Utilizing Remote Sensing to Assess the Effect of Snow on Bark Beetle Outbreaks

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Skills for Undergraduate Participation in Ecological Research

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Research Summary

Spruce bark beetle outbreaks have been negatively impacting Engelmann spruce, so the distribution of Engelmann spruce and spruce bark beetle outbreaks in Colorado was evaluated. In addition, we were exploring how snow depth, snow cover, and physiography could be potentially impacting the severity of the outbreak. This is due to snow cover protecting the spruce bark beetles in the wintertime. Higher elevations have a higher potential for an outbreak because of the increased frequency of Engelmann spruce and abundant snow cover. In this research MODIS data, radar data, and spruce bark beetle outbreak data from prior research were utilized in ArcGIS Pro and the extracted data were analyzed in R software. The expected results are that higher snow cover can have the potential to increase spruce bark beetle outbreaks by increasing the overwintering survival of the beetles. Although climate change is increasing the risk of spruce bark beetle outbreaks to occur, overwintering survival is an important aspect of the outbreak, so snow cover should be considered an indicator of potential outbreak severity.

Introduction

In the western part of the United States, there have been different bark beetle outbreaks, and these different outbreaks occurred due to the peak mortalities appearing at separate times (Hicke et al., 2020). There are ways to measure the severity of an outbreak: fieldwork and remote sensing. Each of these methods has its own benefits, but the combination of the two would be useful due to the complexity of detecting an infestation (Barta et al., 2022). However, remote sensing could be more cost-effective because the data could be downloaded for free (Fernandez-Carrillo et al., 2020). There are a variety of techniques that can be used during remote sensing to examine forest health (Torres et al., 2021). Using different techniques can result in different levels of accuracy, so there are benefits and drawbacks to the combination of techniques (Sterenczak et al., 2017). For forest structure, LiDAR can be an efficient way of determining forest health (Camarretta et al., 2020). However, the primary technique that will be used is satellite imagery. In the western part of the United States, aerial photos were utilized to determine the severity and accuracy of outbreaks of different bark beetle species through different methods (Hicke et al., 2020). However, most published studies focused on Norwegian spruce trees in Europe. Sentinel satellite images had been used in the Czech Republic to detect early stages of infestation, but severe damage was the easiest category to identify (Fernandez-Carrillo et al., 2020). For this report, the focus would on Engelmann spruce trees within Colorado which the distribution of this species is illustrated in figure 1. Therefore, some remote sensing techniques would be used to complete this report.

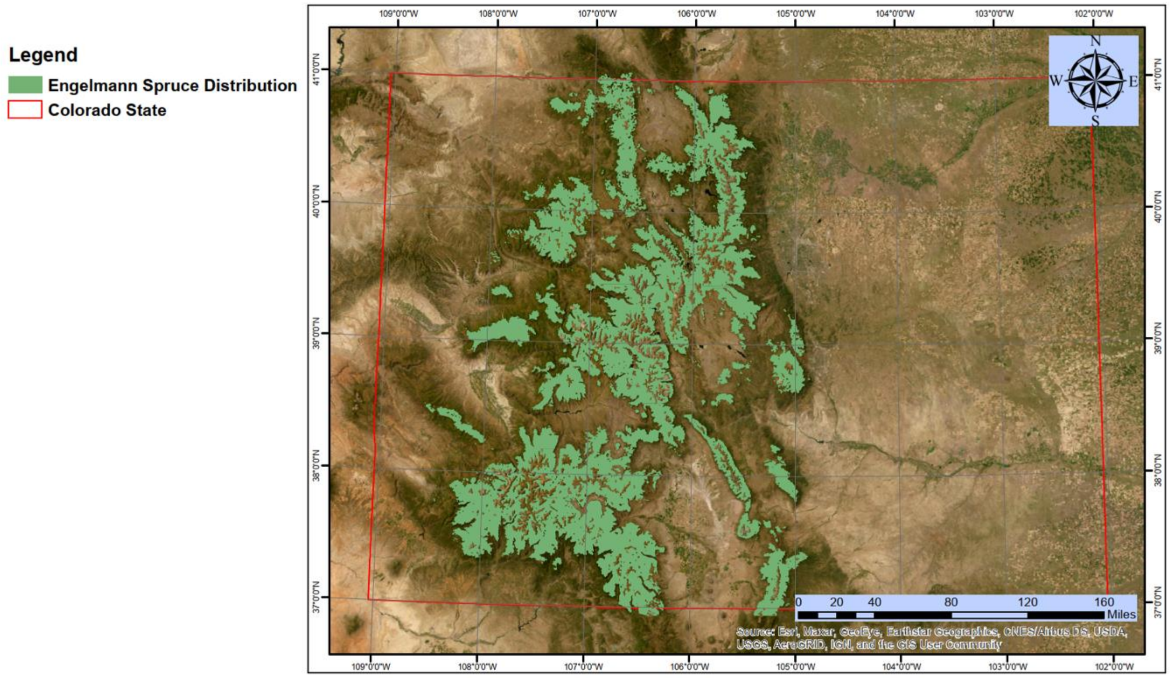

Figure 1. The distribution of Engelmann spruce Source: USDA Forest Service

Furthermore, there has been remote sensing studies on snow. There was a combination of time-lapse photography and MODIS satellite images to map the snow cover in forest areas (Luo et al., 2022). However, there can be less accuracy of snow cover by having larger underestimations in mountains and forested areas (Xiao et al., 2020). To illustrate the difficulty of detecting snow, figure 2 from a field site has uneven snow depth around the Engelmann spruce trees. Therefore, detecting snow cover in mountainous forest areas can be difficult, so a similar study was conducted in the Canadian Rockies with Landsat satellite images and time-lapse photography (Lv et al., 2019). Furthermore, the combination of bark beetle attacks on spruce trees and snow composition had been examined in Utah to determine the risk of avalanches, and each stage does have a different effect on the snow cover (Teich et al., 2019). In Colorado, different bark beetle outbreak stages can impact a watershed by different degrees of severity because of an increase of SWE by having a larger canopy opening, and dust on snow may become more frequent by utilizing clear cutting as a response to bark beetle outbreaks (Livneh et al., 2015). As a result, snow (depth and cover) would be a variable in this report.

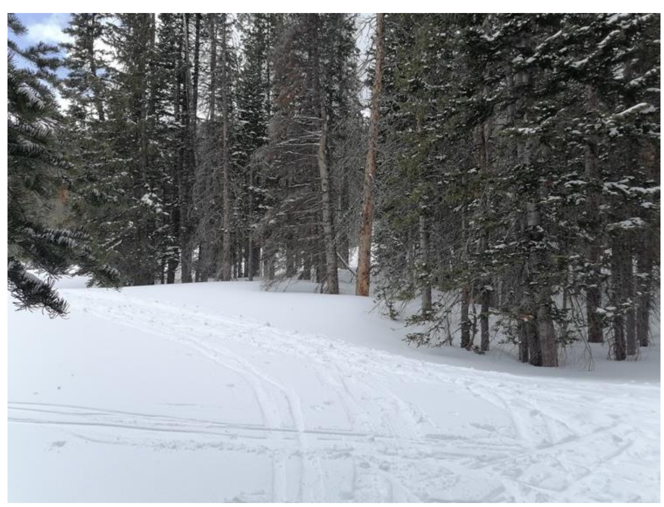

Figure 2. A field site with uneven snow depth Source: photo taken by Ehsan Khedive

Figure 3. Field sites within area of study Source: photos taken by Ehsan Khedive

However, remote sensing appears to not have been used for the combination of bark beetle attacks, snow cover, snow depth, and physiography. Therefore, MODIS data will be used to determine a correlation between bark beetle attacks, snow cover, snow depth, and physiography. The area of study will be the state of Colorado for the distribution of Engelmann spruce which is illustrated by figure 1, and figure 3 show the variation in physiography of this area of study. Overall, this report would be an exploration of these variables.

Research Questions and Hypotheses

Research Question:

How does the following factors affect the bark beetle infestation of spruce trees in Colorado?

(a) Snow Cover
(b) Snow Depth
(c) Physiography

Expected outcome, or research (alternative) hypothesis:

A higher amount of snow cover will protect beetles from winter frost and exacerbate beetle infestation in spruce trees. Snow cover has different patterns depending on the physiography. Higher elevations in the Rocky Mountains usually experience deeper and longer snow covers. North aspects also experience prolonged snow cover.

Emergent null hypothesis:

(a) Snow cover does not have a significant positive effect on beetle infestation in spruce trees.
(b) Snow depth does have a significant positive effect on beetle infestation in spruce trees.
(c) Physiography (elevation, aspect, and slope) does not have an effect on beetle infestation in spruce trees.

Explanation:

Research has shown that spruce bark beetles move to lower parts of the trees at the end of the growth season for overwintering, and snow cover protects bark beetles in the wintertime by insulating the beetles. Therefore, there may be a correlation between snow cover and bark beetle infestation because less insulation from snow may increase the mortality rate of bark beetles in the wintertime.

Methods

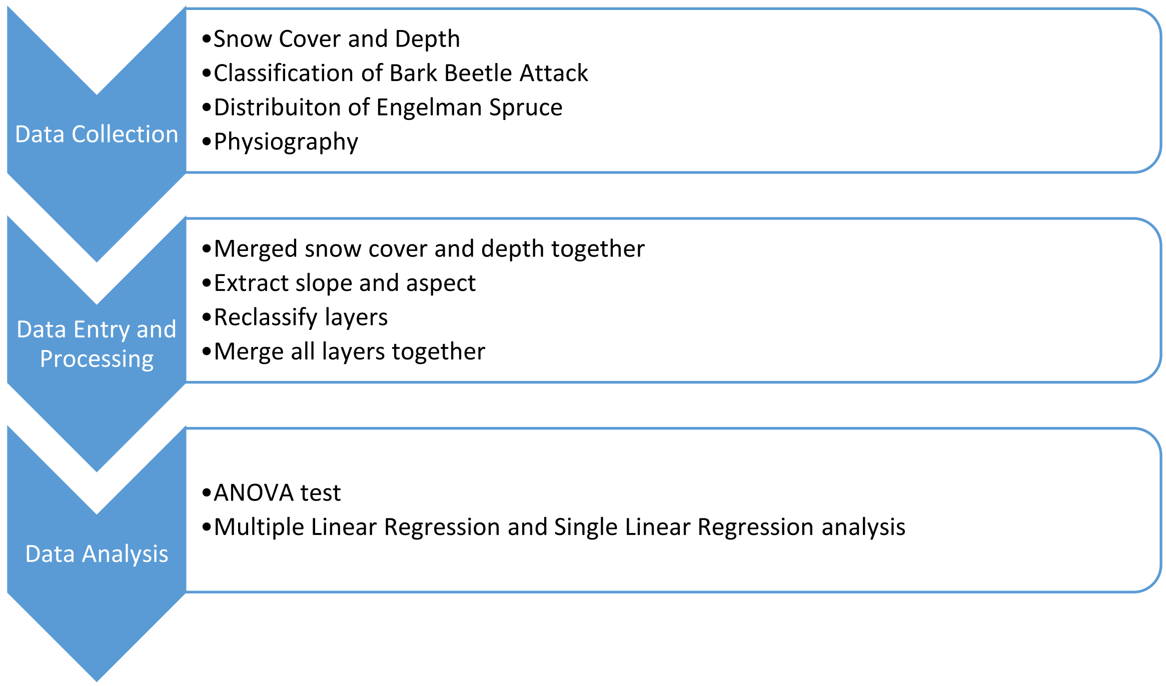

Figure 4. The major steps of the methods. This figure contains three processes to complete this report: data collection, data entry and processing, and data analysis.

Data Collection

Data was collected from multiple sources. Snow cover and depth was collected from NOAA's National Snow Analysis 3D Interface for 5 dates between February and March between 2017 and 2021 which I downloaded. The distribution of Engelman spruce was gathered from US Forest Service, and the physiography (DEM) was gathered from the University of Alaska Fairbanks ALOS PALSAR program which both data sets were downloaded by Ehsan. Lastly, the classification of bark beetle attack was used from prior research by Rodman et al. which was downloaded by Ehsan. These were the data needed to proceed to the next steps.

Data Entry and Processing

Several steps were required to be completed in ArcGIS Pro to transition to data analysis. However, for snow depth, I had to complete a preparation step prior to importing into ArcGIS Pro. In Google Earth Pro, snow depth had to be extracted from the National Snow Analysis 3D Interface KML file. After importing the snow depth into ArcGIS Pro, I converted the files into the correct format by utilizing the KML to Layer tool. Then I clipped the files to the Engelman spruce distribution file to reduce the size of the files, so the files can be averaged together with the Merge Raster tool. Then I imported the DEM and reclassified it into the following 4 classes:

2179 m – 2700 m, 2700 m – 3100 m, 3100 m – 3500 m, and 3500 m – 3900 m, so the slope and aspect could be extracted using the tools Slope and Aspect. These two new layers were reclassified as well. The slope layer will be reclassified into 5 classes: <5%, 5%-30%, 30%-60%, 60%-90%, 90%-120%, and greater than 120%, and the aspect layer will be reclassified into flat, north, south, east, and west. The last layer file that I would need to reclassify would be the map of bark beetle attack severity from Rodman et al. into 10%, 40% (light outbreak), and above 40% tree mortality (severe outbreak). Finally, all the layers would be combined using the Merge Raster tool, so Ehsan and I can export the data into R Studio.

Data Analysis

The final steps illustrated in Figure 4 involved utilizing R Studio. Therefore, the data from ArcGIS Pro would be transferred into R Studio, so Ehsan created a CSV file from the data in ArcGIS Pro. I used an ANOVA for aspect, single linear regression for slope, elevation, and snow depth, and multiple linear regression to determine the statistical significance.

Results

Each variable except the aspect had an individual single linear regression against spruce bark beetle outbreak severity, and the aspect had an ANOVA completed. In addition, a weighted multiple linear regression was completed which indicates statistical significance (p-value <2.2e-16). Overall, each variable has a correlation with spruce bark beetle outbreaks.

The results of snow depth are slightly different from the other variables when compared to spruce bark beetle outbreak severity. The blue line in figure 5 indicates a linear inverse relationship. However, the highest concentration of spruce bark beetle severity being above 75% is between 50 cm to 150 cm. Above 200 cm, the spruce bark beetle outbreak is below 40% severity. Overall, this relationship between snow depth and spruce bark beetle outbreak is polynomial which indicates that the dependent variable (spruce bark beetle outbreak) has a relationship with squared of the independent variable (snow depth), and these

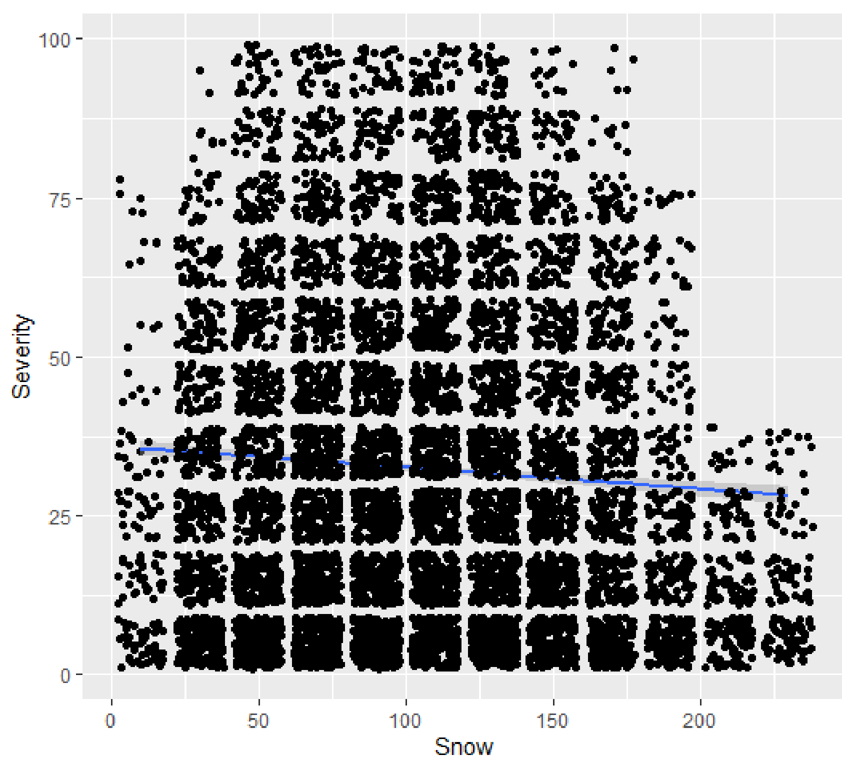

Figure 5. Snow Depth (cm) vs Severity (%). The dots show the concentration of spruce bark beetle outbreaks for different snow depths.

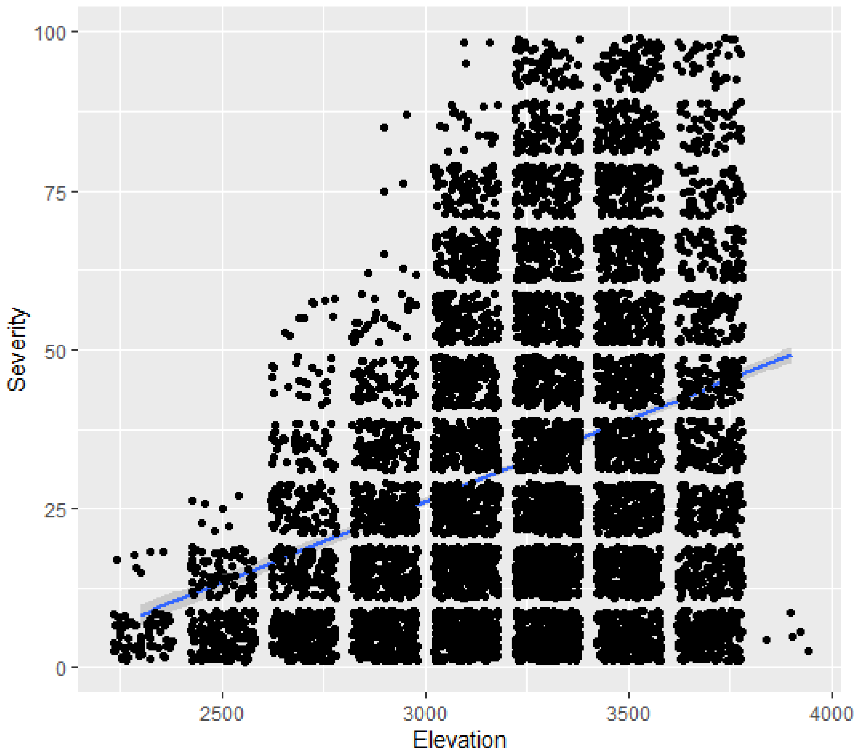

Figure 6. Elevation (m) vs Severity (%). The dots show the concentration of spruce bark beetle outbreaks for different elevation ranges.

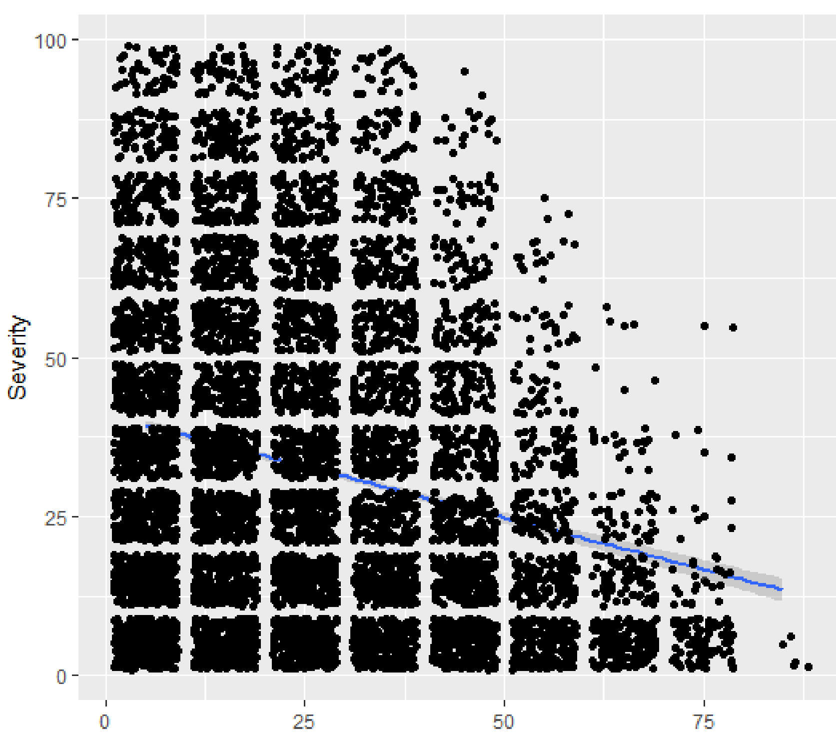

Figure 7. Slope (%) vs Severity (%). The dots show the concentration of spruce bark beetle outbreaks for different slopes.

results for snow depth and spruce bark beetle outbreak severity are significant (p-value of 1.816e-09).

For the elevation variable, there is a correlation between elevation (m) and spruce bark beetle outbreak (%). The highest percentage of outbreak severity is between about 3250 m and 3500 m. After 3750 m, there is a minimal outbreak of spruce bark beetles. The blue line in figure 6 indicates a linear positive correlation between elevation (m) and spruce bark beetle outbreak severity (%). Therefore, there is statistical significance between these two values (p-value is <2.2e-16).

However, the results for the slope indicate differently. A gentle slope (degree) has a higher concentration of outbreak severity while steeper slopes have a lower concentration of outbreak severity. The blue line in Figure 7 indicates a linear inverse relationship between slope and spruce bark beetle outbreak severity. These results are statistically significant (p-value is <2.2e-16).

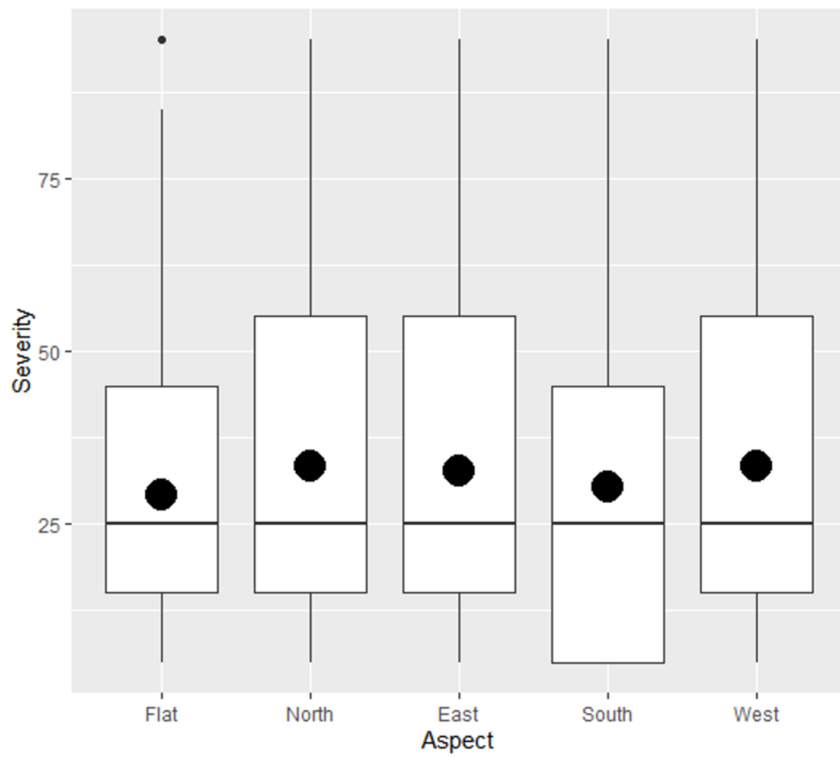

Figure 8. Aspect vs Severity (%). This boxplot shows the relationship between each aspect and spruce bark beetle outbreak severity.

Aspect appears to have a lower impact on spruce bark beetle outbreak severity. The median for all aspects is about 25% severity. However, the south aspect has the lowest first quartile, but the third quartile is the same height as flat surfaces. The north, east, and west upper quartile are above 50% severity outbreak. These results for the aspect are statistically significant (p-value is 4.632e-06).

Discussion

Based on the research questions, each of the factors of snow cover, snow depth, and physiography do have implications on spruce bark beetle outbreaks in Colorado. The two factors that appear to have the highest implications are elevation and slope. As the elevation increases, the spruce bark beetle outbreak severity increases as well. The minimal amount of spruce bark beetle outbreak severity below 2500m may be due to the Engelmann spruce trees' range of tolerance. Furthermore, between 2500 m and 3750 m could be a suitable range for spruce bark beetles to be protected from winter frost with snow cover, but above 3750 m, the growth season could be too short for spruce bark beetles to cause a significant outbreak. In contrast, the slope is an inverse relationship to spruce bark beetle outbreak severity. This may be due to steeper slopes being potentially more difficult for Engelmann spruce trees to grow on. In addition, snow depth appears to influence the peak of the spruce bark beetle outbreak severity between 50 cm to 150 cm which makes this the ideal snow cover range, so below 25 cm does not provide adequate snow cover for spruce bark beetles by not protecting the beetles from winter frost. In addition, by not having enough time to complete their life cycle, above 200 cm would be too much for spruce bark beetles because the time for the snow to melt would be longer. Aspect appears to not have much of an influence on spruce bark beetle outbreak severity. Therefore, the combination of these factors impacts spruce bark beetle outbreaks for different levels of severity. As the result, portions of the null hypothesis may be rejected while other portions may not be rejected. For physiography, slope and elevation do have an effect on spruce bark beetle outbreak severity while aspect does not. For snow cover and depth, there is a slightly negative effect on spruce bark beetle outbreak. Therefore, each of these variables affects spruce bark beetle outbreaks differently.

With this information, predictions could be made to see which areas in Colorado and/or other areas that have Engelmann spruce are more likely to be prone to spruce bark beetle outbreaks, so potential mitigation strategies could be implemented to reduce the risk. Therefore, this information would be beneficial for forest management by organizations such as the US Forest Service. However, due to time constraints, there were a couple of limitations to this study. The first one was the amount of data examined. There may have been benefits to examining snow depth for a longer period of time due to snow depth not being consistent year to year. In addition, fieldwork may help improve the accuracy of spatial analysis, but fieldwork can be pricey to complete. Making these adjustments will reduce the limitations of this study, so the information can be more beneficial for predictions.

Conclusions

With these results, this study was a launching point for understanding how snow depth, snow cover, and physiography impact spruce bark beetle outbreaks. There are indications that these factors do impact the severity of spruce bark beetle outbreaks in Colorado, and this information is relevant to other areas that are experiencing bark beetle outbreaks. To dive deeper into understanding how, the next steps can be implementing some fieldwork to compare results from satellite-derived data. In addition, working in partnership with someone in the field of snow hydrology may help clarify the factors of snow depth, so there could be a possibility to differentiate between physiography factors that impact spruce bark beetle outbreak and snow depth. Overall, there are several directions that can be taken to expand this research.

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Appendix

Appendix 1 - Methods

1. Data Collection
    a. Snow cover: Shannon found this data from NOAA's National Snow Analyses 3D Interface (https://www.nohrsc.noaa.gov/earth/archive.html?season=2019). Snow depth: Shannon found this data from NOAA's National Snow Analyses 3D Interface (https://www.nohrsc.noaa.gov/earth/archive.html?season=2019).
    b. Classification of bark beetle attack: This data is being used from a paper by Rodman et al. (https://doi.org/10.3390/rs13061089) which was found by Ehsan.
    c. Distribution of Engelman spruce in Colorado: Ehsan found this data from the USDA Forest Service.

   d. Physiography: Ehsan found DEM (digital elevation model) using the radar data from the University of Alaska Fairbanks ALOS PALSAR program (https://asf.alaska.edu/data-sets/sar-data-sets/alos-palsar/).
2. Data Entry and Processing
   a. GIS/Remote sensing analysis– Shannon will complete this section
      i. 5 random dates will be selected in Excel using the equation “rand between” for February 1 to March 31 for each year between 2017 and 2021 to determine dates to select for snow depth and snow cover.
      ii. The snow depth layers from NOAA will need to be converted to a format that works in ArcGIS since the file is a .kmz, so the ArcGIS tool KML to Layer will be used.
      iii. Due to the large size of the file, the snow depth raster layers will be clipped to the Engelmann spruce distribution shapefile using the “raster extraction” tool.
      iv. All of the snow depth raster layers from different dates will be averaged together into one new snow depth raster layer using the Merge Rasters function tool.
      v. By using the reclassification tool, the new raster file for snow depth will be reclassified into 3 classes: below 10 in (tends to melt), 10-40 in (snow remains until the end of March), and above 40 in (snow remains until the end of June or July).
      vi. The snow cover files from NOAA will be averaged together into one new snow cover raster layer using the Merge Rasters function tool after the KML to Layer tool was used.
      vii. From the DEM, elevation from 2179 m to 3900 m will be reclassified into 4 classes using the reclassification tool to the following classes: 2179 m – 2700 m, 2700 m – 3100 m, 3100 m – 3500 m, and 3500 m – 3900 m.
      viii. The Aspect tool will be used to extract the aspect layer from the DEM layer.
      ix. By using the reclassification tool, the aspect from the radar data will be reclassified into 4 classes: east, west, north, and south.
      x. The Slope tool will be used to extract the slope layer from the DEM layer.
      xi. By using the reclassification tool, the slope data will be reclassified into 5 classes: <5%, 5%-30%, 30%-60%, 60%-90%, 90%-120%, and greater than 120%.
      xii. Raster files of snow cover, snow depth, elevation, aspect, and slope will be combined using the Merge Rasters function tool in ArcGIS.
      xiii. Then I will convert the combined raster layer into a vector format to be able to calculate areas.
      xiv. The data from Rodman et al. will be organized into the categories of 10%, 40% (light outbreak), and above 40% tree mortality (severe outbreak).
   b. Spreadsheets/R
      i. The data from the GIS files with attributes tables will be exported as CSV files and imported into R.

3. Data Analysis in R – Shannon and Ehsan will work together
    a. GIS/Remote sensing
        i. All analysis will be moved to R.
    b. Spreadsheets/R
        i. ANOVA test will be done in R.
        ii. Simple Linear Regression and Multiple Linear Regression analysis methods will be used in case ANOVA was significant.
4. Data Interpretation – Shannon and Ehsan will work together
    a. GIS/Remote Sensing
        i. There should be difference between the classes of snow depth in terms of tree mortality.
        ii. Higher elevations will have a higher tree mortality, and a lower elevation will have a lower tree mortality.
        iii. For aspects, northern aspect should have higher morality while southern aspects have less.
        iv. For slope, below 5% slope should have a low mortality, between 5%-60% should have an average mortality (10%-40%), and above 60% should have above 40% tree mortality.
    b. Spreadsheets/R