Emerging Hot Spot Analysis and Forests: A Case Study on the Hemlock Woolly Adelgid's Invasion into Nova Scotia using Fine Spatial Resolution Satellite Imagery.

Environmental Science Undergraduate Honours Thesis

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Abstract

Adelges tsugae (hemlock woolly adelgid) is an invasive forest insect first identified in Nova Scotia in 2017. This insect poses a threat to the Acadian Forests, as *Tsuga canadensis* (eastern hemlock) is a keystone species in this ecosystem. The loss of such a critical species has been shown to cause significant ecological changes in area previously infested by *A. tsugae* forests in the northeast United States. Remote sensing techniques have been used to model the spread of invasive forest insects across the globe, including *A. tsugae* in the northeastern United States. In this project, the relatively new method of emerging hot spot analysis - a combination of the Getis-Ord Gi* spatial statistics and the Mann-Kendall trend test for evaluating correlation in temporal data – was used to identify various types of hot spots of the normalized difference vegetation index, derived from PlanetScope satellite imagery, in two study areas in southwest Nova Scotia which correspond to the loss of forest canopy due to *A. tsugae*. While emerging hot spot analysis was not able identify forest loss specifically due to *A. tsugae*, it did provide a novel method for examining forest change when utilizing high spatial resolution sensors at a small (1.5-2km^2) spatial extent.

Key Words

A. tsugae, *T. canadensis*, emerging hot spot analysis, change detection, forest change, Acadian forest.

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Abbreviations

CFIA: Canadian Food Inspection Agency

EHA: Emerging Hot Spot Analysis

EMR: Electromagnetic Radiation

HWA: Hemlock Woolly Adelgid; *Adelges tsugae*

NDVI: Normalized Difference Vegetation Index

NIR: Near-Infrared

NS: Nova Scotia

1. Introduction

Adelges tsugae (hemlock woolly adelgid; hereafter referred to as HWA) is a destructive pest invasive to northeastern North America (Havill et al. 2014). The invasion of *A. tsugae* has been well documented in the northeastern United States, starting in Pennsylvania in the late 1960s (McClure 1987). Since its arrival, this insect has expanded to the northeast, following the distribution of *Tsugae spp.* (Morin et al. 2009). Investigations focusing on HWA are only just beginning in Nova Scotia, where it was first detected in 2017 (Canadian Food Inspection Agency 2017). The Canadian Food Inspection Agency has not provided an estimated first arrival date for HWA in Nova Scotia at the time of writing. This invasive insect feeds on, and eventually kills *Tsuga canadensis* (eastern hemlock). *Tsuga canadensis* is found in forests through out Nova Scotia at all growth stages and is included as one of the six old-growth species in the province; losing *T. canadensis* is likely to lead to a significant ecological change in our Acadian forests (Orwig and Foster 1998; Neily et al. 2010). While remote sensing techniques have been used to examine areas of hemlock decline in the United States generally, these techniques have not yet been specifically used for this purpose in Nova Scotia (Royle and Lathrop 2002; Pontius et al. 2005; Williams et al. 2017), and emerging hot spot analysis (EHA), has not been used to examine forest pest invasions. In this study, I investigate the extent emerging hot spot analysis —a combination of the Getis-Ord Gi* spatial statistic (a local measure of spatial autocorrelation) and the Mann-Kendall trend test for evaluating trends in temporal data— can effectively identify forest damage caused by HWA in Nova Scotia.

Forests are an important natural resource, providing many ecosystem services across the planet (Foley 2005). These ecosystem services include nutrient cycling, carbon sequestration, and improving local air quality; older trees have been found to provide more of these benefits than younger trees (Millennium Ecosystem Assessment (Program) 2005; Luyssaert et al. 2008). In the present study's context, the dominant forest region in Nova Scotia is the Acadian Forest, a mixed-wood forest found in humid climates with large temperature variations between seasons (Ricketts et al. 1999). While old-growth forests used to be common across the majority of Nova Scotia (with a land area of approximately 5.53 million hectares) before European settlement, Mosseler et al. (2003) estimated that now there is approximately 300 hectares of true old-growth forest remaining in the province, with many stands dominated or co-dominated by *T. canadensis*. In addition to being long lived (up to approximately 375 years) another reason for *T. canadensis'* dominance in old-growth plots may be its low desirability as a commercial lumber species (Carey 1993; Tyrrell and Crow 1994; Frelich and Graumlich 1994). In Nova Scotia, hemlock's low desirability is a significant feature as softwood species are often harvested commercially in the province's forestry industry (McGrath et al. 2017).

Invasive species are species which are introduced to a new area where they have not existed before, and which result in negative impacts on the local ecosystems. These species may outcompete others, change nutrient fluxes, and even transform the landscape (Ehrenfeld 2010). *Adelges tsugae* is a species native to Japan which feeds on hemlock species found there (*Tsuga spp.*). While HWA has been confirmed to be present in western North America for over 80 years, and the eastern United States for over 50 years, the species was not detected in Nova Scotia until the August of 2017 (McClure 1987; Canadian Food Inspection Agency 2017). The earlier presence of HWA in the Pacific Northwest for many years has been noted, however, it does not kill western hemlock (*Tsuga heterophylla*) and thus has had limited to no impact on western forests (McClure 1987). Damage to forests with large populations of hemlock in eastern North America has been well documented, where *T. canadensis* mortality has been widely observed within several years of establishment of HWA in new areas (McClure 1987; Vose et al. 2013).

Remote sensing techniques provide a suite of tools that can be a valuable approach to detecting and quantifying the continuing damage caused by HWA. Remote sensing is the science of determining information about an area by using and examining the electromagnetic radiation emitted or reflected from the area (Lu et al. 2004). These techniques have commonly been used to examine change in land use and land cover over time, which have then been used to inform policy decisions or determine the extent of various phenomena (Lu et al. 2004). Remote sensing has been shown to be a particularly effective tool for determining forest loss as there are various spectral indices which show how “green” an area is. One example index is the normalized differential vegetation index (NDVI). This derivative from the imagery is a relatively simple band ratio comprised of the red and near-infrared bands that are often measured in satellite imagery, and is further described in section 3.4 (Rouse 1972). More advanced satellites (or low-flying planes) with improved spectral resolution can take images with additional bands over the same spectral range, such as red-edge (680nm - 730nm); these additional spectral channels can be used in more optimized vegetation indices, however these channels are not common in most freely accessible imagery, such as the Landsat or Sentinel series of satellites, and are also not available in the PlanetScope imagery used in this study (Jackson and Huete 1991).

Many studies have been conducted on the impacts of HWA in the eastern United States and have included hydrology impacts (Ford and Vose 2007), biogeochemical impacts (Lovett et al. 2004), and changes in forest succession (Orwig and Foster 1998). Other studies have used remote sensing to quantify the extent of canopy loss caused by HWA (Royle and Lathrop 1997, 2002; Pontius et al. 2005; Hanavan et al. 2015; Williams et al. 2017). A review conducted by Wulder et al. (2006) examined the strengths of utilizing remote sensing for examining forest damage due to the invasive mountain pine beetle (*Dendroctonus ponderosae*), in western North America. The authors noted that remotely sensed imagery is useful in filling in spatiotemporal gaps in other sources of data, and that remote sensing provides an additional way for forest managers to quantify and locate forest damage (Wulder et al. 2006). Another study examined the negative economic impact of *T. canadensis* loss in forest plots (Holmes et al. 2010). While a large suite of studies exist on the detection of impacts of *A. tsugae* (e.g.

Royle and Lathrop 1997; Williams et al. 2017) and other invasive insects, no published research was found examining the impacts or extent of damage caused by HWA in Nova Scotia.

After being processed, remote sensing imagery can be used in the emerging hot spot analysis (EHA), a relatively new geospatial technique with widespread applications. EHA has been used to examine manatee (*Trichechus manatus latirostris*) mortality in the Florida everglades (Bass 2017), detect patterns of crime in Miami-Dade county (Bunting et al. 2018), as well as find statistically significant hot spots of car crashes in Wuijiang, China (Cheng et al. 2018). Harris et al. (2017) used EHA to detect canopy loss in Brazil, Indonesia, and the Democratic Republic of Congo without explicitly considering the underlying driver of canopy loss (e.g. fire, harvesting, invasive species). At the time of writing no studies were identified where EHA was used to examine tree canopy loss specifically due to an invasive species.

In this study, I will examine the loss of forest canopy due to the invasion of the HWA in southwest Nova Scotia. The objectives are to determine how effective EHA is at quantifying forest lost due to HWA. Satellite imagery from 2016 to present will be examined and will focus on the earlier impacted site of Springhaven, Nova Scotia, and a more recently impacted and lesser documented site of HWA impact within Kejimkujik National Park, NS. The specific research question being addressed is:

To what extent does emerging hot spot analysis identify canopy damage caused by the hemlock woolly adelgid (Adelges tsugae) in Nova Scotia in areas with a known infestation of *A. tsugae*.

This research question will be addressed by applying EHA to the NDVI of 3m resolution PlanetScope satellite imagery obtained over both Springhaven, Nova Scotia, and Kejimkujik National Park. The outputs of this analysis will ideally allow for the quantification of the amount of damage caused by HWA in Springhaven, NS and Kejimkujik National Park, NS.

2. Literature Review

This literature review examines the research conducted on the invasion of HWA in North America, specifically the potential impacts of the species on the Acadian forest, as well as the methods previously used to detect HWA's invasion into the northeastern United States. The most common journals cited in this literature review are: Remote Sensing of Environment, Biological Invasions, Ecological Applications and Environmental Entomology. Common search terms applied in the search were hemlock woolly adelgid, remote sensing, change detection, Acadian forest, emerging hot spot analysis, and disturbance. Invasive insects will be discussed, including a detailed look into the biology and impacts of HWA. Context on *T. canadensis* and their role in the Acadian forest will be provided. Potential methods to assess invasive insect damage will also be reviewed. This literature review discusses the current body of knowledge surrounding the impacts and detection of HWA, and then identifies knowledge gaps in the use of novel geographic analysis methods to detect HWA.

2.1 Invasive Insects and Hemlock Woolly Adelgid (*A. tsugae*)

Generally, invasive species are damaging to the environment where the species is introduced. Various reviews have been conducted examining the impacts of invasive insects on forests especially in relation to today's changing climate. A prominent review by Kenis et al. (2009) examined 403 primary research articles on invasive insects, concluding that species damaging to tree canopies are more likely to be studied due to the visibility of their impacts. These impacts include, but are not limited to: changed biogeochemical cycles, ecosystem structure changes, and trophic interactions (Kenis et al. 2009; Clark et al. 2010) and are likely to have expanded ranges due to a progressively changing climate, especially in temperate forests (Bale and Hayward 2010; Millar and Stephenson 2015). Invasive insect species such as HWA can be heavily damaging to forests and other ecosystems. These species have a high potential to negatively influence local ecosystems through trophic interactions and cascading effects.

Introduced forest pests such as the emerald ash borer, Dutch elm disease, and beech bark disease have increasingly damaged forests in North America. The emerald ash borer (*A. planipennis*) has a history of invading urban forests across North America, and may potentially extirpate *Fraxinus spp.* from cities across the continent (Poland and McCullough 2006; Herms and McCullough 2014). Fungi causing Dutch elm disease in *Ulmus spp.* have produced gaps in tree canopy cover, modifying microclimates and increasing coarse woody debris availability, negatively impacting the local forest ecosystem (Crooks 2002). Beech bark disease causes *Fagus spp.* to experience stronger competition from other species, allowing other non-shade tolerant species to replace the stand, changing the succession regime in the area (Houston 1994). *Adelges tsugae* is another addition to the problem of introduced forest pests in North America and has recently invaded Nova Scotia. *Adelges tsugae* will likely have similar negative impacts to other invasive forest insects in the province.

The hemlock woolly adelgid is an invasive insect in eastern North America, recently introduced to southwest Nova Scotia in 2017 (Canadian Food Inspection Agency 2017). Exhibiting a complex life cycle, HWA transitions through six stages of development (Figure 1) with intermediate host species (hemlock; *Tsuga spp.*) and primary host species (spruce; *Picea spp.*) (McClure 1989). The spruce-hosted HWA dies before reproduction in North America, as it cannot find its desired spruce species, reducing its dispersal rate across the continent (McClure 1987; Havill et al. 2016). Research by Tobin et al. (2013) suggested that a single ovisac can invade a new environment and establish a new population. These small invasion populations lead to genetic bottlenecking, which is theorized to have caused HWA's solely asexual reproduction in North America (Havill et al. 2016). *Adelges tsugae'*s unique biology has led to its ability to easily invade new environments and establish new populations within small numbers of generations (Tobin et al. 2013).

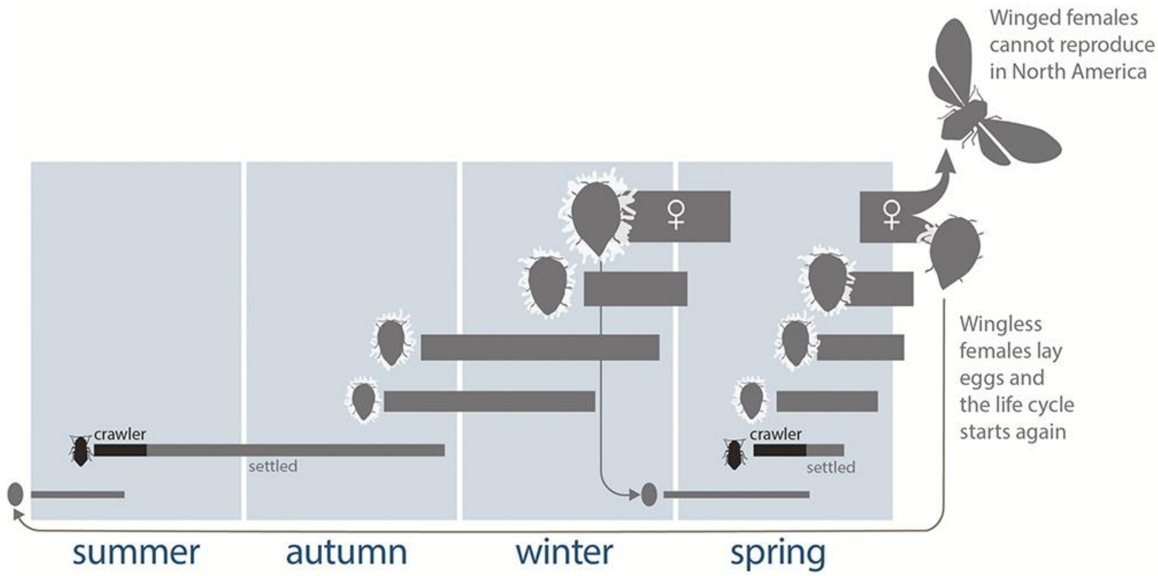

Figure 1 The life cycle of A. tsugae. Source: Limbu et al (2018).

How and exactly when HWA was introduced to southwest Nova Scotia has yet to be determined. Due to HWA's small size and weight, there are many potential dispersal avenues, including wind, birds, deer, and humans (McClure 1990). *Adelges tsugae* has been found as a stowaway on various bird species whose migration patterns align with the peak season for HWA crawlers (Russo et al. 2019). The spread of HWA has been shown to be anisotropic (varies in magnitude according to the direction of measurement), following the distribution of its host species, *Tsuga spp.,* into new areas along North America's eastern seaboard. (Morin et al. 2009; Fitzpatrick et al. 2012). While the Canadian Food Inspection Agency first detected HWA's arrival in 2017, there is no estimate available for when the invasive species arrived in Nova Scotia (Canadian Food Inspection Agency 2017). Most of the literature concerning HWA spread focuses on the direction and extent of dispersion, rather than the dispersal method.

A suite of studies have concluded that temperature can control the mortality and spread of insect species, including HWA. Bale and Hayward (2010) conducted a review on insect cold hardiness, and found that a changing climate will change overwintering strategies and species distributions. Both high and low temperatures have been found to impact HWA's survival, through increased mortality and prevention of the induction of aestival diapause (Salom et al. 2001; Paradis et al. 2008; Mech et al. 2018). Mean winter temperatures in the northeastern United States and Nova Scotia are increasing due to climate change, reducing the overwintering mortality in many invasive species, including HWA (Paradis et al. 2008). Mech et al. (2018) view the invasive insects mortality from the opposite seasonal perspective: as summer temperatures increase, summer survival is reduced. Climate change will influence the range of various species, including HWA. Increasing winter temperatures will allow HWA to expand its range northward due to reduced overwintering mortality; however, increasing summer temperatures may place a limit on HWA's expansion due to high summer mortality.

Much of *T. canadensis'* role in the Acadian forest was discovered while examining forest loss due to HWA. Many researchers have found broad negative impacts stemming from the loss of *T. canadensis* including impacts on forest structure and local biodiversity (Tingley et al. 2002; Ellison et al. 2005; Allen et al. 2009). Other local species have not been found to fill the role that *T. canadensis* plays in the forests of the northeastern United States after its removal due to HWA (Jenkins et al. 1999; Lovett et al. 2004; Ford and Vose 2007). Hemlock mortality is just one of the many negative effects of HWA. While Nova Scotia is a novel environment for HWA, similar negative impacts to the invasion of the northeast United States are likely to be found in the province after *T. canadensis* mortality begins.

2.2 The Acadian Forest and Eastern Hemlock (*T. canadensis*)

The Acadian forest is a mixed wood forest found in humid climates with large seasonal temperature differences (Mosseler et al. 2003). The Acadian forest is the main forest type found in Nova Scotia, with forest stands in this region showing signs of transition between the boreal forest to the north, and deciduous forests to the south and west (Loo and Ives 2003; World Wildlife Fund 2019). Early-successional forests are often deciduous dominated, while late-successional stands are more often dominated by coniferous species (El-Bayoumi et al. 1984). Large stand-replacing disturbances such as fire are uncommon to the region, with windthrow (trees being uprooted or broken by wind) being the most prevalent disturbance regime (Mosseler et al. 2003). While the Acadian Forest region is defined as being mixed wood, stands consisting of solely *P. rubens* (red spruce) or *A. balsamea* (balsam fir) are common (Simpson 2015). While old-growth forests were once common in Nova Scotia, only .0008% of the available forest land has been identified as true old-growth (Mosseler et al. 2003). Loo and Ives (2003) explored the historical impact of humans on the Acadian forest, and found that forestry, disease outbreaks, and increased fires caused *T. canadensis*, among other species, to become less populous. Other pressures on the Acadian forest such as the forestry industry's high grading regimes, where the most valuable trees are removed, have led to an artificially higher proportion of the less economically desirable species, such as *T. canadensis,* across Nova Scotia (Carey 1993). Today's Acadian forest has little remaining true old-growth stands, however the changing species composition of the region still includes many of the old-growth species as younger specimens (Mosseler et al. 2003).

T. canadensis is one of six old growth tree species in Nova Scotia, in part due to its high shade tolerance (Stewart et al. 2003). This species is also common in a non-old growth role in forests across the province, waiting in the low-light understory for disturbances to create a canopy gap before growing to the canopy level (Neily et al. 2010). Kobe et al. (1995) found that *T. canadensis* has slower growth rates as a juvenile tree in low-light conditions. The light and medium disturbances in hemlock forests have been found to favour shade tolerant species, as the younger trees take the place in the canopy of the single older trees that are knocked over or removed (Frelich and Lorimer 1991). *T. canadensis* is an important foundation species found in forests across Nova Scotia, due to the regions low intensity disturbances and *T. canadensis*' high shade tolerance (Ellison et al. 2005).

2.3 Remote Sensing

Passive optical remote sensing is the process of measuring the electromagnetic radiation (or EMR), from a source other than a sensor, that is returned to a sensor after it has been reflected off an object (Emery and Camps 2017). The EMR reflected is measured at specific ranges of wavelengths, commonly referred to as bands or spectral channels. Many passive optical satellite systems include at least four bands (visible blue, visible green, visible red, and the near-infrared), which can be combined in various ways, such as spectral indices, to extract additional information, including relative biomass, plant stress, plant health, and plant water use, among others from the data (Jackson and Huete 1991).

Spectral indices are common ways to estimate vegetation biomass when using remotely sensed imagery (Jackson and Huete 1991). These indices vary in complexity, and some may not be able to be generated depending on the satellite sensor due to missing spectral information. The normalized differential vegetation index (NDVI) is commonly used in vegetation studies, as the index has been shown to be a suitable method for determining relative biomass as chlorophyll reflects red wavelengths back to the sensor and absorbs near-infrared (NIR) wavelengths (Myneni et al. 1995). Carlson and Ripley (1997) illustrate the relationship between NDVI, fractional cover, and leaf area index, all of which are measurements of the vegetation present in an area. However, NDVI has been shown to be sensitive to backscatter and oversaturation in regions of high biomass (Carlson and Ripley 1997; Huete et al. 2002). It is not expected that these limitations will play an important role in the present study, as these phenomenon are less likely to occur in temperate regions such as Nova Scotia (Huete et al. 2002).

Research examining the detectability of various forest invasive insects using remotely sensed imagery has been conducted around the world (Poland and Rassati 2019). The monitoring of the HWA invasion in the northeastern United States has been mostly conducted by examining hemlock forest defoliation using remote sensing methods. Williams et al. (2017) and Royle and Lathrop (1997, 2002) used time series imagery from the Landsat series of satellites to detect forest changes, while Hanavan et al. (2015) used hyperspectral imagery from fixed-wing aircraft equipped with AVIRIS and ProSpecTIR-VS sensors to find hemlock decline in the northeastern United States. Wulder et al. (2006) found that the analysis of remote sensor data is an effective tool for the detection of forest loss caused by *D. ponderosae* (mountain pine beetle) in the rocky mountains. In Sweden, various spatial resolutions of imagery have been used to map damage to *P. abies* (Norway spruce). The more coarse spatial resolution images (MODIS – 250m pixel size) were able to identify landscape level changes, while the higher spatial resolution images (SPOT – 1.5m-6m) could identify stand level losses (Olsson et al. 2012). These studies demonstrate that if the extent of defoliation is sufficiently severe, remote sensing can be used to examine the extent of the impact that various invasive insects have caused to forests at both fine and coarse scales.

Change detection refers to a group of methods used to determine how a landscape, or its land-uses, have changed over time using remotely sensed data. Many change detections methods are used, however there is no single best method that may be used in all situations (Lu et al. 2004). Optical satellites commonly detect wavelengths in the visible blue, green, and red portion of the electromagnetic spectrum, as well as near-infrared wavelengths outside of the visible spectrum. As a consequence, many ecosystem monitoring studies focus on utilizing these bands (Coppin et al. 2004). Change detection studies have examined forest loss across the entire globe using Landsat enhanced thematic mapper imagery without identifying the likely cause of forest loss (Hansen et al. 2010). Collins and Woodcock (1996) concluded that Landsat imagery can identify canopy change, but calculating mortality levels requires field calibration. Change detection can be used to examine how forests change over time by examining the changes in land class from forest to non-forest, or the change in a spectral index. This type of change detection may be especially useful when studying invasive insects which cause defoliation in their host trees.

Emerging hot spot analysis (EHA) is a relatively new and potentially underutilized method used to determine how statistically significant spatial clusters of extreme values change over time by combining two statistical tests. While not a remote sensing specific analysis, data derived from remote sensing imagery are strong candidates for the spatial analysis technique. The EHA combines two statistical methods – the Getis-Ord Gi* hot spot analysis and the Mann-Kendall trend test – to examine how spatial clusters of extreme values (extreme high values = hotspots; extreme low values = cold spots) are changing over time (ESRI 2016). Very few studies have been conducted using this particular method. As a technique, EHA has been used to differentiate between anthropogenic and natural mortality in manatee populations in the Florida everglades (Bass 2017). Other studies have examined socioeconomic phenomena such as crime and traffic accidents to inform policy, for example: where to increase government resources to reduce risks (Bunting et al. 2018; Cheng et al. 2018). Harris et al. (2017) used EHA to examine deforestation in Brazil, Indonesia, and the Democratic Republic of Congo. To accomplish this analysis, the authors used Hansen's (2013) global forest monitoring data and Landsat 8 OLI imagery over 14 years. They examined different spatial scales of deforestation, ranging from the sub-provincial level to the national level, and identified hotspots of forest loss in all three countries (Harris et al. 2017). Emerging hot spot analysis should be able to identify forest changes at a smaller spatial extent when accompanied by a finer spatial resolution, such as that provided by PlanetScope imagery (3m).

Choosing an appropriate spatial scale is important in geographic studies. Some variables may be statistically significant at various scales (both grain – the size of the unit of analysis, and extent – the total geographic study area), while others may not. It is possible that the spatial scaling (3m pixel size; ~1.5km^2 study areas) used in this study may not accurately record the phenomenon, and another sensor could have been more appropriate. There have been reviews conducted on spatial scaling in ecology, as well as remote sensing (Wiens 1989; Marceau and Hay 1999). These reviews advocate for exercising caution when working with spatial data and recommend choosing grain and extent individually for each project. Bian and Walsh (1993) showed that NDVI and topographic variables correlate differently at each scale. They also defined characteristic scale as the value at which a variable is spatially independent above the value, and spatially dependent below the value (Bian and Walsh 1993). Forest variables are heavily influenced by spatial scaling. Wheatley (2010) examined domains of scale (the scale at which a phenomenon is visible, such as forest stand, landscape, region or continent) in Alberta forest plots and found that in general, as observational scale increases, the standard deviation of the values decreases. Spatial scale can impact the outputs of analysis. Some variables may correlate similarly across all observational scales, while others will only correlate at a specific scale. Choosing the most appropriate scale for an ecological study is important as it can influence your results.

2.4 Knowledge Gaps

No peer reviewed studies have been conducted specifically on HWA's recent invasion in Nova Scotia. Some of the potential impacts of this invasion have been studied in the northeast United States (Lovett et al. 2004; Ellison et al. 2005; Ford and Vose 2007). These impacts are likely to be similar in Nova Scotia's Acadian forest due to the large presence of hemlock. In order to fully understand how these impacts may translate to the Nova Scotian invasion, more information is needed on HWA's geographic range and distribution, as well as *T. canadensis*'s range and distribution. A potential method to examine HWA's invasion is through EHA, which has not yet been used to examine invasive insects in forests, and it also has not been used for detecting forest changes using the NDVI spectral index at a fine spatial resolution.

2.5 Conclusion

This literature review has examined the impacts and detection of HWA while placing it in the context of Nova Scotia. The impacts of HWA on forests have been heavily studied in the northeast United States. Methods of detection and the limitations surrounding them were also discussed. Through this literature review, I have identified the need to examine the invasion of HWA in Nova Scotia using remote sensing data. In addition, I have highlighted a new method that will potentially show how the forest has changed in response to the invasion since HWA's arrival.

3. Methods

3.1 Overview

The goal of this study is to determine to what extent emerging hot spot analysis (EHA) is effective at identifying forest loss due to *A. tsugae* in southwest Nova Scotia. This analysis was accomplished by examining Planet's PlanetScope optical multispectral satellite system imagery from 2016 to December 2019. The imagery was processed in the geographic information systems ArcGIS Pro™ and PCI Geomatica™, as well as the programming language R. The multispectral imagery was first processed to calculate the normalized difference vegetation index (NDVI), before being aggregated to a netCDF file structure (Figure 2). This file structure is required by the chosen software platform to apply the emerging hotspot analysis tool. The EHA will allow us to identify and quantify how hotspots of NDVI have changed over time in both Springhaven and Kejimkujik National Park, NS.

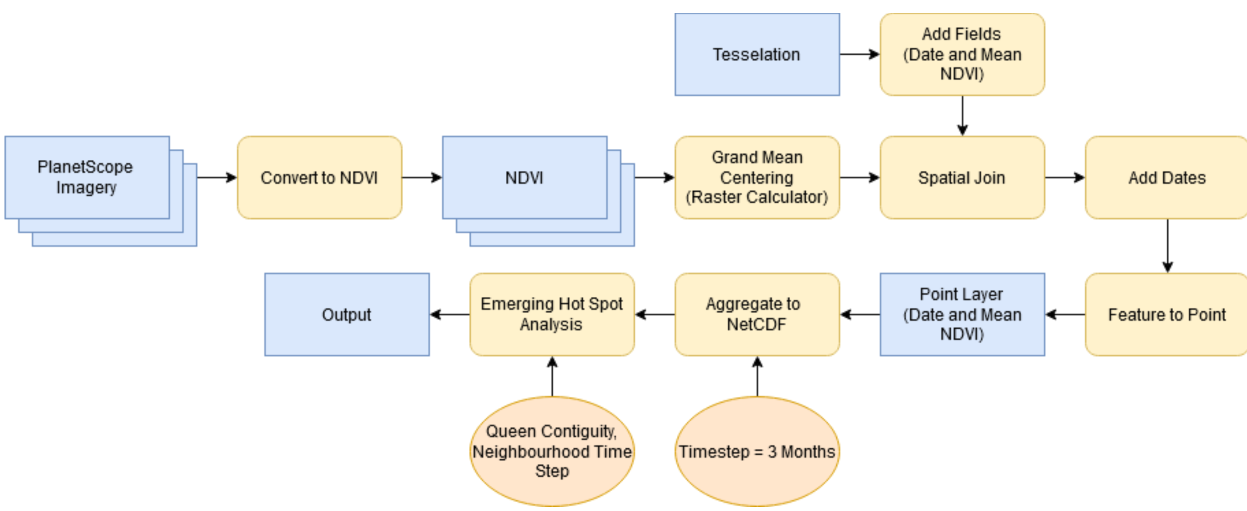

Figure 2 A conceptual workflow for applying the emerging hot spot analysis tool to satellite imagery using NDVI. Blue rectangles represent layers, yellow boxes represent tools, and orange circles represent input parameters.

3.2 Study Areas

For this study, two study areas in southwestern Nova Scotia were examined (Figure 3). The first of which is near Springhaven NS (~1.5km^2), and was chosen as it was one of the three first areas in Nova Scotia with confirmed presence of HWA (Canadian Food Inspection Agency 2017). Additionally, of the first identified locations, Springhaven was visually found to have the most damage in the summer of 2017 (Canadian Food Inspection Agency 2017). The second study area is located near a campground in Kejimkujik National Park, NS (~2km^2). This area was chosen based on unpublished data provided by the Parks Canada Agency of *A. tsugae* sightings within Kejimkujik National Park (Parks Canada Agency 2020). The specific location within the park was chosen as it contained a large amount of HWA confirmed locations in an area similar in size to the Springhaven study area. The data provided did not have accuracy measurements, so it was used as a general location for a study area, however, it could not be used to validate the results. Both locations are part of the Acadian forest region, and have areas previously or currently dominated by *T. canadensis*, as confirmed by Parks Canada Agency unpublished data, and the Canadian Food Inspection Agency (Neville 2018; Parks Canada Agency 2020).

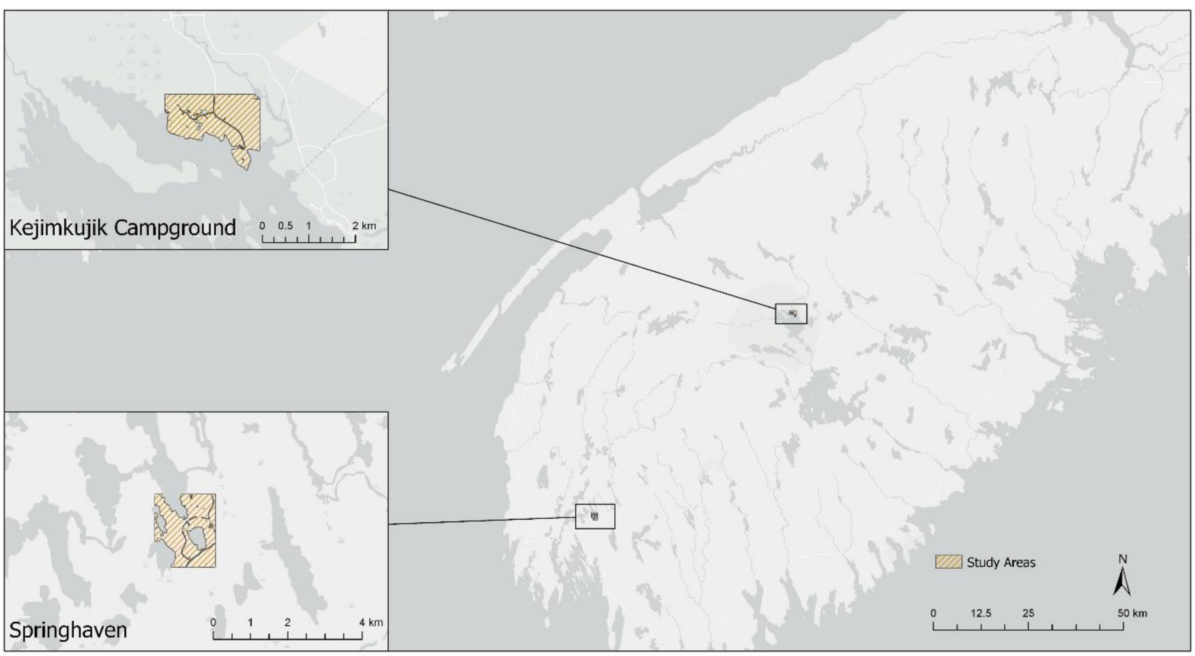

Figure 3 The location of the two study areas (Springhaven and a campground within Kejimkujik National Park) in the province of Nova Scotia, Canada (Spatial reference: NAD 1983 UTM Zone 20N).

3.3 Data

The imagery used in this study was Planet's PlanetScope Analytic Ortho Scenes. These images have four spectral bands or channels (i.e., blue, green, red, and near-infrared), a spatial resolution of 3m, and ideally a near daily temporal resolution. These images are orthorectified (correcting for topographical variations), and geometrically (correcting for the x, y locations of a given pixel), atmospherically, and radiometrically corrected (Planet 2019). The atmospheric correction is completed before the imagery is downloaded by first converting to top of atmosphere reflectance via at-sensor radiance, before being converted to surface reflectance using the 6SV2.1 radiative transfer model as well as data from Moderate Resolution Imaging Spectroradiometer (MODIS) scenes at the same locations (Planet 2019). The images were also corrected for surface reflectance using PCI Geomatica's ATCOR algorithm. If haze was present in the images, it was also masked out during this process. Due to the short time frame for available imagery, images were selected from all months, and as many images as possible were collected that are cloud free in the study area. Cloud free images were selected using Planet's Explorer website's search tools as well as visual inspection of the imagery. Images were collected from various dates between April 2016-December 2019 for the Springhaven Study Area, and between May 2017-November 2019 in the Kejimkujik campground study area (Table 1).

Table 1 The capture dates of images selected for each time step at both study sites.

Time Step	Springhaven	Kejimkujik Campground
July to September, 2016	July 1st, 2016; September 22nd, 2016	N/A
October to December, 2016	November 12th, 2016	N/A
January to March, 2017	No imagery available	N/A
April to June, 2017	May 13th, 2017	May 21st, 2017
July to September, 2017	September 13th, 2017	September 24th, 2017
October to December, 2017	October 19th, 2017	November 25th, 2017
January to March, 2018	February 23rd, 2018	March 2nd, 2018
April to June, 2018	April 22nd, 2018	June 4th, 2018
July to September, 2018	July 8th, 2018; September 14th, 2018	September 30th, 2018
October to December, 2018	October 16th, 2018	October 15th, 2018
January to March, 2019	March 27th, 2019	January 29th, 2019
April to June, 2019	May 25th, 2019; June 23rd, 2019	June 23rd, 2019
July to September, 2019	September 13th, 2019	September 30th, 2019
October to December, 2019	November 16th, 2019; December 16th, 2019	November 26th, 2019

3.4 Data Pre-processing

The NDVI for each image was calculated using Rouse's (1972) equation (1) in an R script (Appendix A-1; Figure 4). The resulting values range between -1 to +1 indicating high amounts of biomass (1) or no biomass (-1), where vegetation generally ranges from .3 to 1. This ratio of difference / sum is effective due to the chloroplasts in the vegetation's chlorophyll reflecting the NIR EMR and absorbing the red EMR.

Equation 1 Calculation for NDVI: from Rouse (1972)

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

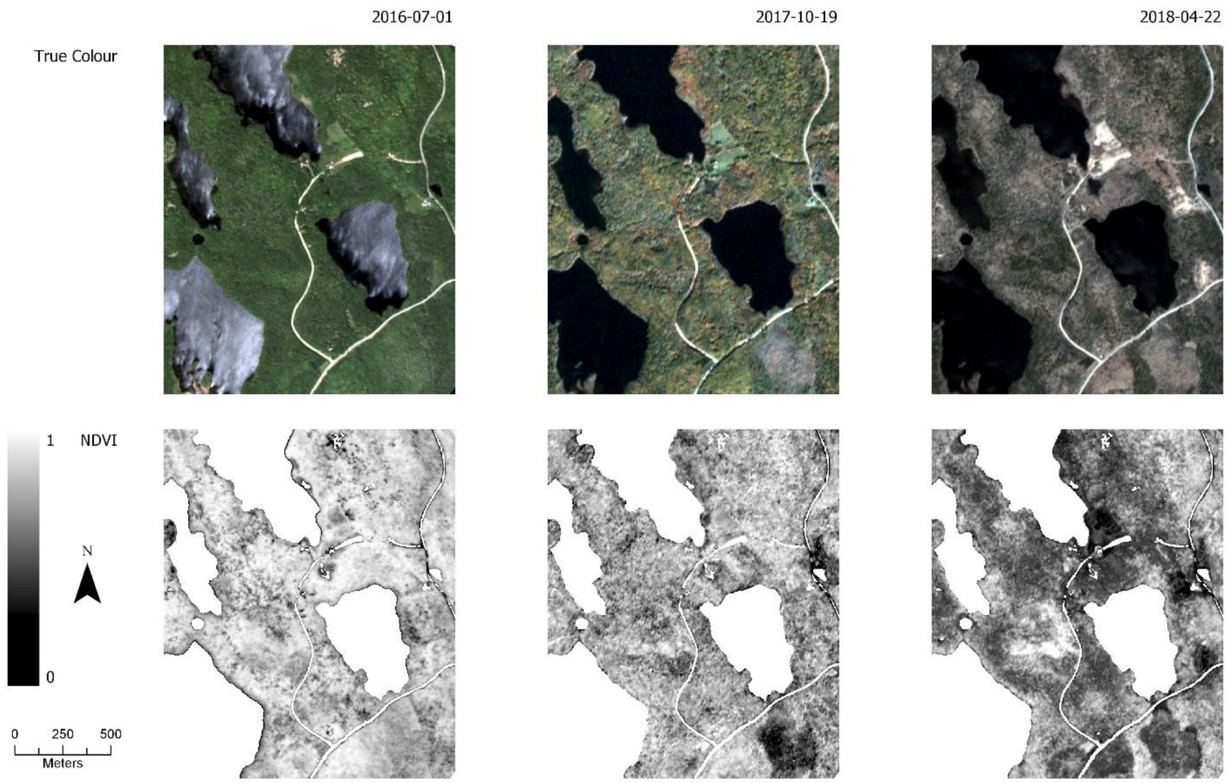

Figure 4 True colour imagery (top), and the NDVI values generated from this imagery (bottom) for three different years and seasons in Springhaven, NS (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

Grand mean centering (subtracting the mean value from each observation) was applied to each image's NDVI values to remove seasonal variation, as winter NDVI values are often much lower than summer NDVI values. This seasonality could possibly generate large amounts of oscillating EHA outputs. The grand mean centred NDVI values were then aggregated to a hexagonal tessellation with a 20m major axis and converted to points in an ArcGIS Pro model (Appendix A-2). This point layer was then separated back out into time steps in order to add an individual date field in R (Appendix A-3). These point layers were then merged back into a single layer to be used as an input for ArcPro's Create Space Time Cube By

Aggregating Points tool. Each point corresponds to a single bin in the space-time cube, which also has a 20m height. This file format also records the date of collection, allowing it to be used as an input in the Emerging Hot Spot Analysis tool (Figure 5).

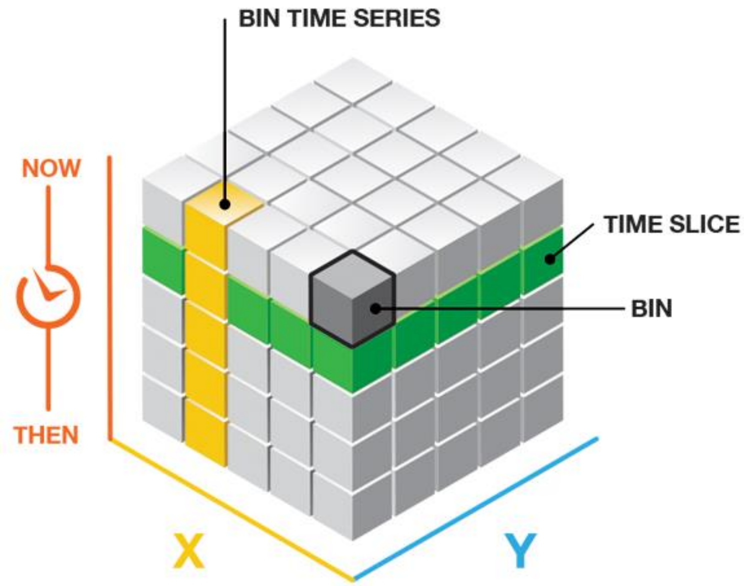

Figure 5 A visualization of the space time cube. Each time slice includes one or more multispectral images. At a given (x, y) location, each time slice in sequential order creates a bin time series (Source: Esri 2019).

Before applying the grand mean centering, a mask (Figure 6) was applied to remove water and roads from the analysis to prevent these features from artificially lowering the time step's mean NDVI. Applying the mask more accurately shows the within-class difference of the forest, allowing EHA to find differences in forest NDVI without considering the water, soil, or roads NDVI. This mask was generated by using PCI Geomatica software to conduct an unsupervised classification of the first summer imagery in the time series as vegetation or non-vegetation. Both study areas had an overall classification accuracy above 90%, using 200 randomly generated accuracy assessment points.

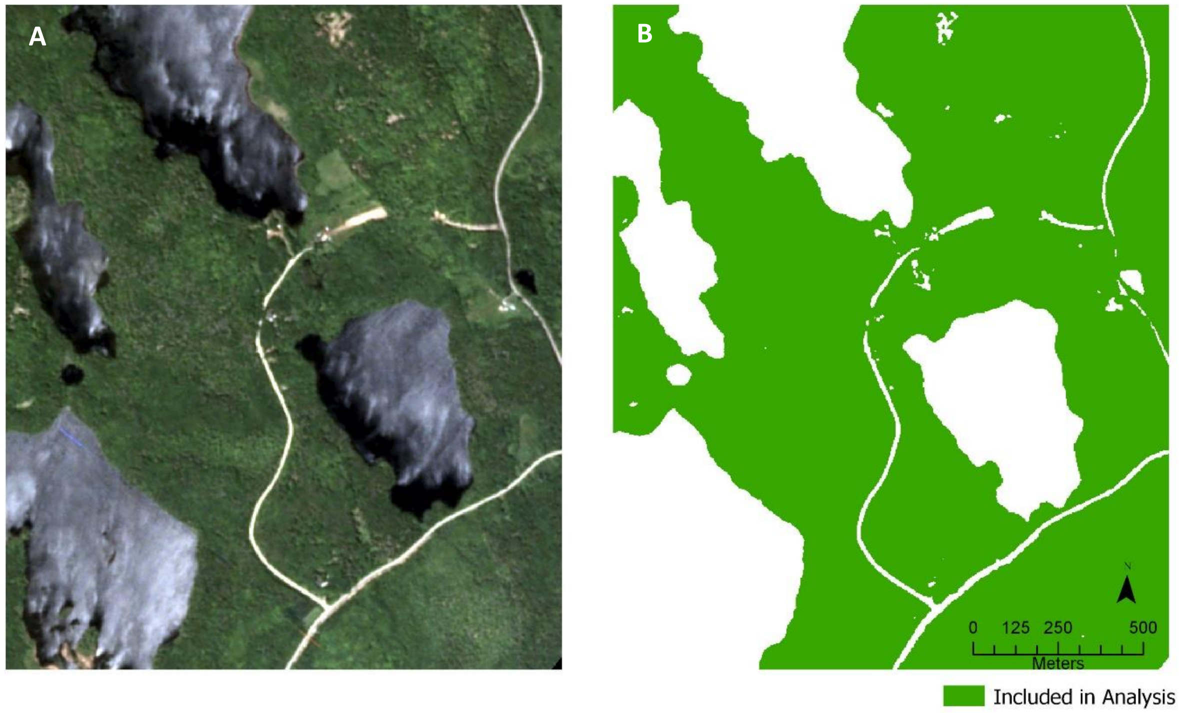

Figure 6 True colour summer imagery (A) used to create the mask (B) for the analysis of the Springhaven, NS Study Site (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

3.5 Data Analysis

The pre-processed netCDF file was analyzed using ArcPro's Emerging Hot Spot Analysis Tool. This tool is a combination of two statistical tests, the Getis-Ord Gi* statistic and the Mann-Kendall statistic (ESRI 2016). These two tests are used to categorize each bin in the netCDF file into hot or cold spot categories. There are seventeen total types of nominal categories, one for no change, and eight for both hot and cold spots. Intensifying cold spots and diminishing hot spots are likely to be areas of evergreen tree loss, ideally corresponding with damage due to HWA. As imagery from the summer season was necessary to meet the minimum requirement for time points, the oscillating categories allowed for the identification of where broadleaf trees are changing with the seasons from no-leaf cover, to full leaf cover, and again to no-leaf cover. The diminishing hot spots and intensifying cold spots identify where NDVI is reducing over the time steps, thus showing us where trees are becoming damaged or dying, and not recovering in the following season.

A detailed description of the emerging hotspot analysis is provided by Harris et al. (2017) and Esri (2016). In brief, the Getis-Ord test used in EHA first examines the data in each aggregated bin and compares it to the global average for the time step, as well as the surrounding bins. If it finds that the bin and its neighbors are statistically different from the global mean, it will classify it as a hot or cold spot with an associated P-value and Z-score. These Z-scores are then be compared over time using the Mann-Kendall test to examine the temporal trends of the data. The Mann-Kendall test extracts each spatial bin into its own time series of z-scores. This time series is examined for changes between years; a higher value than the previous step assigns the time series a value of +1, while a lower value than previous assigns a -1. These are summed over the time series, where there is no variation expected (a sum of zero). The Mann-Kendall test then determines if the sum is significantly different from the expected sum. These significance values from each test are then used to classify each bin into one of the 17 EHA categories. ESRI (2016) provides detailed descriptions of the 17 categories and how they are calculated.

A three-month time step interval was used for the EHA, with a reference time of December 31st, 2019. Queen case contiguity was used to define spatial neighbours, and a neighbourhood time step of one was also applied. The global window (what each bin is compared against to determine statistical significance) used was the neighbourhood time step in order to further examine how NDVI is changing over time within the same spatial neighbours.

Band differencing was performed on two November images in the Springhaven study area to determine the change in NDVI for temporal end points, 2016 and 2019. Band differencing was also performed at the Kejimkujik Campground study site between 2017 and 2019. Grand mean centering was not applied to the images used in the band differencing. The result of this differencing was visually compared to the emerging hot spot analysis results.

3.6 Constraints

3.6.1 Temporal Constraints

Many of the constraints of this study will be derived from temporal issues surrounding the remotely sensed imagery. The EHA requires ten timesteps in order to be statistically valid (ESRI 2016). Due to the nature of the study, the best time of year for imagery would be after autumn defoliation but before snowfall (November-early December). These two factors create a temporal constraint, as the first available imagery in the study areas is from 2016, due to the first Planet satellites being launched in late 2014 (Boshuizen et al. 2014). As such, it was not be possible to achieve leaf off and snow free imagery for each of the ten required timesteps. This constraint was alleviated by utilizing imagery from all seasons, and examining the output maps for oscillating hot and cold spots, which are likely to be broadleaf deciduous trees, not defoliation due to HWA. Another potential limitation is the recent arrival of HWA. While HWA was first detected by the Canadian Food Inspection Agency in 2017, this recent arrival does not necessarily mean that the invasive insect has not been here for a longer period of time. (Canadian Food Inspection Agency 2017). The recent arrival may mean that the trees were damaged at the start of range of available dates of imagery, making it harder to detect NDVI losses.

3.6.2 Methodological Constraints

The aggregation methods used to create the netCDF files from section 3.4 will also impact the outputs of this study. Changing the grain of the aggregated file will impact the averages created for each bin. As the size changes, the amount of hemlock included in a single bin will change, thus changing the averaged NDVI value. The 20m major axis of the hexagonal grain was chosen to allow for a large number of bins in the small extent of the study areas. This grain size also allows for one or more pixels ($3m^2$) of potentially HWA infested hemlock to lower the average of the hexagonal bin, without being drowned out by a large amount of healthy vegetation. Additionally, while the fine pixel size of the PlanetScope satellites may capture a fully damaged hemlock tree, it is possible for healthy canopy to also be included in the pixel, raising the NDVI value of said pixel.

3.6.3 Other Constraints

The final constraint associated with this study is that the model will be unable to differentiate *T. canadensis* canopy loss from the loss of foliage from other coniferous species. While the model should differentiate broadleaf forest loss due to their seasonal defoliation, native coniferous trees in Nova Scotia (except for *Larix laricina*) do not defoliate in the winter. Other coniferous species dying at the same time as the *T. canadensis* will be indistinguishable from of forest loss due to HWA. This is unlikely to be an issue in Springhaven, as there is a large amount of known damaged hemlocks, however, the Kejimkujik campground study area may have dying coniferous trees that are not yet located.

4. Results

4.1 Springhaven

4.1.1 Emerging Hot Spot Analysis

No diminishing hot spots or intensifying cold spots were found. The Springhaven site has various types of both hot and cold spots (Figure 7). The most common cold spots are oscillating cold spots and persistent cold spots, which are often found near one another. Persistent cold spots are often found near the areas which have been masked out, often roads or waterA large patch of persistent cold spots is found in the southeast corner of the study area. The most common hot spots are sporadic hot spots and persistent hot spots, and there are also three patches of intensifying hot spots in the northeast corner of the study area. Generally, the different types of cold spots are found in a contiguous area, and the same pattern is true for the hot spots. No pattern is often detected in between the groups of hot and cold spots. Oscillating cold spots take up the largest number of hexagons and are seen in all quadrants of the map.

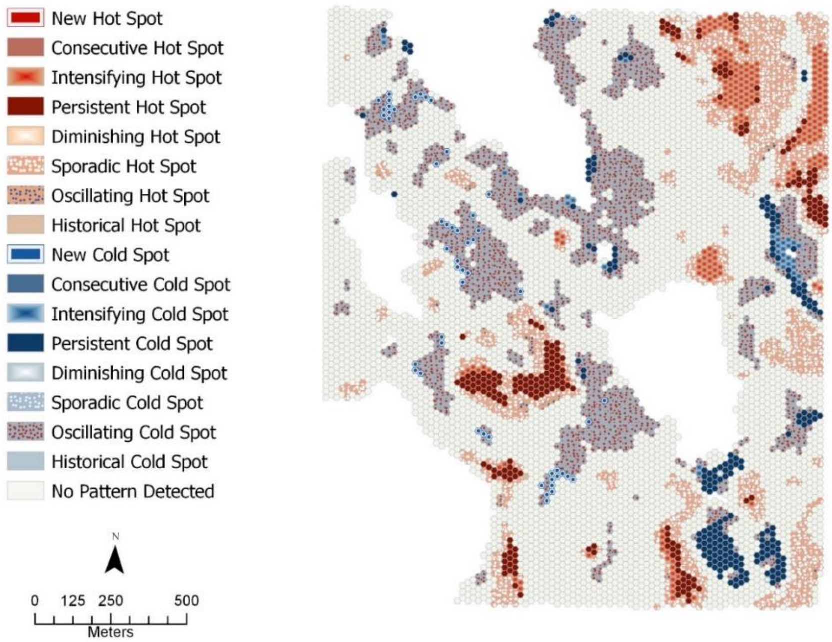

Figure 7 Results from the emerging hot spot analysis tool on the NDVI values from 18 PlanetScope images between July 2016 and December 2019 near Springhaven, Nova Scotia (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

4.1.2 NDVI Differencing

NDVI differencing shows areas of NDVI gain and loss at the Springhaven study site (Figure 8). The northeast, southeast, and centre regions of the map generally show NDVI gains, while the northwest and southwest regions show loss, along with a small patch of NDVI loss in the eastern portion of the map.

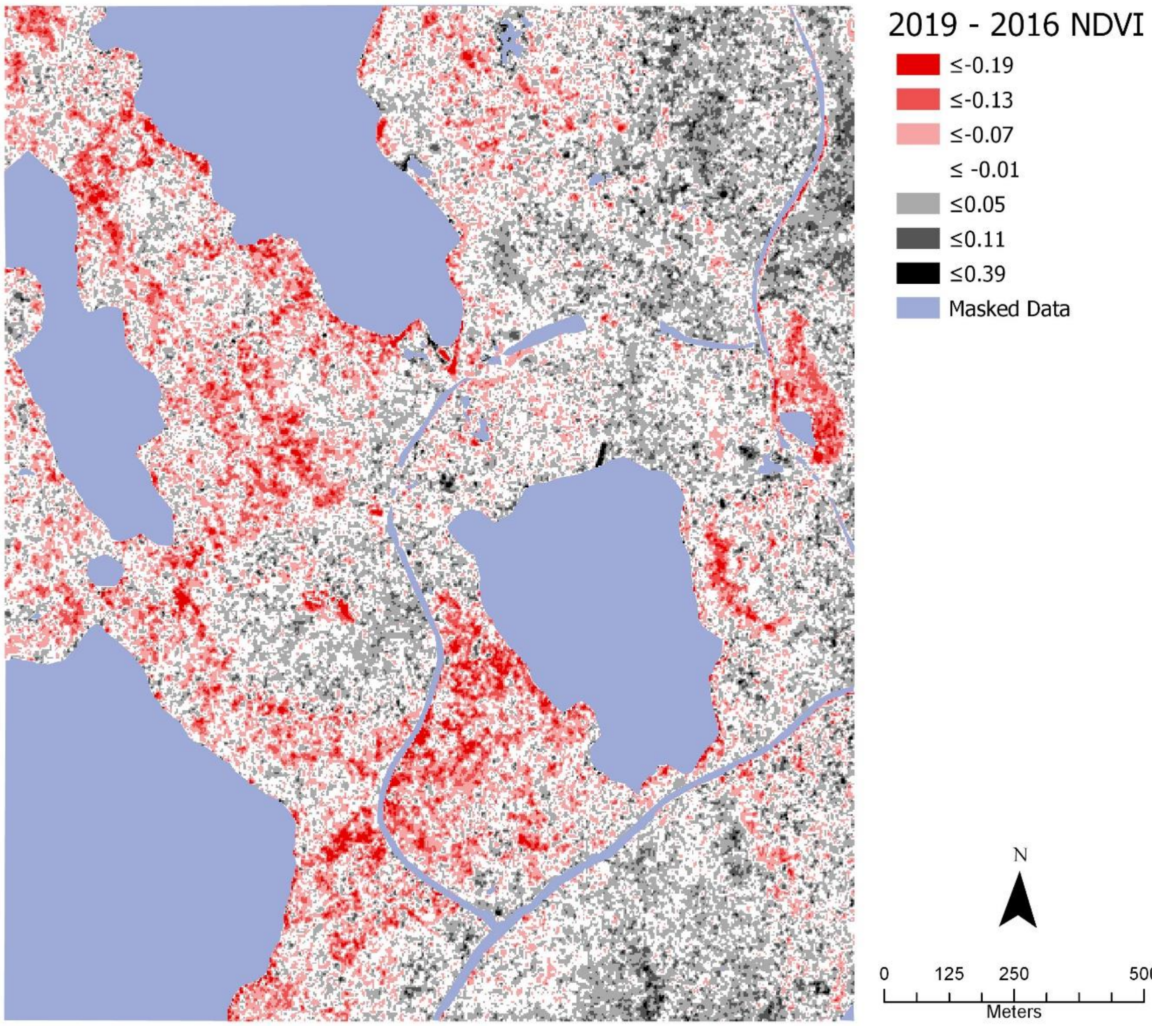

Figure 8 Band differencing results for the Springhaven study area created by subtracting the November 2016 NDVI values from the November 2019 NDVI values. Symbology is based on standard deviations of the raster layer (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

4.2 Kejimkujik Campground

4.2.1 Emerging Hot Spot Analysis

No diminishing hot spots or intensifying cold spots were found. The main hot spot types representing in the Kejimkujik Campground study area are persistent hot spots and sporadic hot spots (Figure 9). These two hot spot types are found in contiguous regions with one another and are found in large clusters in the northern region of the map, with a large amount of persistent hot spots in the northeast corner. Oscillating cold spots and persistent cold spots are found in smaller contiguous regions, and sporadic cold spots are often present near these two types of cold spots.

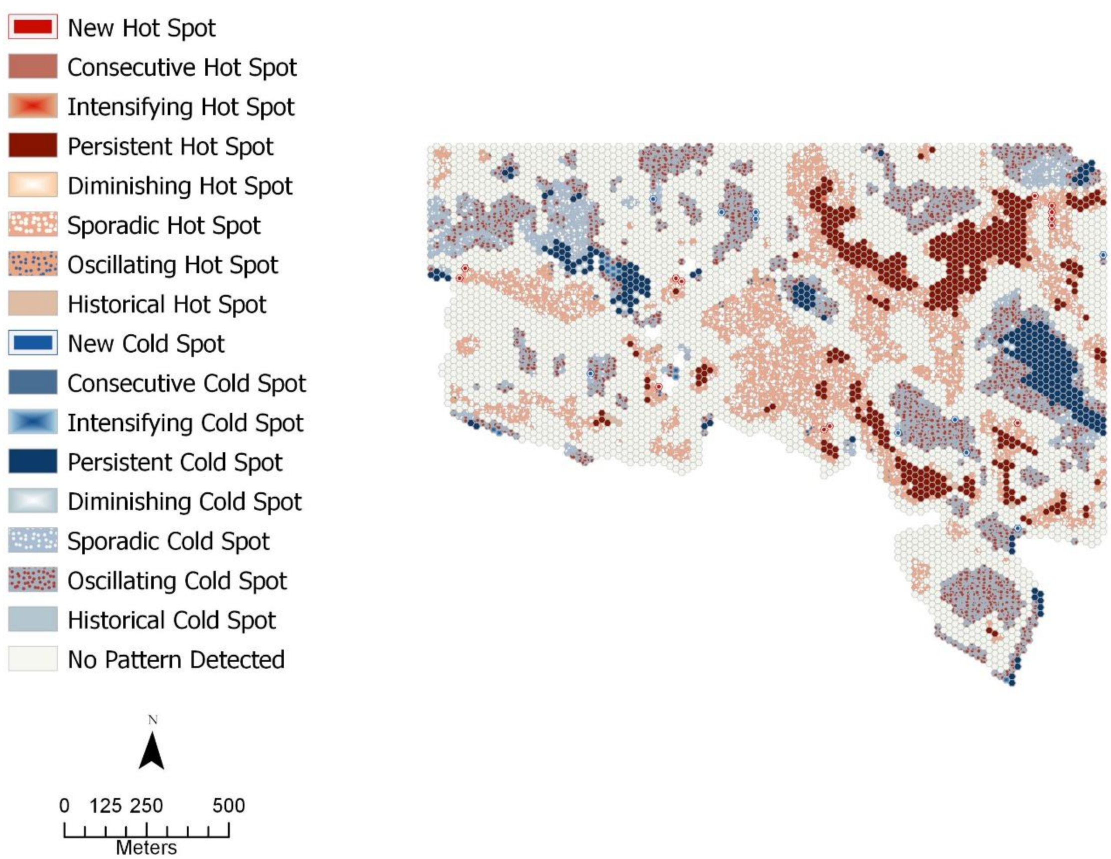

Figure 9 Results from the emerging hot spot analysis tool on the NDVI values from 18 PlanetScope images between July 2016 and December 2019 at the Kejimkujik campground study site (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

4.2.2 NDVI Differencing

The Kejimkujik campground study site shows NDVI gains across nearly the entire study area (Figure 10). The highest NDVI gains are found around masked out regions, except for those directly on the coastline of Kejimkujik lake (southern border of the NDVI difference layer). A few small zones of nearly no change (the darkest red values) are found near high NDVI gains.

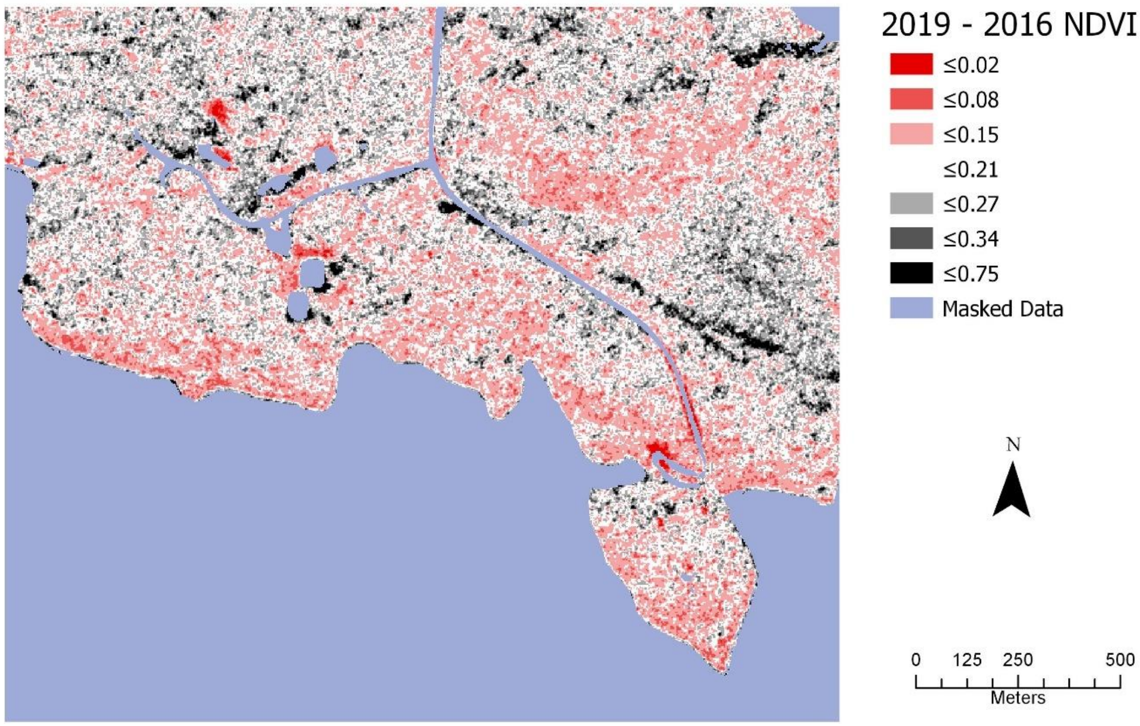

Figure 10 Band differencing results for the Kejimkujik campground study area created by subtracting the November 2016 NDVI values from the November 2019 NDVI values. Symbology is based on standard deviations of the raster layer (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

5. Discussion

The assumption that diminishing hot spots and intensifying cold spots would like be areas of canopy loss was made. Neither of these cold spots were found in either of the study areas (Figures 7 and 9). Many of the areas that show the various types of cold spots correspond with NDVI losses (Springhaven; Figures 7 and 8) or very low amounts of NDVI gain (Kejimkujik Campground; Figures 9 and 10). These corresponding results from each method validate that EHA is properly examining the NDVI values across time. The persistent hot spots identified by the emerging hot spot analysis (EHA) are likely coniferous trees, having a higher NDVI value year-round (approximately 0.5). The oscillating cold spots present in both study areas (Figures 7 and 9) are significantly cold at the final time step, while they were significant hot spots at previous time steps (ESRI 2016). Examining the NDVI values of oscillating cold spots indicates that these are likely deciduous trees, having significantly high summer NDVI values and significantly low winter NDVI values. Visual inspection of summer and winter imagery shows that oscillating colds spots correspond with deciduous forest, and that persistent hot spots correspond with coniferous trees.

While it was not possible to definitively distinguish forest loss due to HWA, the emerging hot spot analysis did provide insight into each study sites forest and forest changes. Seasonal variation is captured by EHA, as oscillating cold spots visually correspond with deciduous forest, and persistent hot spots correspond with coniferous trees. Successional processes can also be found in Springhaven, where persistent cold spots correspond with an area of NDVI gain in the final time step, indicating that while this area had significantly low NDVI values for 90% of the time step, the final time step was not significantly low. Visual inspection of the true colour imagery in this location shows that the persistent cold spots are getting greener in the final time step, potentially indicating that coniferous trees are encroaching on an area previously inhabited by smaller or lower biomass deciduous forest or bushes.

Harris et. al (2017) suggested that EHA is not necessary to be used at finer spatial and temporal scales, as other change detection methods can show forest change results with respect to the change agent (e.g. deforestation, forest pest invasion, forest fires etc.) more accurately. The findings presented in this study agree that EHA did not effectively distinguish the agents of forest change in terms of hemlock canopy loss as a result of HWA, however, the analysis was useful in that it provided more insight into the time series of data than other change detection methods, such as band differencing (Figures 8 and 10). Other methods such as change vector analysis, or principle components analysis were not included in this study, however they are also often used to detect change in remotely sensed images. Of these three other methods, band differencing and change vector analysis only provide information on the change between two time points, and principle component analysis can be difficult to visually interpret, often being used as an input to classification algorithms (Hussain et al. 2013). The advantage of using EHA is that it provides a visually interpretable output that considers more than just the temporal end points.

One major advantage of using EHA as a method is that it makes comparisons over multiple time steps and can be used to examine forest changes at a small geographic extent. Various types of hot and cold spots can be linked to coniferous of deciduous trees and does give insight into how the forest is changing. The analysis does not specifically identify the agent of change, however, ground referencing the area would likely help with linking EHA results to the processes happening at the study sites, and future studies should take this into consideration. One important thing to note when using EHA is the date of the final time step, especially if there is seasonal variance in the data, as determining the hot or cold spot output often relies on the final time step. For instance, if a study's time steps end in winter, oscillating cold spots have a significant cold spot in the final (winter) time step, and are likely deciduous trees. If the same study is conducted with a final time step in the summer with an oscillating cold spot, that implies that the non-summer seasons have statistically high NDVI values, which is more difficult to interpret.

Visual analysis of the first image (July 1st, 2016) and its NDVI values in the Springhaven time series (Figure 4) show low starting NDVI values in regions identified as oscillating cold spots (Figure 7). These low summer NDVI values may be showing forest loss prior to the start of our time series. If this loss is due to HWA, this provides evidence for an earliest arrival date for HWA in Nova Scotia beyond the earliest detection date provided by the CFIA (Canadian Food Inspection Agency 2017). In relation to this, it is possible that these regions of the forest have entered a new successional stage, leading to higher NDVI values than expected if there had only been *T. canadensis* mortality and no new forest growth. This process may be especially prevalent in Nova Scotia, as natural reseeding and regeneration is common in the Acadian forest region (Bataineh et al. 2013). The saplings and seedlings of other species may quickly grow, filling in the gaps in the canopy, leaving only a few time steps with an empty canopy, and low NDVI values.

In the Kejimkujik Campground study site, there are very few areas with NDVI losses at the temporal end points (Figure 10). While Parks Canada has positively identified HWA in this region (2020), it is possible that HWA arrived too recently for the insect to have reduced the NDVI in *T. canadensis* in the area. Further monitoring of this site's NDVI values over time should be considered.

Future research into forest change using vegetation indices and EHA should likely use satellites with a longer available time series, such as Landsat. While the fine spatial resolution of PlanetScope is desirable, the shorter time series availability makes it difficult to find enough imagery to standardize the analysis across a single season, which is especially important in temperate forests such as those found in eastern Canada. Temperate forests require these standardizations if multi-seasonal imagery is used, as the average NDVI will be much higher in the summer, and much lower in the winter. Additionally, with EHA, it may be possible to use a fusion of data sources, combining the decades of available Landsat data with the more recent, finer spatial resolution PlanetScope data, as EHA can take the mean of the cells in each hexagon. This analysis would require a larger extent, as the grain size (hexagons) would also need to increase in order to incorporate multiple NDVI pixels into each. Emerging hot spot analysis using medium spatial resolution imagery such as Landsat is likely to be more functional at the extent of a National Park, Province, forest region, or even country. The changed grain and extent will shift the detection limits for damage to be much larger as well, as individual trees would no longer be able to be identified.

Another factor to consider even with the larger time series of data provided by the Landsat satellites is that it will likely be difficult to differentiate between conifer canopy losses due to NDVI lowering in the same time steps but from different causes. For instance, if HWA and *Choristoneura fumiferana* (spruce budworm) arrive in the same study area at the same time, NDVI will begin to reduce at approximately the same time (however not necessarily at the same rate). Emerging hot spot analysis may be able to delineate between rates of change through some of the nominal categories. If the NDVI of the forest is reduced quickly (and at the start of the time series), it will likely produce a consecutive or persistent cold spot. If the NDVI is reduced quickly at the end of the times series, it will likely be identified as a new cold spot or a diminishing hot spot. Other factors that could impact rate detection using EHA is large amounts of insect mortality in any season, possibly allowing for some of the forest to recover from the invasive species. These factors could cause false positives in identifying invasive insect damage, and due to this, it is important to conduct ground-truthing to ensure which species is causing the mortality.

6. Conclusion

A workflow and model specifications for utilizing emerging hot spot analysis (EHA) on vegetation indices such as the normalized difference vegetation index (NDVI) was utilized to examine the change in forests in areas infested with *A. tsugae* (HWA). While EHA could not explicitly differentiate between forest loss due to HWA, it provided a novel method for gaining insight into forest changes and the forest itself, at a forest stand scale with a high spatial resolution. Emerging hot spot analysis was used at two different study sites known to be infested with HWA in southwest Nova Scotia. The results show that EHA does show similar results to band differencing, with cold spots being present in areas of NDVI loss, and hot spots found in areas of higher NDVI gain. Atmospheric correction and grand mean centering likely allowed EHA to provide more accurate results by reducing the amount of distortion and seasonality in the images which were converted to NDVI values. Visual interpretation of some of EHA's output bins showed that EHA identified seasonal differences despite the grand mean centering, and has potential to identify successional processes. In order to delineate between the agents of forest change, future research should include ground truthing of HWA locations and forest composition. Additionally, the larger time series provided by Landsat's data may provide more accurate results, as the images could be picked at a leaf-off anniversary date, allowing EHA to solely compare coniferous forest loss.

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Appendix A – R Scripts and ArcGIS Models

A-1 Raster to Raster (RMarkdown)

```
---

title: "R_NDVI_Raster_to_Raster"

author: "Evan Muise"

date: "06/02/2020"

output: html_document

---

Available from https://github.com/emuise/R_NDVI



```{r setup, include=FALSE}

knitr::opts_chunk$set(echo = TRUE)

```


Packages used


```{r}

library(raster)

library(rgdal)
```
```

````
library(rgeos)

library(tidyverse)

#library(reticulate)

#library(RColorBrewer)

dir.create("R_Outputs")

dir.create("Clipped_Rasters")

```



## Input Datasets



```{r}

folder <- "Inputs"

filez <- as.list(list.files(folder, full.names = TRUE))

study <- c(readOGR("Study_Areas/Kejimkujik_study.shp"))

```



## Scripts



```{r}
````

```
Calculate_NDVI <- function(NIR_band, Red_band){

  NDVI <- (NIR_band - Red_band) / (NIR_band + Red_band)

  return(NDVI)

}

NDVI_from_filename <- function(filename, study_area){

  sTime <-  Sys.time()

  #getting new filename using the date of the original image

  date <- gsub(".*/", "", filename)

  date <- gsub("_.*", "", date)

  new_filename <- paste("NDVI", date, sep = "_")

  new_filename <- paste(new_filename, ".tif", sep = "")

  new_filename2 <- paste("RGB", date, sep = "_")

  new_filename2 <- paste(new_filename2, ".tif", sep = "")



  #convert from filename to a brick raster as these are apparently faster for calculation

  multi <- filename %>% stack() %>% brick()



  #clip the raster by the input study area

  multi <- crop(multi, study_area)
```

````
  #calculating NDVI
  #apparently using overlay with a premade function is faster, but this is the same as calling the function
  NDVI <- overlay(multi[[4]], multi[[3]], fun = Calculate_NDVI)

  #save into outputs folder
  writeRaster(NDVI, filename = file.path("R_Outputs", new_filename), format = "GTiff", overwrite = TRUE)
  writeRaster(multi, filename = file.path("Clipped_Rasters", new_filename2), format = "GTiff", overwrite = TRUE)

  eTime <-  Sys.time()
  transpired <- eTime - sTime
  print(transpired)

  return(NDVI)
}
```
## Create Files
````
````

````
```{r}

#test <- vector(mode = "list", length = length(filez))

eTime <- Sys.time()

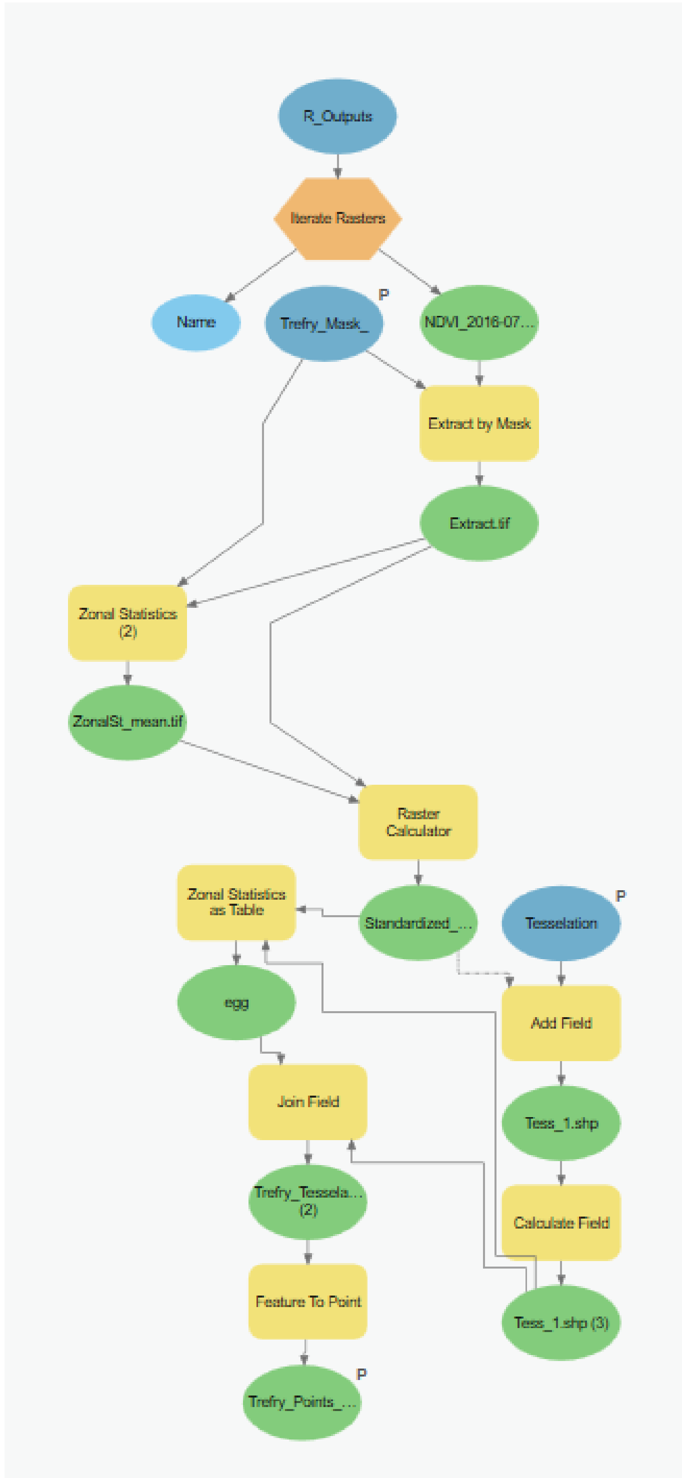
test <- map2(filez, study, NDVI_from_filename)

sTime <- Sys.time()

print(sTime - eTime)

```
````

A-2 R Output to STCube Input (ArcGIS Pro)



Appendix A-2 Screenshot of the model used to generate a points layer in ArcGIS Pro. The output from this model was then used in Appendix A-3.

A-3 Model to Space Time Cube (RMarkdown)

````
---

title: "Model_to_STCube"

author: "Evan Muise"

date: "11/02/2020"

output: html_document

---

Available from https://github.com/emuise/R_NDVI



```{r setup, include=FALSE}

knitr::opts_chunk$set(echo = TRUE)

```



## Packages used



```{r}

library(raster)

library(rgdal)

library(rgeos)
````
````

```
library(tidyverse)

#library(reticulate)

#library(RColorBrewer)

dir.create("R_Outputs2")

```

Data

```{r}

NDVI_points <- readOGR("Out_From_ArcPro/Trefry_Points_NDVI.shp")

```

Functions

```{r}

ToSTCInput <- function(ModelOutput){

  layers <- length(grep("Date", colnames(ModelOutput@data)))

  sTime <- Sys.time()

  for (i in 1:layers) {
```

```
    backup <- ModelOutput

    first <- 2 + 2 * i

    second <- 3 + 2 * i

    backup@data <- backup@data[,c(1:3, first:second)]

    colnames(backup@data)[4] <- "Date"

    colnames(backup@data)[5] <- "Mean_NDVI"

    backup@data[,4] <- as.character(backup@data[,4])

    filename <- gsub("\\..*", "", backup@data[1,4])

    date <- sub(".*_", "", filename)

    backup@data[,4] <- date



    writeOGR(backup, dsn = "R_Outputs2", layer = filename, driver = "ESRI Shapefile", overwrite_layer =
TRUE)

  }

  eTime <-  Sys.time()

  transpired <- eTime - sTime

  return(transpired)

}
```

ToSTCInput(NDVI_points)

```
```

Appendix B – Full Size Figures

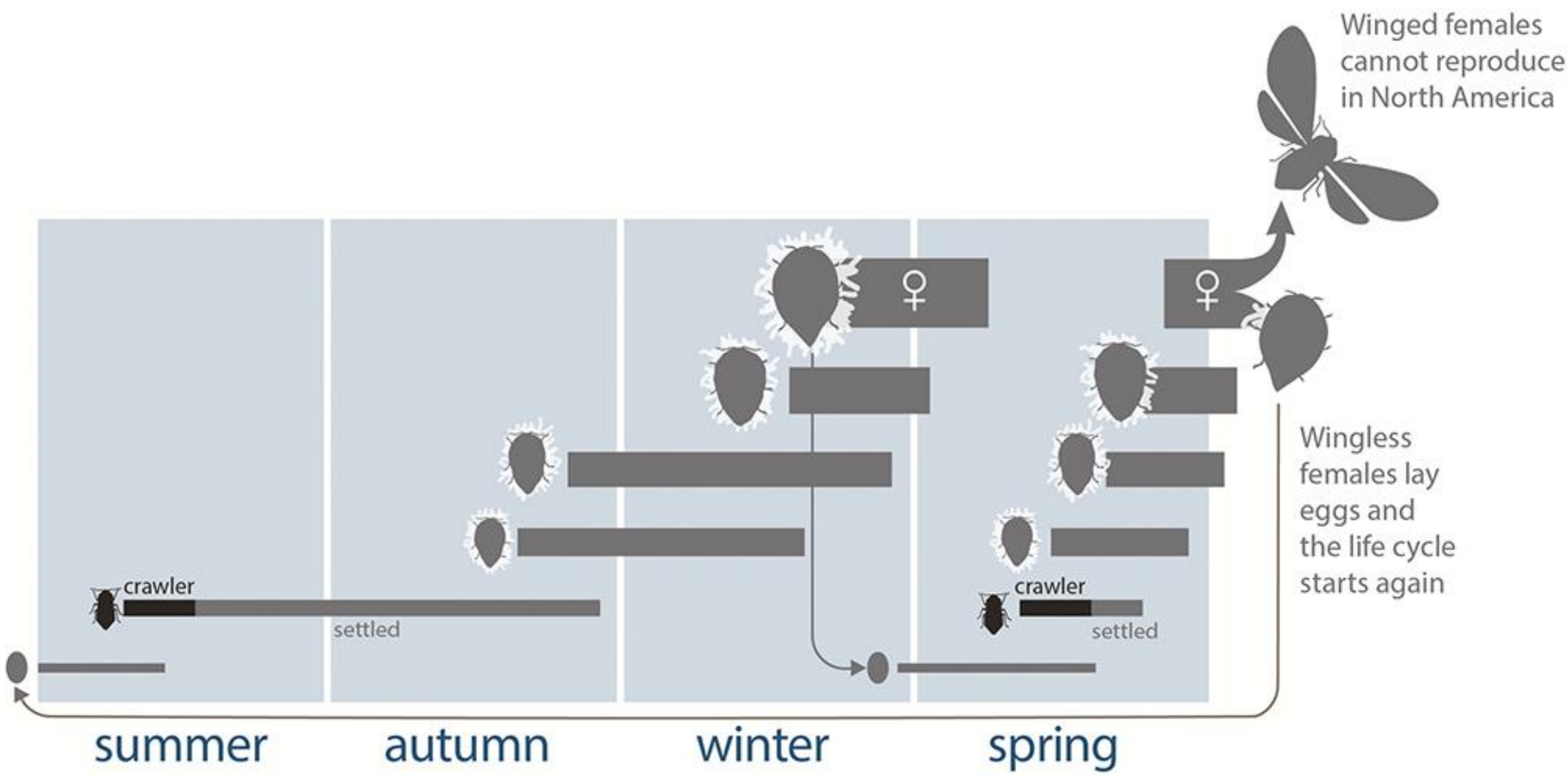


Figure 1 The life cycle of the hemlock woolly adelgid. Adapted from Limbu et al (2018).

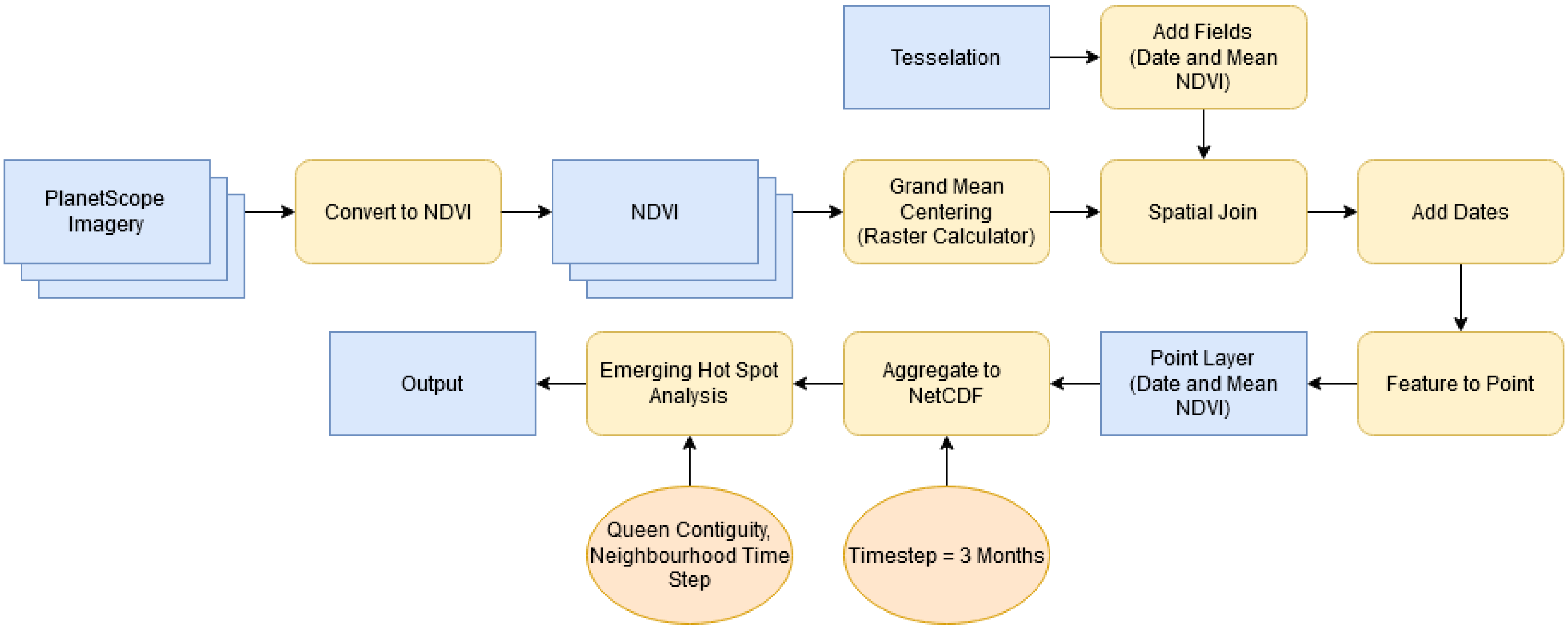


Figure 2 A conceptual workflow for applying the emerging hot spot analysis tool to satellite imagery using NDVI. Blue rectangles represent layers, yellow boxes represent tools, and orange circles represent input parameters.

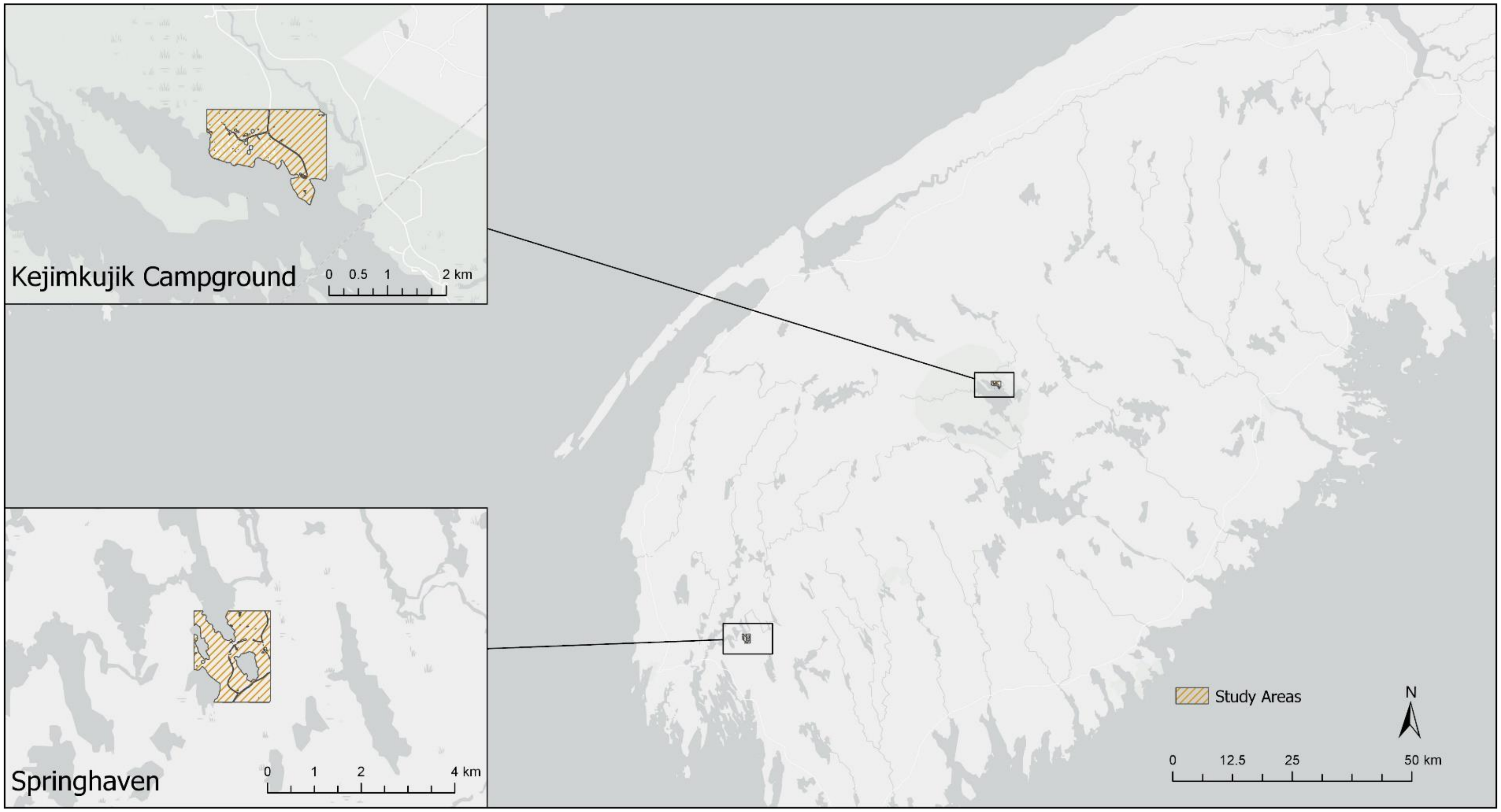


Figure 3 The location of the two study areas (Springhaven and a campground within Kejimkujik National Park) in the province of Nova Scotia, Canada (Spatial reference: NAD 1983 UTM Zone 20N).

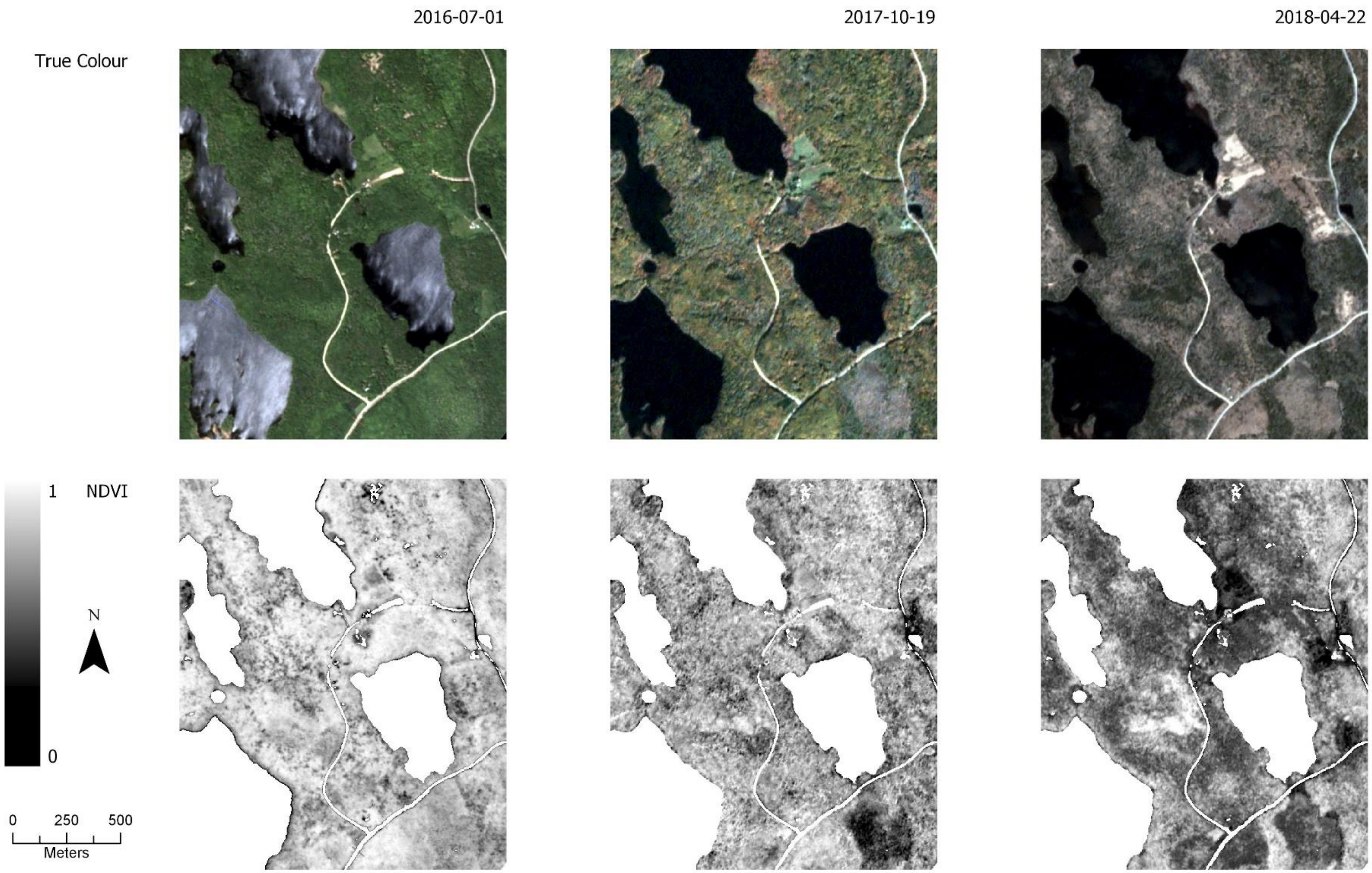


Figure 4 True colour imagery (top), and the NDVI values generated from this imagery (bottom) for three different years and seasons in Springhaven, NS (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

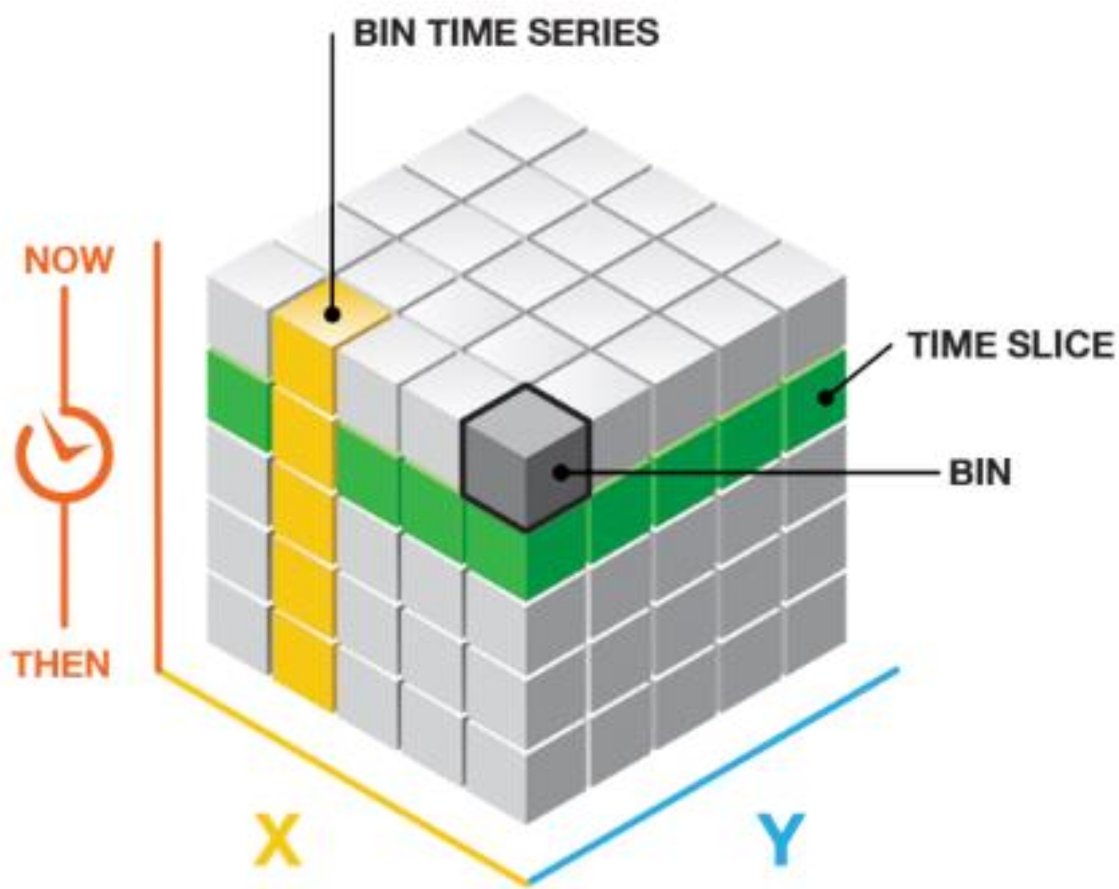


Figure 5 A visualization of the space time cube. Each time slice includes one or more multispectral images. At a given (x, y) location, each time slice in sequential order creates a bin time series (Source: Esri 2019).

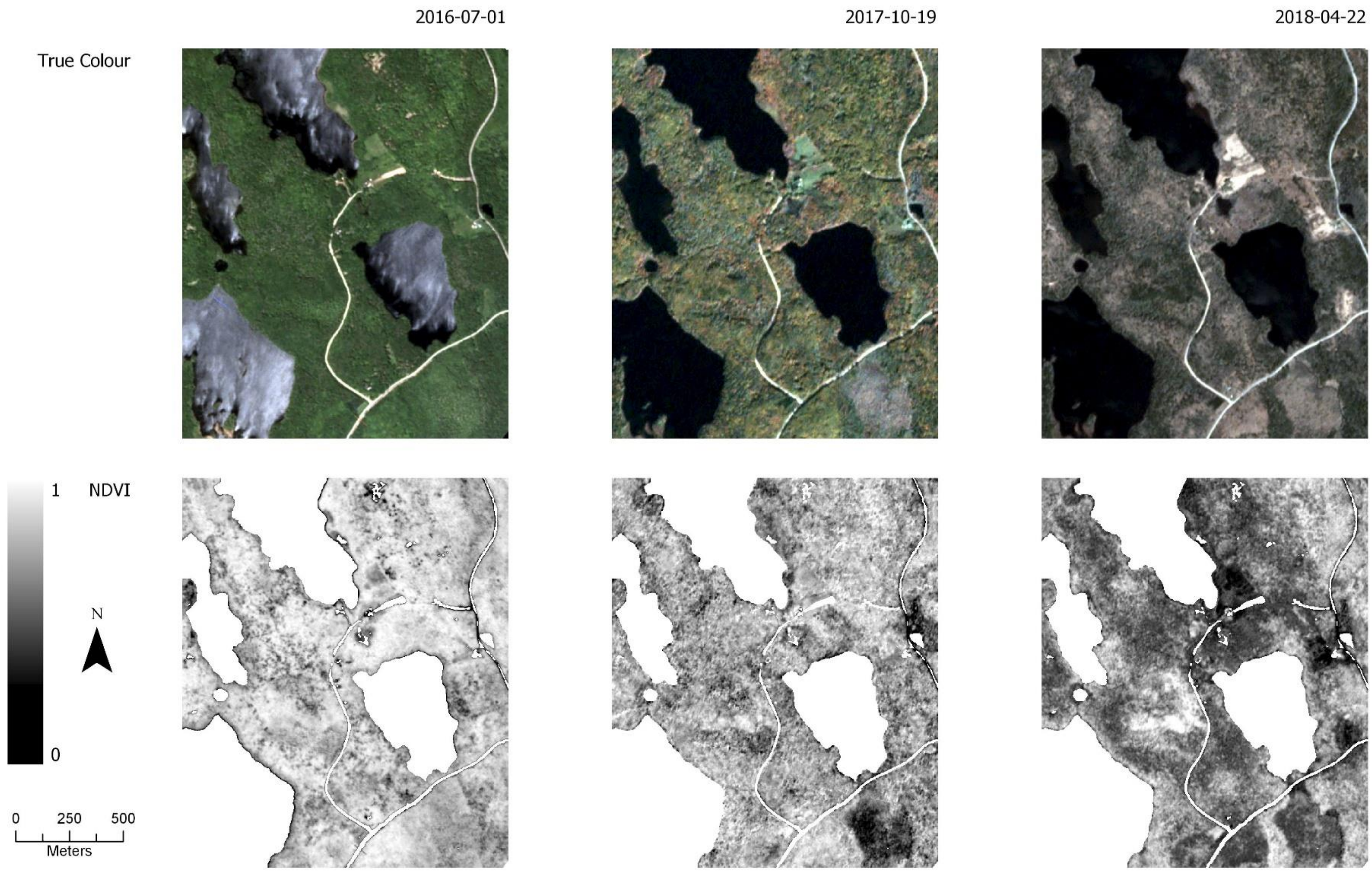


Figure 6 True colour summer imagery (A) used to create the mask (B) for the analysis of the Springhaven, NS Study Site (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

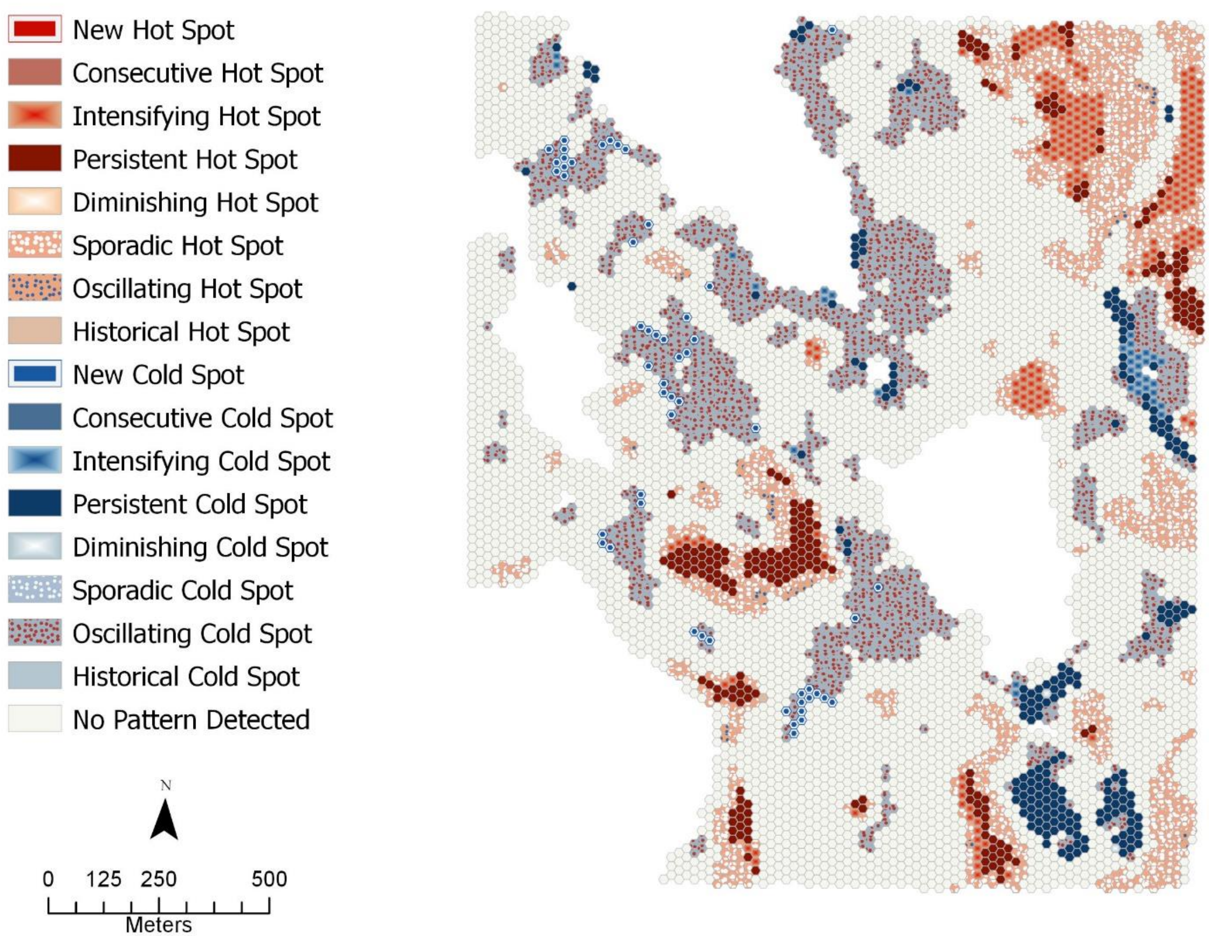


Figure 7 Results from the emerging hot spot analysis tool on the NDVI values from 18 PlanetScope images between July 2016 and December 2019 near Springhaven, Nova Scotia (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

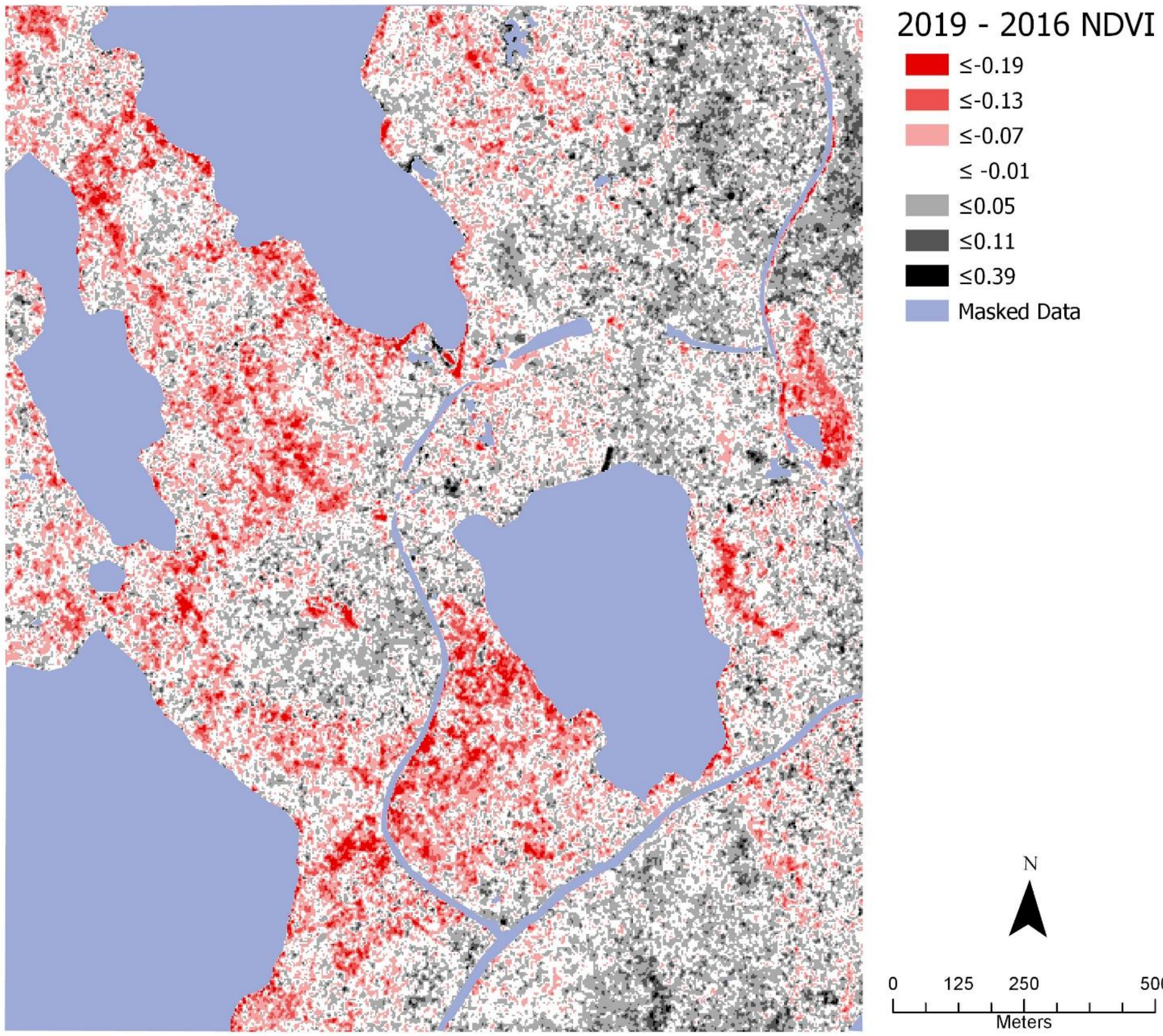


Figure 8 Band differencing results for the Springhaven study area created by subtracting the November 2016 NDVI values from the November 2019 NDVI values. Symbology is based on standard deviations of the raster layer (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

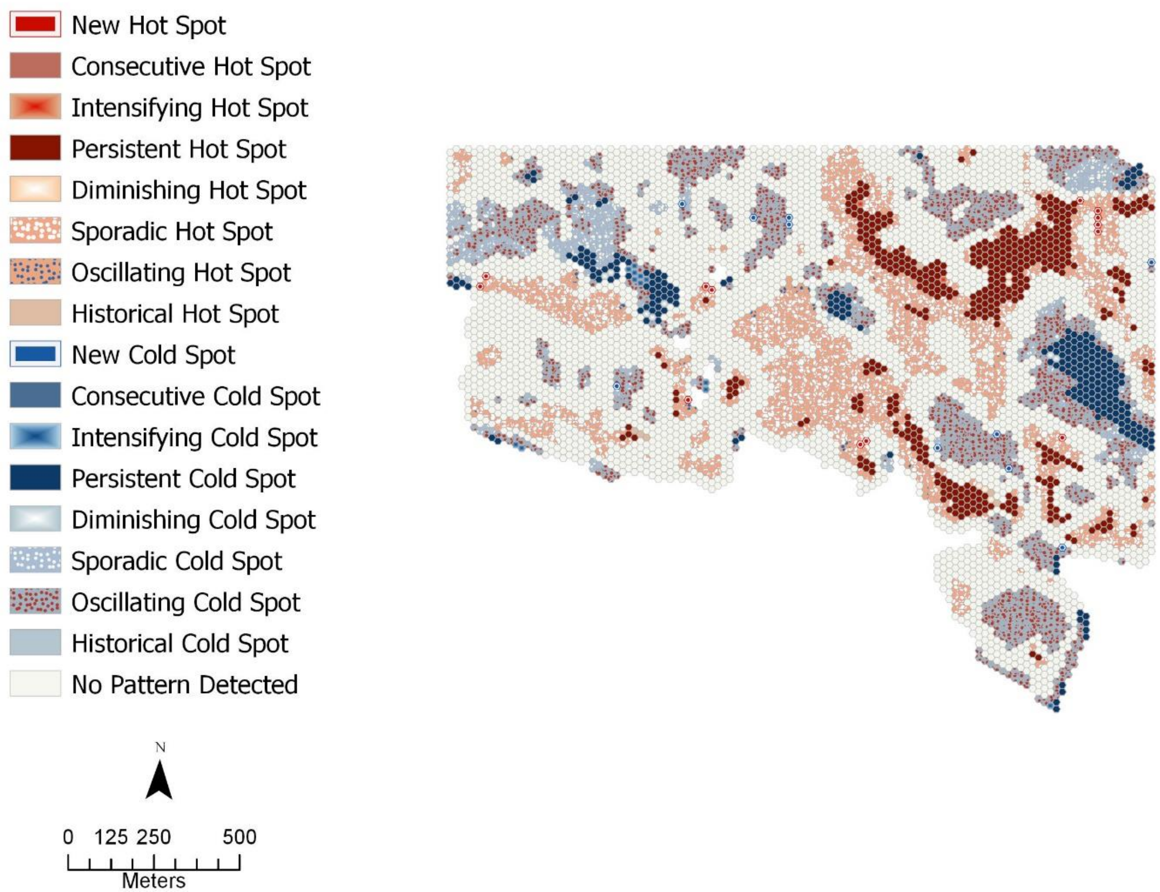


Figure 9 Results from the emerging hot spot analysis tool on the NDVI values from 18 PlanetScope images between July 2016 and December 2019 at the Kejimkujik campground study site (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).

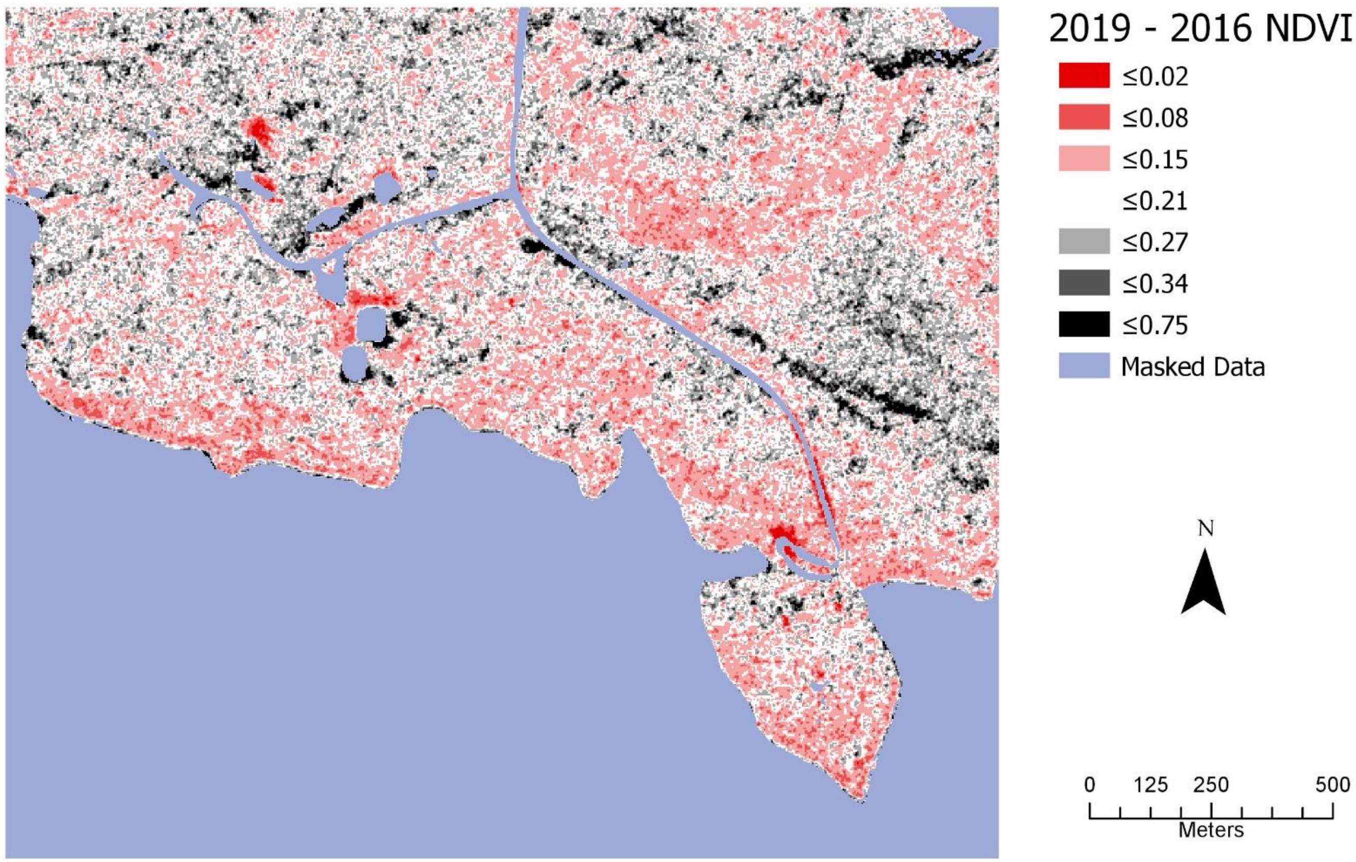


Figure 10 Band differencing results for the Kejimkujik campground study area created by subtracting the November 2016 NDVI values from the November 2019 NDVI values. Symbology is based on standard deviations of the raster layer (Data source: Planet Labs Inc.; Spatial Reference: NAD 1983 UTM Zone 20N).