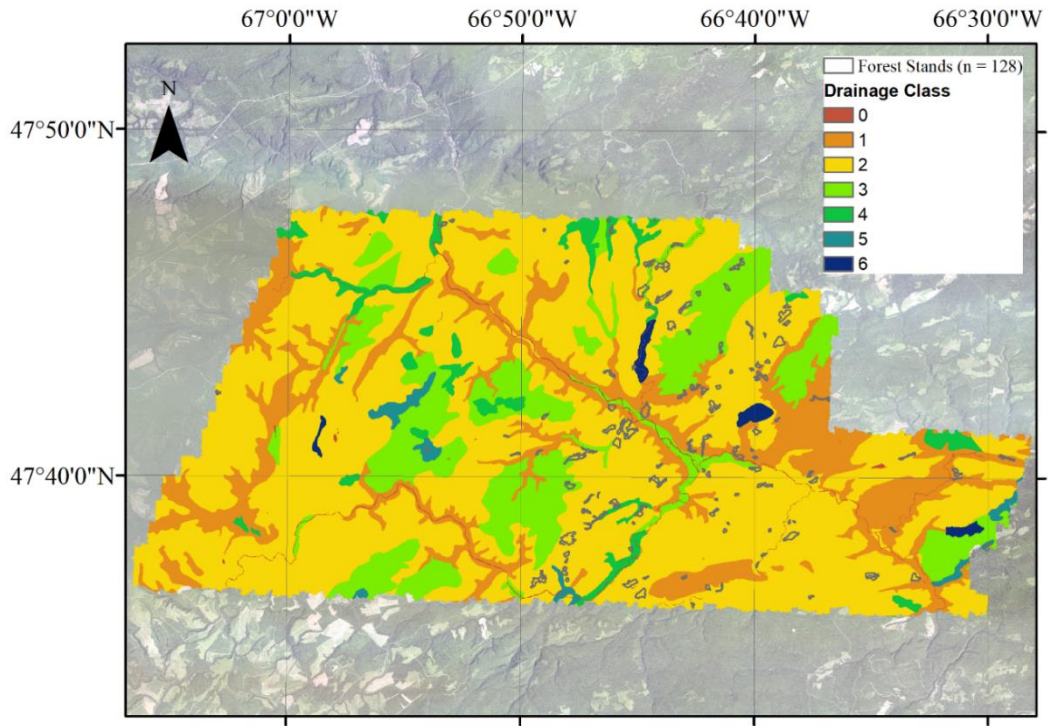


Figure AP3.12. Drainage classes (Study Area)

Curriculum Vitae

Candidate's full name: James Edward Broom

Universities attended:

University of Cumbria (2013 – 2017), BSc. Hons Forest Management

University of New Brunswick (2019 – 2023), Master of Science in Forestry

Conference presentations:

Broom, J., Zhou, Y., Costanza, K.K.L. Sudden Fir Mortality in New Brunswick: Causal Mechanisms. Northeast Forest Pest Council Annual Meeting, Portland, ME, USA, 28 Jan 2020.

Broom, J. Investigating the climate anomalies associated with Sudden Fir Mortality in eastern North America. Your Forest in a Changing Climate 2022 conference, Fredericton, NB, Canada, 1 Feb 2022.

Teaching assisted courses at UNB:

Autecology of Forest Vegetation. Recognition and identification of species, environmental requirements, and persistence mechanisms of various life-forms of forest vegetation; interpretation of silvical characteristics of tree species; analysis of stands of trees in relation to general site conditions and relative stage of development; and evaluation of interrelationships among components of forest vegetation over time, including likely responses to perturbation or to interventions of various kinds. (Sep – Dec 2020, 2021, 2022).

Forestry Inventory and Growth. This course focuses on the design and analysis of forest-level inventories. Concepts of stratification and multistage sampling are presented. Approaches to modelling and predicting stand growth and inventory updates are explored. (Jan – Apr 2021).