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Cost-effectiveness of remote sensing technology for spruce budworm monitoring in Maine, USA

Allison Foster,[a,*] Parinaz Rahimzadeh-Bajgiran,[a] Adam Daigneault, [a,b] Aaron Weiskittel. [a,b]

a: School of Forest Resources, University of Maine, Orono, ME, USA.
b: Center for Research on Sustainable Forests, University of Maine, Orono, ME, USA.
[*]Corresponding author: E-mail: aefoster0406@gmail.com

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ABSTRACT

Forest pests are a major disturbance factor in forest ecosystems, which can result in tree mortality and loss of ecosystem services, leading to further negative impacts on the forest economy. Spruce budworm (*Choristoneura fumiferana* (Clem.); SBW) is a native forest pest in the northeastern USA and Canada, including the state of Maine, which defoliates balsam fir (*Abies balsamea (L.) Mill.*) and spruce (*Picea spp.*) trees with cyclical outbreaks every 30-60 years. SBW is typically monitored via ground sampling techniques such as pheromone traps and overwintering second instar larvae (L2) branch sampling. Remote sensing data can also provide information about defoliation patterns across the landscape and forest susceptibility to outbreaks. This study presents a cost-effectiveness analysis comparing remote sensing data, ground sampling techniques, and an integrated monitoring approach, combining remote sensing change detection with field sampling. Over a 10-year project period, Sentinel-2 imagery emerged as the most cost-effective option, ranging from US$33 to US$63/square kilometer (sq km), offering wide spatial coverage and moderate resolution suitable for the identification of defoliation patterns. PlanetScope imagery ranged from US$77 to US$241/sq km, and unmanned aerial vehicle (UAV) imagery had the greatest variation, from US$9,220 to US$58,481/sq km. Labor costs are the most influential in our study, ranging from 30% of total costs for remote sensing approaches to 80% for field sampling. The integrated monitoring approach proposed in this study presents a synergistic strategy for effective and timely SBW monitoring, ranging from US$144 to US$213/sq km. Utilizing this integrated approach leverages both remote sensing and L2 branch surveys to enhance the accuracy and timeliness of monitoring efforts, leading to more effective management strategies for mitigating pest outbreaks for landowners. Our research highlights the importance of adaptive monitoring strategies and integrating remote sensing for forest pest detection.

INTRODUCTION

Forest pests are a global issue, influenced by changes in land cover, climate change, and the distribution of organisms (Ayres and Lombardero 2018). Forest pests can result in widespread mortality of tree species and loss of ecosystem services (Boyd et al. 2013; Simler-Williamson et al. 2019), and forest responses to pest outbreaks are heavily dependent upon forest composition and structure, among other factors (Sánchez-Pinillos et al. 2019). While some pests are introduced into the environment, some are native to the landscape and can have cyclical outbreaks that serve as disturbances that regulate the ecosystem (Canelles et al. 2021). In a changing world, forest pests continue to threaten our forests; therefore, understanding their population dynamics through monitoring for effective pest management is important to ensure forest health and productivity (Fischbein and Corley 2022).

Traditionally, forest pests are monitored via ground sampling or aerial surveys. To monitor landscape-scale pest and pathogen-induced disturbances, federal and state agencies in the United States conduct aerial insect and disease surveys, typically done on a plane with a crew of skilled technicians that observe the disturbances on the land and attribute them to the pest or pathogen of concern (Kosiba et al. 2018). Likewise, ground sampling[1] techniques such as insect traps on the ground are common and are usually employed before any visible sign of damage can be detected. Also, forest pests can inflict damage in different ways, influencing the methods used to detect damage. For example, some pests such as eastern spruce budworm (*Choristoneura fumiferana* (Clem.); SBW) are defoliators and damage foliage by feeding on needles whereas non-herbivore insects such as emerald ash borer (*Agrilus planipennis*), 'bore' into the tree (Coyle et al. 2005) and interrupt water/nutrient movement in the plant which later leads to defoliation (Villari et al. 2015).

Recently, the advancement of remote sensing techniques and precision-based approaches have aided in monitoring forest health. Remote sensing can supplement traditional pest monitoring approaches and be used to inspect and validate events seen on the ground closely (Meng et al. 2018; Ye et al. 2021; Hanavan et al. 2022;). Remote sensing has also been used for forecasting

[1]We use the term "ground sampling" to refer to all pests in general and "field sampling" is the actual monitoring approaches studied in our project.

and predicting pest outbreak patterns (Abd El-Ghany et al. 2020) and has helped forest managers by providing maps of host species susceptible to defoliation (Bhattarai et al. 2021, Bhattarai et al. 2022). In the same way that there is no universal approach for traditional pest monitoring approaches, there is no universal remote sensing approach for pest-induced damage detection.

SBW is a forest insect native to the northeastern USA and Canada, including the state of Maine that causes cyclic severe landscape-scale defoliation to balsam fir (*Abies balsamea (L.) Mill.*) and spruce trees (*Picea spp.*). Spruce-fir forests in this region are ecologically and economically important as they are the main source of raw material for lumber and fiber production and provide a variety of ecosystem services (Wagner et al. 2015). The previous SBW outbreak in the 1970s and 80s is estimated to have affected 55 million hectares of forestland in Canada and Maine and caused the loss of between 72 and 90 million m^3 of spruce and fir (Wagner et al. 2015). A new SBW outbreak has started in the region, and Maine has been experiencing the first signs of outbreak since 2018 (Parisio 2023). Compared to the outbreak in the 1970s-1980s, more sophisticated SBW trapping technology and remote sensing options are available now that can greatly improve the outbreak assessment (Wagner et al. 2015). Previously, SBW defoliation was mapped via aerial surveys, which provided very coarse information and lacked detail, limiting their applications for effective pest management as well as further quantitative data analysis (Rahimzadeh-Bajgiran et al. 2018). In preparation for the current outbreak, the Maine Forest Service (MFS), in collaboration with Maine's forest community, has led monitoring activities that include the coordination of a state-wide pheromone trapping network and the establishment of a SBW lab at the University of Maine to process overwintering branch samples (Foster et al. 2024).

Remote sensing technology using satellite imagery, such as Landsat and Sentinel-2, can provide landscape-level information on SBW defoliation and its patterns with promising accuracies. In general, the accuracies are higher for more advanced defoliation categories with a threshold of about 10%, above which defoliation and its severity can be effectively monitored (Rahimzadeh-Bajgiran et al. 2018; Bhattarai et al. 2020). Despite the capabilities, remote sensing technology has been used less frequently for forest health monitoring compared to other applications in Maine due to a lack of personnel capacity (Foster et al. 2024). While there are many tools that landowners can use to monitor for SBW, there is a clear need to understand how these monitoring approaches can work together to supplement annual products needed for effective SBW suppression. These tools should also be cost-effective so the forest community, including industry, federal, and state agencies, can adopt them.

The value of information (VOI) method helps decision-makers quantify the benefit of acquiring additional information for decision analysis (Zabeo et al. 2019). The VOI for geospatial data (satellite imagery) is the economic value added from more informed decisions based on greater information in the presence of uncertainty (Bernknopf and Shapiro 2015). For example, the Copernicus satellite program provides continuous and objective monitoring, which supports policy implementation and enforcement (Tassa 2019). Using satellite imagery enables decision-makers to cost-effectively respond to natural disturbances, such as wildfires. Specifically, using Landsat imagery to inform post-wildfire responses instead of just helicopter monitoring in Idaho, managers could reduce total costs by more than 75%, and save $35 million over 5 years (Bernknopf et al. 2019).

Forest pest detection and management can be improved through integrated approaches that combine remote sensing data and ground sampling techniques, although these integrated approaches are often more costly than any single intervention. The need and potential advantages for such integrated approaches have been highlighted in recent literature (Pause et al. 2016; Hanavan et al. 2022). For example, Hanavan et al. (2022) evaluated the relative effectiveness of aerial detection surveys, remote sensing, and field work for forest health monitoring, and found that a combination of the three methods provided the most robust results. However, Pause et al. (2016) noted that linking remote sensed data and field data requires considerations of how spatial and temporal information match up, which often poses challenges. Any successful integrated monitoring approach must consider a cost-benefit analysis to ensure additional incurred costs do not overshadow the added benefits.

To consider how remote sensing can supplement traditional pest monitoring techniques, we can quantify its costs and determine its effectiveness compared to other monitoring methods (Mumby et al. 1999; Li et al. 2017). To our knowledge, there is no literature on the cost-effectiveness of remote sensing technology for forest health monitoring compared to ground sampling techniques. In our study, the main goal was to understand the cost-effectiveness of remote sensing technology for SBW monitoring, and the specific objectives were: 1) to quantify the costs of different SBW monitoring methods, including ground and remote sensing approaches, and to understand their effectiveness; 2) to propose an integrated approach for SBW monitoring through cost-effectiveness analyses and the VOI approach; and 3) provide recommendations for future monitoring efforts based on these findings. Our study defines effectiveness as the accuracy of the monitoring approach to detect SBW defoliation across the landscape per square kilometer.

MATERIALS AND METHODS

SBW monitoring using remote sensing data

To conduct a cost-effectiveness analysis of remote sensing technology to understand the tradeoffs of using different forest pest monitoring approaches in Maine, we focused on the following three optical remote sensing platforms: Sentinel-2 satellite imagery, PlanetScope satellite imagery, and the DJI 3 Multispectral Mavic unmanned aerial vehicle (UAV) system. Current research focuses heavily on satellite-based imagery such as Landsat and Sentinel-2 for forest health monitoring, but UAVs and PlanetScope data have an advantage by providing information at finer spatial and temporal resolutions. Table 1 provides information about the remote sensing data we considered for this study based on findings from literature review and expert discussion with partners in Maine's forest community (Hall et al. 2016; Bhattarai et al. 2024). The spatial coverage of the studied remote sensing platforms for the state of Maine is presented in Figure 1.

Remote sensing sensors can provide information to detect the presence or absence of SBW defoliation, whereas ground sampling techniques will inform about the population levels of SBW in the forest and movement patterns. There are two types of SBW defoliation that can be detected by remote sensing data, including current-year (annual) defoliation that needs to be detected in a short window in late June to early July on an annual basis and cumulative defoliation that can generally be detected in August (Rahimzadeh-Bajgiran et al. 2018). In this work, our focus was on current-year (annual) defoliation.

Table 1. Remote sensing data used in the study and descriptive information.

Remote sensing	Imagery access	Data type	Spatial resolution	Temporal resolution	Spectral resolution	Accuracy	Spatial extent
Sentinel-2	Public	Multispectral	10-20 m	5 days	13 bands 400 – 2500 nm	75 – 85%[a]	~10000 sq km
PlanetScope	Commercial	Multispectral	3 m	1 day	5 bands 400 – 800 nm	80 – 85%[b]	~625 sq km
DJI Mavic 3M UAV	Private	Multispectral	< 1 m	As needed	5-7 bands 400 – 800 nm	> 80%[c]	1 sq km

Source [a]Bhattarai et al. 2020; [b]Bhattarai et al. 2024; [c] Fraser et al. 2024.

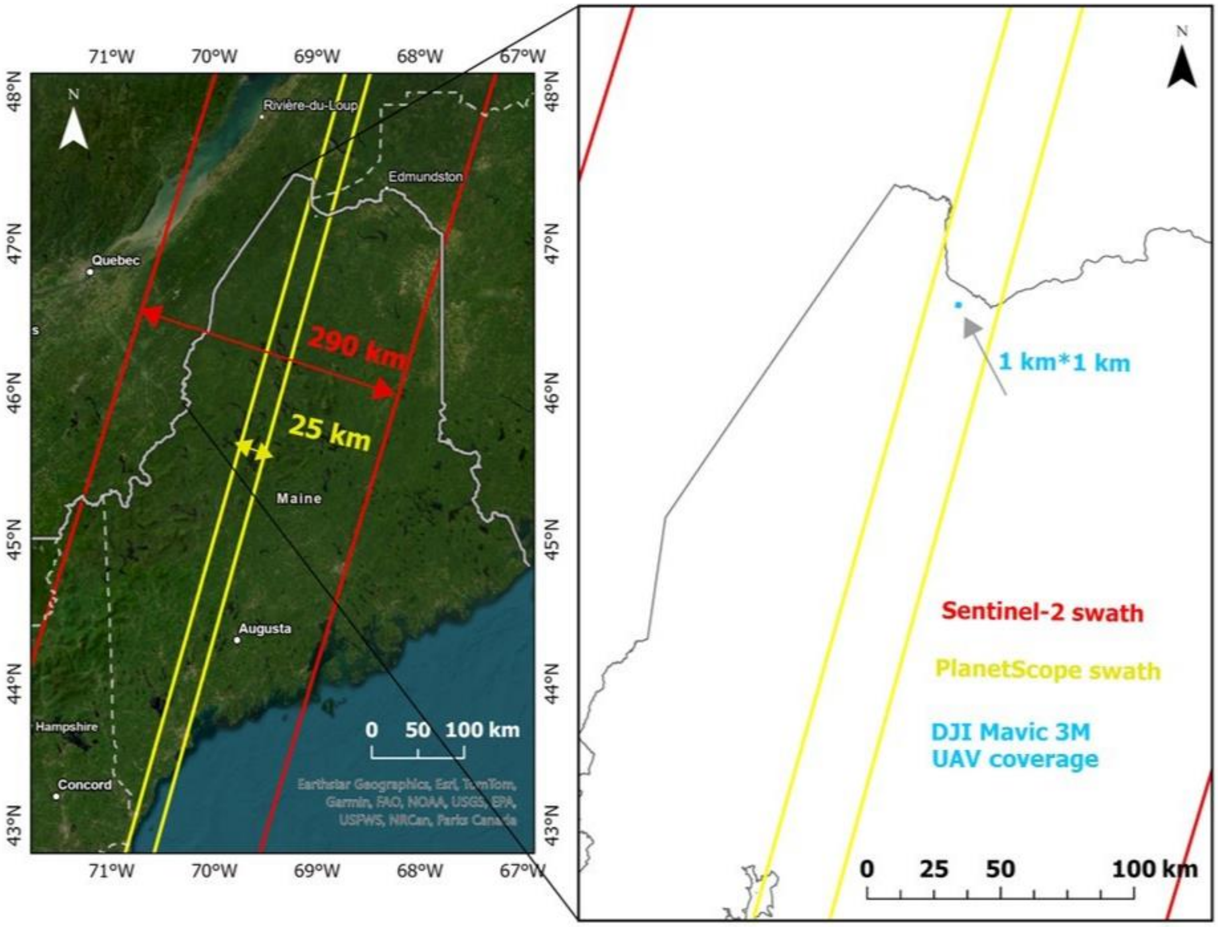

*Figure 1. Spatial coverage comparison of remote sensing data. Left: Sentinel-2 swath width in red (horizontal distance covered by a satellite sensor during image acquisition) compared to PlanetScope swath width in yellow. The downloadable size of Sentinel-2 and PlanetScope images are 100*100 km and 25*35 km, respectively. Right: Closer view comparing the average area (1 km*1km) that can be covered by UAV in one day with those by Sentinel-2 and PlanetScope imagery. Using the UAV system, at a flight altitude of 120 m, spatial resolution of 10 cm and image footprint width of 64 m, ~ 1060 images should be collected to cover a 1 km*1 km area, assuming 60% overlap. Ground sampling covers an area of 8 km*8 km.*

Copernicus Sentinel-2 mission by the European Space Agency (ESA) is currently a constellation of two satellites, Sentinel-2A and Sentinel-2B missions, which have been in orbit since 2016. There are many tools available to help with data processing and applications to process Sentinel-2 data, including Sentinel Application Platform (SNAP), Google Earth Engine and machine learning applications (Ranghetti et al. 2020). Data can be downloaded from Dataspace Copernicus[2] at no cost. Detecting SBW-induced defoliation using Sentinel-2 satellite imagery has been

[2] Refer to https://dataspace.copernicus.eu/

demonstrated before (Bhattarai et al. 2020) with an accuracy above 80% for single-year binary defoliation classification (defoliated vs non-defoliated). Sentinel-2 data have finer temporal (5 days), spatial (10 and 20 m) and spectral resolutions (specifically the presence of three red-edge bands) compared to Landsat, which make them more advantageous for SBW monitoring (Bhattarai et al. 2020).

PlanetScope is operated by Planet Labs Inc., and the imagery comes from a collection of satellites that orbit the Earth. Currently, there are more than 130 satellites that image the Earth's surface on a daily basis, with imagery going back to 2014. PlanetScope imagery is commercially available, which requires users to purchase data that they are using. The imagery starts at $2.25 per sq km for multiple polygons and a minimum order size of 250 square km and can be ordered through API Planet Tile Services.[3] PlanetScope preprocessing requires initial data cleaning and cloud masking, and radiometric correction (Keay et al. 2023). PlanetScope data has finer temporal and spatial resolutions than Sentinel-2 imagery, which is important to consider when monitoring the phenomena of SBW defoliation over the landscape (Bhattarai et al. 2024).

UAVs are increasingly used for forestry purposes because of their versatility, including forest health monitoring, storm damage detection, and tree identification (Michels et al. 2023). Using a UAV for monitoring SBW requires additional consideration than using satellite imagery, primarily because SBW defoliation is a landscape-scale phenomenon, and flying a UAV is complex and can only cover limited extents of forest area in a day. In this project, we considered the DJI Mavic 3M, which is a UAV equipped with a red, blue, and green (RGB) camera as well as near-infrared and red edge bands. We chose this UAV system because of its common use in the region, its effective application for aerial surveying, and its features, such as a sunlight sensor and 20-megapixel image sensor (Fraser et al. 2024). Using a UAV requires additional processing steps, from data collection to image radiometric and geometric corrections (personal communication, Wheatland Geospatial Lab 2024). Similarly, imagery obtained from a UAV is from a significantly smaller area compared to tile sizes of Sentinel-2 and PlanetScope imagery (Figure 1).

SBW monitoring using ground sampling

Two SBW monitoring methods commonly applied in Maine are pheromone trapping and L2 (second instar larvae or the overwintering stage of the SBW) branch surveys. In our study, we use

[3] Refer to https://developers.planet.com/docs/basemaps/tile-services/

the term “ground sampling” to refer to all pests in general and “field sampling” is the actual monitoring approaches studied in our project. Pheromone traps provide information about SBW population dynamics and moth migration movements, and L2 surveys offer a precise measure of L2 population levels (Wagner et al. 2015). We are not considering visual estimates of defoliation through ocular or aerial surveys, as they are less common in Maine and are influenced by weather conditions and observer training and experience (Wagner et al. 2015; Donovan et al. 2024).

For pheromone trapping, the MFS coordinates a network of landowners in northern Maine who participate in data collection. One pheromone trapping site includes three traps arranged in a triangle with traps 130 feet (~40 m) apart. The materials needed for a site to put up a pheromone trap include the trap itself x 3 (Multi-Pher II), which is reusable for up to 10 years, assuming no damage from wildlife. The trap setup also requires the pheromone trap lures and pesticide strips, which are single use every year. These trap sites are deployed during the first three weeks of June and retrieved in mid-August or later (Parisio 2022). After the traps are retrieved, the samples are processed at the MFS Insect and Disease Lab in Augusta, Maine, with information being provided back to the landowner around mid-Autumn each year. Pheromone traps can provide information about early SBW population patterns, which can aid in planning management interventions, but do not provide accurate details about current-year defoliation (Rhainds et al. 2015).

The SBW lab at the University of Maine conducts L2 counts on branch samples. Using the Fettes method, we are able to quantify the defoliation of trees based on the foliage on current-year tree growth with a relative accuracy of 93% (MacLean and Lidstone 1982). While the Fettes method is more time-consuming, it provides a greater advantage to detect current-year defoliation as the branch sample is in hand and yields accurate defoliation estimates on a plot level (Donovan and MacLean 2024). Branch samples need to be taken when SBWs are overwintering from September to March (Figure 2). Three branch samples from each site are clipped and sent off to be processed at the lab. The processing includes dissolving the silk on the branches, separating the SBW larvae from the plant material, and finally, identifying the larvae as SBW, which altogether takes about three hours, and landowners are notified about the result of their sample after processing (personal communication, SBW Lab, 2023).

1

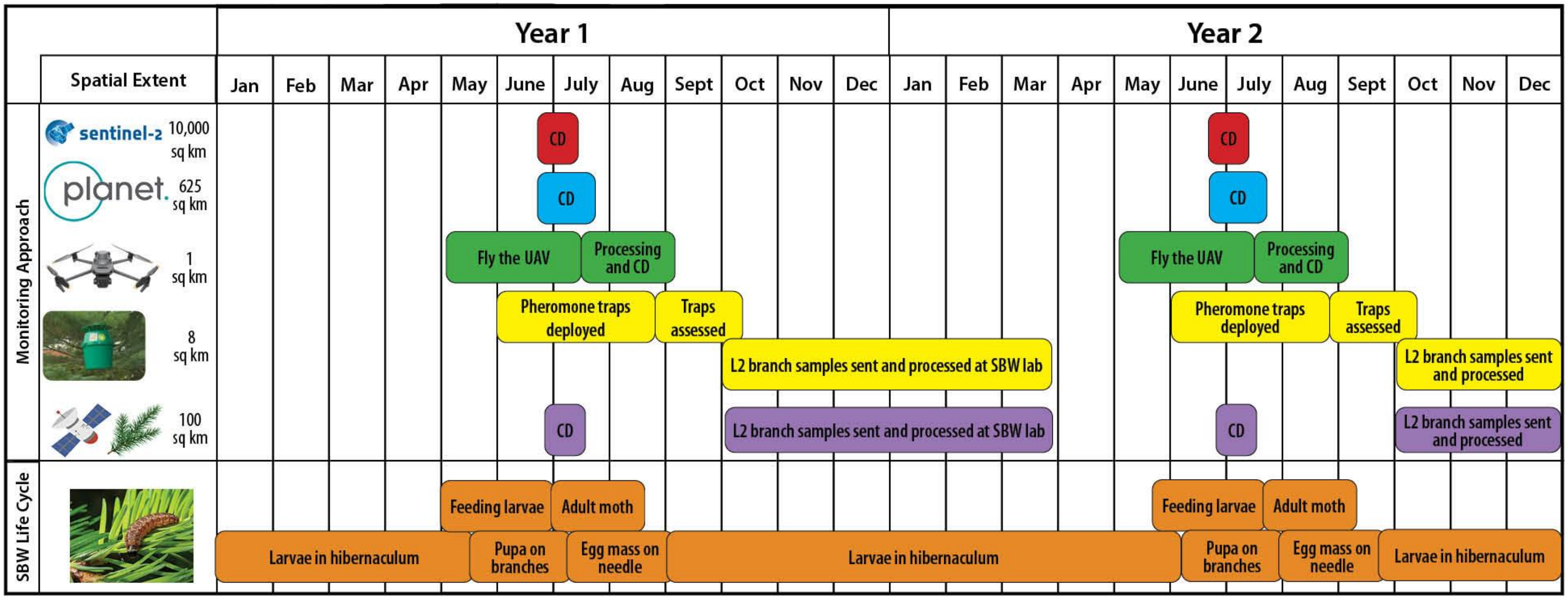

Figure 2. Timeline of SBW monitoring approaches and life cycle over a two-year time period. CD = change detection. Red = Sentinel-2, blue = PlanetScope, green = UAV, yellow = field sampling approach, purple = integrated monitoring approach, orange = SBW life cycle.

Integrated monitoring approach

This study also evaluates an integrated monitoring approach that couples remote sensing change detection and L2 surveys to obtain timely and effective information about SBW defoliation. Using both monitoring techniques can improve the timeliness and accuracy of detection that might not be achievable under any single technique (Pause et al. 2016). Due to the cyclical nature of SBW outbreaks, having a continuous time series of data allows for proactive detection and management activities. Table 2 highlights the advantages and disadvantages of each monitoring approach. Still, it is important to note that data obtained from these approaches can aid in other applications as well, including biomass estimation and land use/land cover mapping (Fassnacht et al. 2023).

Table 2. Advantages and disadvantages of monitoring approaches for spruce budworm.

Monitoring approach	Advantages	Disadvantages
Sentinel-2	Free; Wide spatial coverage; Widely available image processing platforms, Information on location, extent and severity of defoliation	Images may be cloudy; Moderate spatial resolution, No information on SBW population
PlanetScope	High spatial resolution (< 3 m); High temporal resolution, Information on location, extent and severity of defoliation	Cost of imagery; Images may be cloudy; May require more processing steps, No information on SBW population
UAV	On-demand and flexible use; Hot spot detection, Information on location, extent and severity of defoliation	Operational complexity with flying UAV High labor costs; High investment costs, No information on SBW population
Field sampling	Pheromone trapping network; High accuracy; Timely monitoring during the overwintering period, Information on SBW population dynamics and defoliation	Limited coverage area for landscape detection; Increased reliance on landowner partnerships
Integrated approach	Combination of data sources; Effective use of human and capital resources	Higher demand for lab processing capacity; Greater need for coordination between partners

In the integrated monitoring approach, the annual remote sensing change detection is done around late June to early July to provide annual defoliation maps for a single year. The defoliation maps will be used to determine where to concentrate L2 sampling efforts in highly susceptible areas. Pheromone trapping is not necessary when using remote sensing. To supplement monitoring information in the winter, branch samples will be tested for SBW larvae populations, and information is reported back to the landowners (Figure 2). Specifically, the L2 surveys will be used by landowners to validate the hotspot and the extent – expanding outward in each cardinal direction by one sq km increments with the presence of a positive hotspot (L2 greater than seven budworms) during the overwintering period. This continues as an iterative approach, with landowners taking applicable management actions to suppress hotspot populations.[4] Remote sensing and L2 sampling complement each other well because change detection is done during late June and early July, and L2 surveys are analyzed from September to March (Figure 2). In our study, we estimate the effectiveness of the integrated monitoring approach to be 90%, considering the relatively high accuracies of field estimates (Coleman et al. 2018).

Cost-effectiveness analyses

Conducting a cost-effectiveness analysis requires evaluating the efficiency and value of projects by comparing costs with outcomes (Drummond 2016). In our analysis, we quantify the cost-effectiveness as the cost required to achieve a 1% increase in accuracy for monitoring. Cost-effectiveness analyses allow users to judge the most cost-effective options for achieving a particular environmental objective (Balana et al. 2011). Similarly, in environmental management, cost-effectiveness methodology is applied to evaluate the effectiveness of conservation measures or pollution control strategies (Boardman and Vining 2017). Cost-effectiveness analyses help decision-makers make informed choices about how to use resources efficiently (Balana et al. 2011). Importantly, cost-effectiveness analyses can provide vital information to landowners that can impact their management decisions. The values that landowners have, such as generating timber revenue or using land for outdoor recreation, will impact how they choose to manage their land (Zhao et al. 2020).

In this study, we obtained cost and time efforts through expert discussions with remote sensing specialists and forest technicians from the University of Maine’s Rahimzadeh Remote Sensing

[4] Note: in this study we are not evaluating management costs.

Lab, USFS, MFS, University of Maine Wheatland Geospatial Lab, and industry partners from Maine's forest community. Table 3 depicts the cost information associated with each monitoring approach. All costs are estimated from the perspective of the landowner. The aerial extent of each monitoring approach is shown in Figure 2. In our analysis, we are solely focusing on the costs of monitoring for SBW, not on management interventions or assessing the averted costs.

Table 3. Cost information and assumptions for the cost-effectiveness analysis. Y0 is year 0, Y4 is year 4, and Y9 is year 9. Cost assumption in 2023 US$.

Cost Component	**Unit**	**Time accrued**	**Cost assumption**			**Source**
			Low	Medium	High	
Labor costs	Hour	Annual	$24.86	$32.74	$38.30	Bureau of Labor Statistics (2022)
UAV rental	UAV	Annual	-	$995.00	-	Blue Skies Drone Rental (2024)
Capital costs						
DJI Mavic 3M	UAV	Y0	-	$4,618.00	-	E38 Survey Solutions (2024)
Computer and workstation	Computer	Y0, Y4, Y8	-	$2,388.30	-	Mobile workstation (2023); Tower workstation (2023)
UAV insurance	Year	Monthly/ Annual	$44.00 (Monthly)	$466.00 (Annual)	-	Skywatch insurance (2024)
UAV imagery processing software	Year	Monthly/ Annual	$330.00 (Monthly)	$1,650.00 (Annual)	-	Pix4Dfields software (2024)
PlanetScope imagery	Tile	Annual	-	$1,125.00	-	PlanetScope imagery (2024)
Pheromone trap	1 trap	Y0	-	$40.74	-	Multi-Pher II, personal communication with Mike Parisio (2023)
Pheromone trap lures	3 lures	Annual	-	$10.20	-	Trap lures, personal communication with Mike Parisio (2023)
Pesticide strips	3 strips	Annual	-	$4.50	-	Trap strips, personal communication with Mike Parisio (2023)
L2 branch sample supplies	Sample	Annual	-	$30.00	-	SBW Lab Sample Cost (2024)
Net present value calculation						
Discount rate	%	Annual	2%	5%	8%	Daigneault et al., (2021)

To estimate the present value (PV) of costs (in 2023 US$) of each SBW monitoring approach *i*, we follow Equation 1:

$$PV\ Ci = \sum_{t=1}^{T} \sum_{j=1}^{J} \left(\frac{C_{i,j,t}}{(1+r)^t} \right) \quad (1)$$

, where $PV\ C_i$ is the sum of the discounted total costs of monitoring approach i, C_j is the cost of monitoring input *j* (labor, imagery, computer, field materials, etc.), *t* is the year the cost is accrued, and *r* is the discount rate.

By using available tools and algorithms, change detection can be done using Sentinel-2 data with 11 hours of labor per annum – including data pre-processing and running the change detection (personal communication, Rajeev Bhattarai 2024). To conduct change detection using PlanetScope data, additional time is required for pre-processing and, specifically the creation of data indices, which increases the labor time to 23 hours (personal communication, Rajeev Bhattarai 2024). Similarly, for flying a UAV, the fieldwork is 25 hours, including flying the UAV and obtaining ground control points; pre-processing takes 12 hours, including the creation of data indices, and change detection takes 8 hours (personal communication, Wheatland Geospatial Lab 2024).

Field sampling includes the costs of both pheromone trapping and L2 sampling to monitor SBW across a standard area of 8 sq km and includes the costs of both techniques. Labor includes setting up the traps and processing the branch sample, and capital costs comprise of the branch sample and pheromone trap supplies, including the trap, lures and pesticide strips (Table 3). We estimated 8 hours of fieldwork/yr to deploy and retrieve the traps (personal communication, Maine Forest Service 2024), as well as 3 hours/yr to process the branch sample (personal communication, SBW lab, 2024).

The integrated approach includes the costs of both remote sensing and L2 sampling. This includes the labor and capital costs of the satellite imagery change detection, and equivalent costs of branch sampling methods. In our study, we assume 12 branch samples across a 100 sq km area. With each L2 sample > 7 budworm, the sampling is extended outwards in each cardinal direction, and the costs will increase subsequently, but we do not account for increased detection in our study.

We then standardized the costs across detection methods to estimate the cost effectiveness (*CE*) of each intervention *i* on a US$ per sq km basis to aid in comparison between monitoring approaches using Equation 2:

$$CE_i = \frac{PV_i}{A_i} \quad (2)$$

where A is the aerial extent of each approach (see Figure 1). The total and annualized costs of monitoring were calculated over a 10-year project period to capture the dynamics of a SBW outbreak and allow for continuous monitoring efforts. We calculated a cost-effectiveness ratio *(CER)* to compare the cost required to achieve 1% monitoring accuracy for each approach using Equation 3:

$$CER = \frac{CE_i}{\%\,accuracy_i} \quad (3)$$

where % accuracy is determined by the monitoring approach and listed above in Table 1 and the text.

Discounting and sensitivity analysis

When looking at a 10-year project, not all the costs will happen at the same time. In cost-effectiveness analyses, we use a discount rate to calculate the net present value (NPV) of annual costs and benefits. The discount rate can play a significant role in the overall cost-effectiveness, especially since costs typically occur up front, and savings accrue over the long term (Levin and McEwan 2001). The discount rate will portray a specific viewpoint, e.g., a landowner or societal perspective. For a large landowner, a discount rate of 10% may be appropriate, considering the average cost of capital (Vicary 2008). Alternatively, a rate of 5% is more standard across natural resource cost-effectiveness analyses. Alternatively, recent guidance on estimating the NPV of impacts that could occur over a very long timeframe, such as climate change, suggests using a social discount rate, which is closer to 2% (White House 2024). For our study, we used a standard discount rate of 5%, with sensitivity rates of 2% and 8% (Daigneault et al. 2021).

To consider different scenarios, we look at a range of sensitivities regarding the use of UAVs for monitoring SBW defoliation to see the effect of different capital costs, since landowners may find the use of UAVs favorable. Table 4 depicts the different scenarios used and the parameters changed in the analysis. In Scenarios B and C, landowners are renting the drone, which reduces initial capital costs, but in Scenario B it is still flown two separate times to obtain imagery at the beginning and end of the growing season. Scenario C involves renting the UAV once, meaning the change detection in this approach is based on the previous year defoliation, and not the current growing season. In these scenarios, insurance and imagery software costs are reduced to monthly expenditures compared to annual costs (Table 3). Scenario D varies from the baseline by purchasing three dates of PlanetScope imagery at a smaller spatial resolution of 100 sq km. PlanetScope provides data for smaller areas in one polygon at a minimum order of 100 sq km over three dates, which reduces the cost of the imagery and increases the temporal resolution but decreases the spatial resolution (personal communication, Planet Inc. 2024). By comparing these scenarios, we assess the robustness of our analysis and aim to identify missing assumptions in our research (Thabane et al. 2013).

We use estimates from the U.S. Bureau of Labor Statistics for hourly costs for forest technicians in Maine. For each monitoring approach, the labor hours are varied to reflect the amount of time dedicated to that activity, as forestry technicians are trained to conduct forest monitoring using a range of tools, from ground sampling to remote sensing (Sharma et al. 2024). To account for uncertainty in labor and capital costs, we used a capital adjustment factor of 0.5 to 1.5 to analyze changes in capital costs and using the 25% and 75% percentile hourly labor wages for different scenarios (Scenarios E – H).

*Table 4. Sensitivity analysis information and assumptions. Capital adjustment factor is a multiplier factor to increase/decrease the capital cost assumption and baseline = 1.0. (changes to Baseline in **bold**)*

Scenario	Labor (hours per year)			Cost Assumptions						
	Sentinel-2 labor	Planet labor	UAV labor	Labor ($/hour)	Planet imagery ($/imagery)	UAV ($/drone)	UAV imagery software ($/year)	Drone insurance ($/year)	Capital Adj.	Discount rate
A. Baseline	11	23	45	$32.74	$1,125	$4,618	$1,650	$466.00	1	5%
B. Renting a UAV – flying it twice	11	23	**193**	$32.74	$1,125	**$1,990**	**$660** ($/month)	**$88** ($/month)	1	5%
C. Renting a UAV – flying it once	11	23	**99**	$32.74	$1,125	**$995**	**$330** ($/month)	**$44** ($/month)	1	5%
D. PlanetScope data – increased temporal resolution	11	**30**	45	$32.74	**$675**	$4,618	$1,650	$466	1	5%
E. Low labor costs and 25% less capital costs	11	23	45	**$24.86**	$1,125	$4,618	$1,650	$466	**0.75**	5%
F. Low labor costs and 50% less capital costs	11	23	45	**$24.86**	$1,125	$4,618	$1,650	$466	**0.5**	5%
G. High labor costs and 25% higher capital costs	11	23	45	**$38.80**	$1,125	$4,618	$1,650	$466	**1.25**	5%
H. High labor costs and 50% higher capital costs	11	23	45	**$38.80**	$1,125	$4,618	$1,650	$466	**1.5**	5%
I. Low discount rate	11	23	45	$32.74	$1,125	$4,618	$1,650	$466	1	**2%**
J. High discount rate	11	23	45	$32.74	$1,125	$4,618	$1,650	$466	1	**8%**

RESULTS

Cost-effectiveness

Annual monitoring costs are influenced by capital investments and labor costs (Figure 3). The cash flow peaks at years 0, 4, and 9, representing capital investment costs in computers. The most influential costs in our analysis were the labor costs since they accrue on an annual basis. For each of the remote sensing monitoring approaches, labor costs accounted for around 30% of the NPV (Figure 3). Labor costs accounted for 35% of costs in the Sentinel-2 approach, 30% in the PlanetScope approach, and 31% for using the UAV system. This does not mean that there is less labor for a UAV, but that there are greater capital costs that comprise the total cost. Contrarily, labor costs accounted for 89% of the costs for field sampling. The integrated approach falls in between these, with labor costs representing 53% of total costs.

The accuracy of detecting SBW defoliation with remote sensing approaches ranges from 70-85% (Table 1). Using Sentinel-2 imagery is the most cost-effective, with a *CER* of 0.70. PlanetScope has a higher value at 1.31. It is the least cost-effective to use the UAV at least for landscape-level monitoring as the *CER* is 602.06. Ground-based monitoring approaches have a higher accuracy, yet are still less cost-effective, at least compared to Sentinel-2 and PlanetScope change detection. While field sampling has a *CER* of 6.04, the integrated approach has a *CER* of 2.52, offering a more efficient alternative for monitoring SBW defoliation across landscapes.

The change detection accuracy for remote sensing increases with costs, notably with UAV-based monitoring. Even in years without capital investment costs, such as computers, the annual costs per sq km for using a UAV system are $3,590, whereas the annual costs for monitoring using Sentinel-2 and PlanetScope imagery are $2 and $8, respectively (Figure 3).

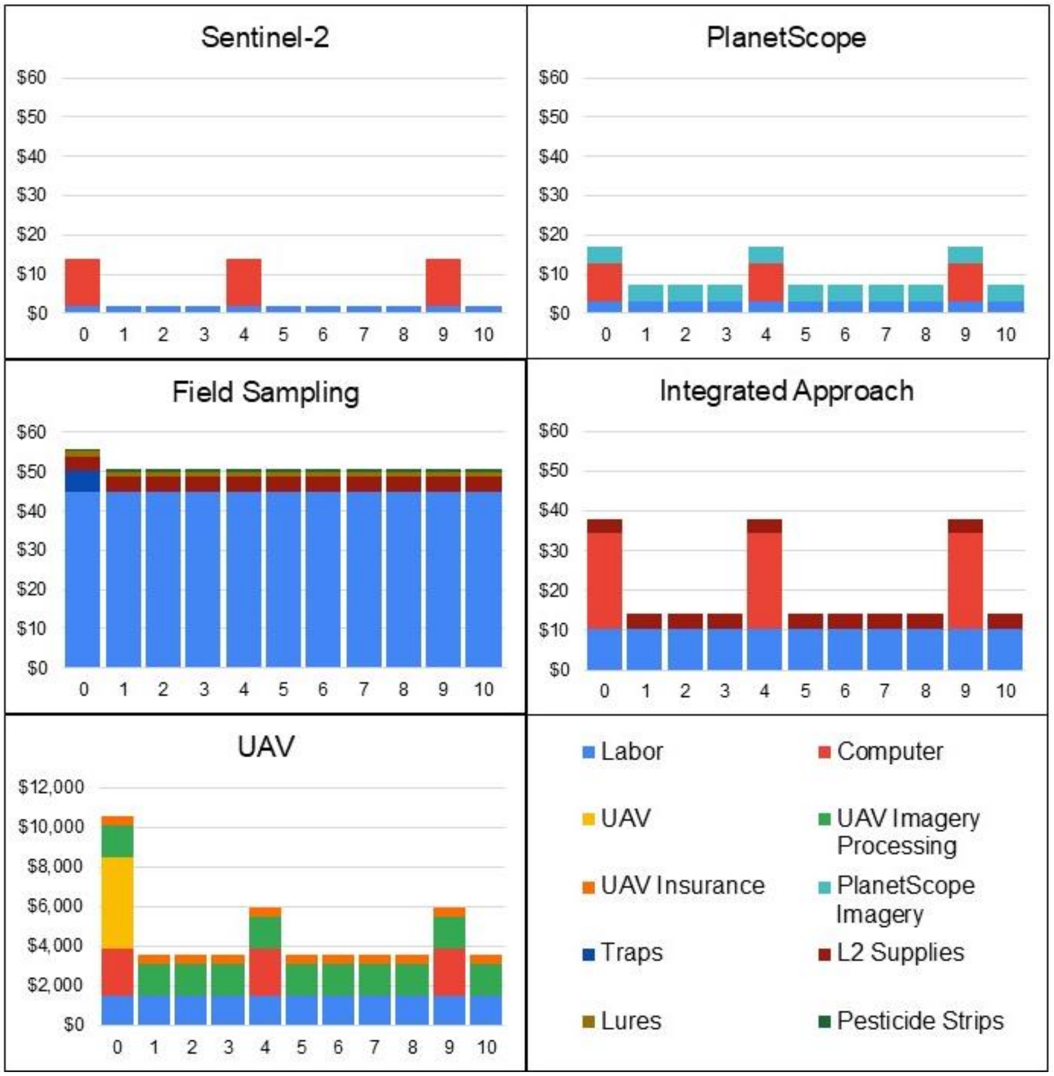

Figure 3. Undiscounted annual cash flow per sq km over a 10-year project period for each monitoring approach by cost item for baseline assumptions (Scenario A). Sentinel-2 – labor and computer; PlanetScope – labor, PlanetScope imagery, and computer; Field sampling – labor, L2 supplies, pheromone traps, pheromone lures, pesticide strips; Integrated approach – labor, computer, L2 supplies, pheromone traps, pheromone lures, pesticide strips; UAV – labor, computer, UAV, UAV insurance, and UAV imagery processing software.

Sensitivity analysis

In our analysis, we found that Sentinel-2 defoliation detection was the least expensive monitoring approach at $45 per sq km, discounted at a rate of 5% over 10 years. Using PlanetScope data resulted in a cost of $89/sq km, and a UAV system was the most expensive remote sensing approach at $41,816/sq km over 10 years. Field sampling was more expensive than monitoring using either Sentinel-2 or PlanetScope data, at $446/sq km. The integrated monitoring approach was $213/sq km. Table 5 provides the discounted cost per sq km for each sensitivity we ran, where the approach based on the UAV system has the greatest variation (from $9,220 to $58,481).

Using Sentinel-2 data does not show much variability based on monitoring approaches; however, the difference in labor costs and capital adjustment do influence the cost per sq km. While the cost of PlanetScope imagery was reduced between scenarios A and D, the cost per sq km is more than 2.5 times the baseline scenario, which comes from the increased labor costs of processing more imagery (Table 5).

Table 5. Discounted cost per sq km for each monitoring approach and sensitivity analysis over a 10-year project period.

Control option	Sentinel-2	PlanetScope	UAV	Field sampling	Integrated approach
A. Baseline	$45	$89	$41,816	$486	$213
B. Renting a UAV system- flying it twice	n/a	n/a	$16,977	n/a	n/a
C. Renting a UAV system - flying it once	n/a	n/a	$9,220	n/a	n/a
D. PlanetScope data – increased temporal resolution	n/a	$241	n/a	n/a	n/a
E. Low labor costs and 25% less capital	$34	$77	$31,481	$368	$175
F. Low labor costs and 50% less capital	$33	$82	$29,515	$506	$168
G. High labor costs and 25% higher capital	$55	$99	$51,239	$576	$242
H. High labor costs and 50% higher capital	$63	$105	$58,481	$599	$250
I. Low discount rate	$51	$101	$47,042	$556	$242
J. High discount rate	$41	$79	$37,630	$429	$190
Sensitivity analysis range ($/km^2)	**$33-63**	**$77-241**	**$9,220-58,481**	**$368-599**	**$144-213**

The costs between renting and purchasing a UAV system vary greatly, as seen in Table 5. Even so, in scenario C, renting a UAV reduces the cost of using a UAV from $41,816 to $9,220 per sq km/year, which is still much greater than any of the non-UAV approaches. Scenarios G and H, with higher labor costs and increased capital adjustment show increases of 40% (Figure 3). The sensitivity analyses do not show significant variation in terms of ranking, indicating the robustness of the analysis.

DISCUSSION

Cost-effectiveness of SBW monitoring approaches

Among five SBW monitoring methods (two field and three remote sensing approaches) evaluated in this study, monitoring using Sentinel-2 imagery was the least expensive approach, followed by monitoring based on PlanetScope imagery. Sentinel-2 imagery has wide spatial coverage, fine temporal resolution and free availability, making it a valuable tool for landowners. Using Sentinel-2 imagery for routine monitoring of SBW defoliation is a practical choice based on the affordability and accessibility of imagery. Bernkopf et al. (2019) also found that remote sensing methods are more cost-effective than field approaches in providing burn severity information for wildfire response. Similarly, it was estimated that using satellite imagery (Landsat) compared to acquiring aerial imagery would save states in the USFS Rocky Mountain Research Station an average of $300,000 per inventory cycle for stratification of forest inventory plots (Peterson et al. 1999). Sentinel-2 imagery was also found to be a cost-effective approach used to detect the presence of invasive species in Chilean temperate forests (Martin-Gallego et al. 2020). The tradeoff between accuracy and cost is evident in the variation in *CER*s. Similar to our findings, Timothy et al. (2016) found that the relationship between predictive sensor accuracy and image acquisition costs increases with finer resolution (2016). Advancements in artificial intelligence (AI) and machine learning will reduce this cost tradeoff, which can increase the accessibility and adoption of remote sensing technologies. Coarser resolution imagery can be beneficial in seeing landscape-scale defoliation patterns, and landowners may opt for this when SBW activity levels are not high.

Scenario D, with PlanetScope imagery from three dates at 100 sq km coverage, was still significantly more expensive per sq km, at $241/sq km, compared to only obtaining imagery from two dates, at $89/sq km. This is influenced by the increased time and labor costs of processing additional data. However, this approach may be preferable to landowners, as it gives them enhanced temporal resolution, which is important during targeted monitoring for SBW during an outbreak. PlanetScope imagery can effectively detect defoliation despite its limited spectral information compared to Sentinel-2 imagery (85% accuracy for SBW defoliation detection in two non-defoliated and defoliated classes) thanks to their finer spatial resolution (Bhattarai et al. 2024). Notably, data fusion is a common technique in remote sensing analysis, which can increase spectral and spatial resolution (Zhang 2010). Gašparović et al. (2018) found that data fusion between Sentinel-2 and PlanetScope imagery results in higher accuracy than using just Sentinel-2 or PlanetScope imagery alone.

We recognize that using UAV systems to monitor SBW defoliation is significantly more costly than other approaches in this analysis due to a number of factors, including capital investment costs, operational complexity, and labor costs that come with flying a UAV. Using UAVs can also pose the danger of aircraft collisions and nuisance (Tarr et al. 2021). It is important to note that even though UAVs have a costly initial investment expense, they can be used for many applications (Duarte et al. 2022; Fraser et al. 2024). UAVs can be effective in obtaining information about hotspots and small areas, especially if landowners already use them for other purposes. If the landowner already owns a UAV, it can be deployed multiple times to detect defoliation as needed, which will increase the temporal resolution, but also requires labor time. When using a UAV system, there are many different models both for the platform and the sensor, each with their advantages and disadvantages. Since SBW is a landscape-scale pest, using a UAV system will require a lot more labor time by technicians to cover the land area. However, UAVs are still useful for monitoring SBW outbreaks, especially as they can provide aerial views of top-kill from trees at higher spatial resolutions (Duarte et al. 2022) and make sure defoliation is not missed due to cloud contamination.

Integrated monitoring approach

The integrated monitoring approach combines remote sensing change detection annually with branch sampling, providing a more comprehensive picture of SBW across the landscape. We propose using Sentinel-2 imagery because it is the most cost-effective of the remote sensing options we evaluated. It provides the landowner with change detection on a moderate resolution (10–20 m) and can be done annually, year–by–year, or it can provide information over a snapshot of years. This approach allows landowners to optimize field sampling efforts by utilizing defoliation maps or susceptibility maps (Bhattarai et al. 2022), ensuring field sampling efforts are efficiently allocated to areas susceptible to outbreaks, rather than deploying traps in areas with no pests. Using remotely sensed imagery to focus field sampling efforts on areas with high populations will also make it more efficient to process the lab samples. Having a timely turnaround of this information (L2 numbers and pheromone trap density) enables treatment planning for the upcoming season (Johns et al. 2019). The combination of low-cost and widespread availability of Sentinel-2 data and the field sampling's effectiveness makes this a cost-effective approach for landowners. Note that when Sentinel-2 imagery is not available due to cloud contamination, other more costly imagery may be needed to produce a seamless map of the target area, contributing to increased total costs.

The integrated monitoring approach reduces monitoring costs by 52% per sq km compared to field sampling techniques alone. Targeted sampling reduces monitoring costs over time and increases sampling efficiency (Strunk et al. 2019). Forest managers can use any remotely sensed imagery with proven performance for SBW monitoring to detect damage and enhance spatial and temporal resolution (Abd El-Ghany et al. 2020). Importantly, the remotely-sensed data used for change detection can also be used for alternative forestry applications, such as estimating forest inventories (Fassnacht et al. 2023). As others have already realized, monitoring SBW is a multi-faceted approach, and it is best to use information from all approaches to inform management actions (MacLean et al. 2019; Parisio 2023). When considering adopting this approach in Maine's forest industry, many of the ground sampling techniques are already widely used by managers and supported by the MFS (Parisio 2023), facilitating the adoption of the suggested method.

As a novel approach proposed in this work, the authors could not find similar integrated approaches in the literature, so a direct comparison with other potentially cost-effective integrated methods could not be made; however, other studies have recommended integrated approaches for forest health monitoring. For example, an integrated approach using field sampling, Sentinel-2 satellite imagery, and UAV data to assess pine invasion in burned forests was found to be crucial for early detection of the invasion (Leal-Medina et al. 2024). Other findings underscore the importance of using satellite imagery in conjunction with field sampling to keep up to date with forest damage detection and mortality (Junttila et al. 2024). Notably, the USDA Forest Service Forest Inventory and Analysis program has integrated remote sensing into their workflow to detect invasive species, highlighting the benefits of using freely available data for forest managers (Parker et al. 2021).

Limitations and future outlook

In our analysis, we included costs that are incurred by landowners, but we recognize that other costs are not accounted for in this analysis, such as the launch of the Sentinel-2 satellite and maintenance, estimated at around $212 million (ESA 2008). Additionally, the effectiveness of monitoring approaches is likely to vary with SBW population levels in the ecosystem, necessitating a focus on monitoring efforts in more susceptible areas, thus increasing costs. This analysis is solely focused on the cost-effectiveness of monitoring SBW defoliation, not managing once detected. Future research to understand the tradeoffs of different management interventions can aid in decision-making for landowners.

Despite limitations, our results highlight the added benefits of remote sensing for forest health monitoring, supporting suggestions that remote sensing data can be useful in mapping forest insect damages (Abd El-Ghany et al. 2020; Hanavan et al. 2022). However, using remote sensing can still have challenges with cloud cover and detecting defoliation within dense forest canopies. In our study, we looked at scenarios flying a UAV only once or twice, while in actuality, landowners could survey additional land area, it just comes at an increased cost of UAV deployment and labor. However, advancements in artificial intelligence (AI) with automated flight paths and UAV technology could reduce these costs. AI offers advantages in processing time for analysis, fusion of data sources, and training computer models (Kanga 2023). Likewise, algorithms already exist for image processing and analysis. Due to the specialized nature of some forest pests (i.e., defoliators, bark beetles, wood borers, etc.), more research is needed to understand how remote sensing can complement field sampling techniques effectively.

Beyond pest damages, satellite imagery helps landowners cost-effectively respond to human and natural disturbances. For example, a case study in Brazil found that using near real-time satellite monitoring helps to effectively detect and report illegal forest clearing (Mullan et al. 2022). The methodology presented in this research can be used to evaluate the cost-effectiveness of remotely-sensed data in other forestry applications, such as estimating biomass and assessing ecosystem services (Resources for the Future 2023).

CONCLUSIONS

SBW will continue to threaten the northeastern forests of the USA and Canada, including the state of Maine with outbreaks for years to come. It is important to detect defoliation before the outbreak becomes too severe so that timely interventions are possible. While there are collaborative efforts within Maine's forest industry, MFS and the University of Maine to mitigate the impacts of SBW, this research explored the cost-effectiveness of using remote sensing for monitoring SBW. Through our analysis, we found that monitoring using Sentinel-2 data stands out as the most cost-effective option, at a range of $33-63 per sq km. We also acknowledge the utility of other monitoring approaches, such as the flexible spatial and temporal resolutions of PlanetScope imagery and UAVs, albeit at a higher cost. The integrated monitoring approach proposed in this study combines remote sensing change detection with field sampling, offering a complementary strategy to monitor SBW and other forest pests. By leveraging the strengths of each approach, landowners can obtain timely and accurate information about pest outbreaks, enabling proactive management and intervention strategies. It is important to note that the cost-effectiveness of remote sensing approaches may vary depending on factors such as labor costs, capital investments, and the specific objectives of forest managers. The sensitivity analyses conducted in this study highlight the robustness of our analysis and provide insights into cost-saving measures. As the costs estimated for this research were informed by expert opinion at state and federal levels, it is likely that they can be used as a baseline for other pest-induced damage monitoring efforts and other areas. This research depicts the importance of utilizing a combination of remote sensing and field-based techniques in forest pest monitoring programs. Continuing to rely on the information that is provided through field sampling, coupled with defoliation observed via remote sensing will equip forest managers with valuable information to manage their forests.

CONFLICTS OF INTEREST

The authors confirm there are no conflicts of interest.

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