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FOREST FRAGMENTATION ANALYSIS FROM MULTIPLE IMAGING FORMATS

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ABSTRACT

In landscape ecology, forest fragmentation studies with emphasis on effects of scale on fragmentation patch metrics, is an important research area. With increasing availability of satellite data at multiple scales and varied resolutions, it has become important to understand effects of comparing fragmentation metrics acquired from coarse resolution images and those from finer resolution imagery. This is crucial because coarse resolution images such as Landsat imagery, are relatively easier to find because of their cheaper costs, availability and broad coverage, whereas finer resolution imagery is more expensive and therefore, spans only small areas. This paper examines effects of varied spatial resolutions on common fragmentation metrics using Landsat, Sentinel, National Agricultural Imagery Program (NAIP) and Unmanned Aerial Vehicle (UAV) imagery obtained in November, 2017 of the Whitethorne area near Blacksburg, Virginia. The images are analyzed using FRAGSTATS and ArcGIS software programs. The results show significant differences in fragmentation metrics despite simultaneous acquisition of all images in the same area. Discussion of results obtained in this study centers on the reasons for this disparity, and examines uses of imagery of different resolutions for forest fragmentation analysis.

Keywords: Forest Fragmentation, Landsat, UAV, forest patches, spatial resolution, Patch metrics

INTRODUCTION

Forest fragmentation, one of the major threats to biodiversity and forest conservation, is the process through which formerly large and continuous forest areas are converted to small, isolated patches (Haila, 1999; Loyn & McAlpine, 2001). Reduction in sizes (areas) of remaining forest patches, increased isolation and loss in connectivity; and increased edge effects are the three main consequences of forest fragmentation (Saunders *et al*., 1991; Forman, 1995). Thus, forest fragmentation indices have the capacity to serve as spatial indicators for assessing health of forest ecosystems and are commonly considered biodiversity indicators in national forest inventories (Soledad & Saura, 2005). Forest fragmentation indices are important for assessing whether critical components and functions of forests are being maintained over time (Soledad & Saura, 2005).

The purpose of forest fragmentation analysis is to allow users to visualize and quantify the extent of forest fragmentation while tracking changes in fragmentation and connectivity over time (Riitters *et al*., 2000). Research conducted by Riitters *et al*. (2000) which forms the basis of most forest fragmentation work, was originally developed to assess forest fragmentation at the global level using 1-km land cover information premised on the use of image convolution where a fixed area, roving ‘analysis window’, is centered over a forest pixel identified by a raster land cover map.

In remote sensing, one of the most widely used processes involves image classification. Image classification is the process of converting the information in an image based on the spectral response of the Earth’s surface, into a thematic map that shows several classes of interest (Foody, 2008). In order to measure the accuracy of resulting thematic maps from the image classification process, it is necessary for users of these maps to evaluate their quality. The process of measuring the quality of classified thematic maps is referred to as Image Classification Accuracy Assessment, shown to be a difficult variable to assess because of problems associated with class discrimination and the spatial resolution of the images used in the classification process (Foody, 2008; Pontius & Cheuk, 2006; Lu & Weng, 2007).

Spatial resolution of the input land cover information is one of two most significant considerations in forest fragmentation analysis; the second being the desired width of the forest edge (Hurd & Civco, 2008). In forest fragmentation analysis, both of these two considerations are related and play significant roles in remote sensing, where images are analyzed and classified in order to map forest patches. Remote sensing analysis of forest fragmentation is very sensitive to scale of the maps used. With the availability of remote sensing data at varying spatial scales, a primary concern in fragmentation analysis is in defining an appropriate spatial resolution that ensures that results represent good ecosystem indicators (Lausch & Herzog, 2002).

In analyzing effects of spatial scale on landscape pattern indices, Saura (2004), found lower fragmentation at coarser spatial resolutions. Results from Saura (2004) contradicts that of Garcıa-Gigorro & Saura (2005) who concluded that images with finer spatial resolution underestimated forest fragmentation and reasoned that the utility of finer resolution images for forest fragmentation analysis is probably overestimated. Other studies have also shown that despite the usefulness of high-resolution imagery in capturing small habitat patches compared with lower-resolution imagery, high resolution imagery has the disadvantage of producing more canopy shadow and complicates processing and comparisons of multiple images (Masouka *et al*., 2003; Kennedy, 2009; Asner & Warner, 2003).

Characteristics of sensors do not only affect levels of image detail (spatial resolution) but also the radiometric resolution (the sensitivity of the sensors to detect differences in reflected or emitted energy (Narayanan *et al*., 2002). This means that the brightness of remote sensing imagery is dependent on sensors used to record electromagnetic energy of the objects in the scene (Narayanan *et al*., 2002). For instance, while the Landsat MSS has a radiometric resolution of 6 bits, the Landsat ETM+ has a radiometric resolution of 9 bits which emphasizes differences between agricultural and forest covers despite the small differences in their reflected energy.

In this study, we aim to determine effects of spatial resolution of remote sensing images on calculation of landscape metrics commonly used in forest fragmentation studies. Our study area in Virginia, where landscapes are heterogeneous in nature and rates of development, determined by human activities, have resulted in significant landscape changes, is ideal. This study differs from previous studies such as Wickham & Riitters (1995), Frohn (1998) and Wu *et al*. (2002) who concentrated solely on effects of spatial resolution on landscape indices devoid of the consideration of the dates of acquisition of the satellite images. In this study, we directly compare fragmentation indices on simultaneously acquired satellite images of different spatial resolutions for the same landscape. Hence, it offers a better understanding of the effect of spatial resolution on forest fragmentation and connectivity analyses.

Despite knowledge of significant differences in fragmentation metric values from images of different spatial resolution, effects of spatial resolution on fragmentation metrics is not fully understood. Forest fragmentation studies such as those of McGarigal & Marks (1995) have cautioned against comparison of fragmentation metrics obtained from images of varying spatial resolutions. This lack of comparability limits the importance of quantitative forest fragmentation analysis (Saura, 2004). This study therefore provides further insight into effects of spatial resolution of different satellite imagery on forest fragmentation metrics and identifying those metrics that can be compared across differing spatial resolutions.

In remote sensing, spatial resolution is important for determining levels of detail obtained from an area. Satellite imagery with high spatial resolution has produced more accurate estimates, where the accuracy of their classifications, have been assessed (Geza & McCray, 2008; Lin *et al.*, 2010; Boyle *et al.*, 2016). However, high resolution imagery although mostly beneficial because of the level of detail it affords, the issue of shadows, a nuisance that obscures important details, is more compounded in high resolution imagery. Because different services require different spatial resolutions, it is important for remote sensing research to identify the most appropriate resolution for specific objectives, given the classes of interest to be classified, in order to save both time and money. This research therefore, highlights advantages and disadvantages of satellite imagery of various resolutions for forest fragmentation analyses. Knowledge of what satellite imagery to use for what analysis is of particular value to scientific researchers and institutions that collect remote sensing data for forestry inventory collection and management.

METHODS

Study Area

Virginia, surrounded by the states of Maryland, West Virginia, Tennessee, Kentucky and North Carolina, has a population of approximately 8.5 million and occupies an approximate area of 42,775 square miles. Virginia includes major cities such as Norfolk, Chesapeake, Newport, and Richmond, its capital. Oak hickory is the most common forest type in Virginia accounting for about 61 % of the forested land (Rose, 2015; Virginia Department of Forest (VDOF), 2016). While the most productive sites in Virginia have northern red (*Quercus rubra*) and white oak (*Quercus alba*), mockernut hickory (*Carya tomentosa*) and pignut hickory (*Carya glabra*), the less productive sites in southwest Virginia, have mostly chestnut (*Castanea*) and scarlet oak (*Quercus coccinea*) trees (Gagnon, 2016). Pine trees account for approximately 20 percent of Virginia's forest cover with native pine species like the longleaf (*Pinus palustris*) and shortleaf (*Pinus echinata*), dominating in these forests. The remaining 20 % of forest areas in Virginia comprises oak-pine forest types. Throughout Virginia, especially in low-lying wet areas, Bottomland hardwoods, stable since 2001, make up approximately 5 % of forests (Gagnon, 2016). Bottomland hardwood forests have a lot of tree diversity including swamp chestnut (*Quercus michauxiik*), cherrybark oak (*Quercus pagoda*) and American sycamore (*Platanus occidentalis*). State forests in Virginia are only about 0.5 % of the total forest in Virginia while over 80 % of the forests are privately owned and managed (VDOF, 2014).

Many factors such as population growth rate, influence the quantity, quality and sustainability of forest resources in Virginia. In 1992 when the Virginia Department of Forestry (VDOF) performed a Forest Resource Assessment using GIS analysis, the result showed increasing fragmentation of its forest areas as a result of commercial and residential development. The trend of forest fragmentation in Virginia continues as confirmed by a recent study assessing the extent of forest fragmentation between 2001 and 2011 (Fynn *et al*., 2018).

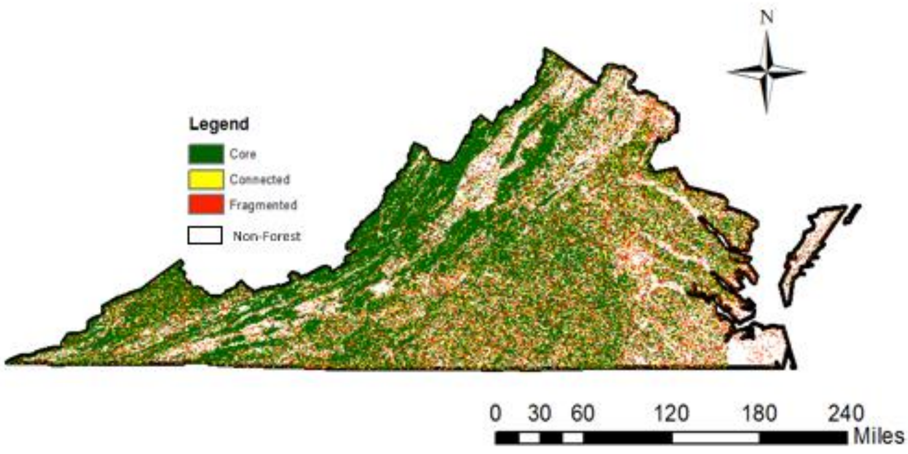
Stemming from concern for forest resources in Virginia, VDOF, using previously collected data in their Forest Inventory Analysis (FIA) pool, in conjunction with 2000 Landsat TM satellite imagery, classified the Virginia landscape into forest, non-forest, and water. The output of this analysis has been used in forest resource assessments, forest fire risk modeling, water quality management, fragmentation analyses, forest economics, and conservation efforts (VDOF).

With the widespread use of Landsat data at 30 meter resolution for forest analyses in Virginia, the concern for many ecologists lies in whether conservation efforts will be more useful if finer resolution satellite imagery is used. For instance, missed detection of forest edges will lead to false conclusions about the real status of forests, with some forests identified as intact and therefore, not receiving the needed attention even though they may have experienced disturbances. Overall, Virginia will benefit from improved information derived from satellite imagery, given that it has forest areas with varying states of disturbances (Figure 1).

Within Virginia, it was important to identify an area that has undergone a lot of anthropogenic changes and therefore, has lost a great percentage of its original habitat, in order to accurately capture effects of satellite imagery resolution on forest fragmentation studies. Myers *et al*. (2000) explain that in order for conservation efforts to be effective, a promising approach is to identify 'hotspots', or areas featuring exceptional concentrations of endemic species and experiencing exceptional loss of original habitat.

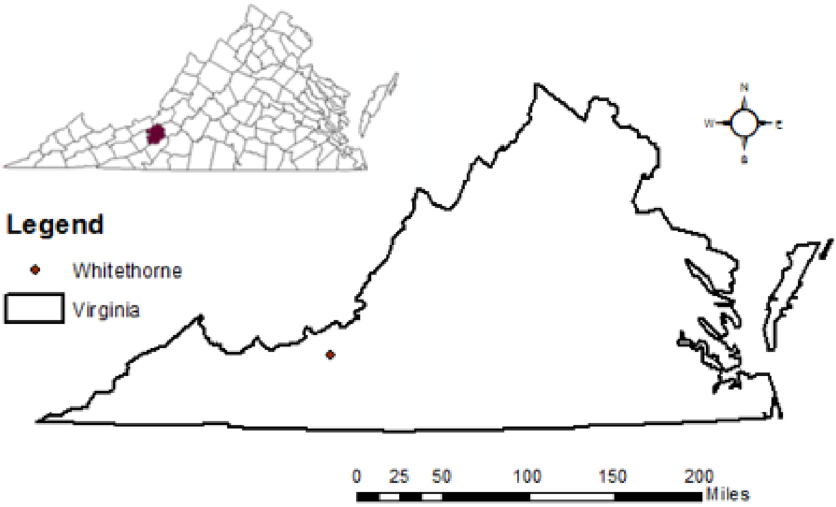
Fig. 1: A map of Virginia showing three types of forests: Core, Connected and Fragmented.

Most of the Core forest areas are in the Appalachian Plateau, Valley and Ridge and Blue Ridge physiographic regions.



Whitethorne, located near Blacksburg, within Montgomery County, Virginia, includes parts of the New River and Toms Creek (Figure 2). It includes forested and agricultural areas, interspersed with residential constructions. Previously, with a mainly forest outlook, urbanization of the Montgomery County due to the expansion of Virginia Tech, has resulted in the establishment of residential facilities and agricultural lands. The Whitethorne area was selected for this study because of the increasing human population in the area and resulting increases in forest fragmentation. Changes in the land use patterns of the Whitethorne region over the years, make the area conducive for forest fragmentation studies.

Fig. 2: A map of Virginia showing the Whitethorne region.
The map of Virginia above shows Montgomery County where Whitethorne is located.



Spatial data

To examine the Whitethorne landscape, we obtained cloud-free geometrically corrected satellite scenes for the region. These included a four band (red, blue, green and infrared) Landsat Thematic Mapper (TM) scenes (30 meter resolution) acquired on 15th November 2017 from the United States Geological Survey (USGS) archive, Sentinel imagery acquired on 18th November 2017 (Sentinel 2; only 10 and 20m resolution bands were used) from the Scientific Hub, National Agriculture Imagery Program (NAIP) imagery dated 30th November, 2017 (0.25 meter resolution) from the United States Department of Agriculture (USDA) Farm Service Agency databases, and Unmanned Aerial Vehicle (UAV) imagery obtained on 8th November, 2017 (0.03 meter resolution) (Table 1).

Landsat, Sentinel and NAIP imagery were used because they are readily and freely available and represent commonly available satellite imagery used for forest fragmentation analyses. NAIP imagery, administered through the United States Department of Agriculture's Farm Service Agency, comprising of red, blue, green and near infrared bands, is made up of individual image tiles with each tile based on a 3.75-minute longitude by 3.75-minute latitude quarter quadrangle plus a 300-meter buffer on all four sides. Dates of acquisition for all data used were close in time to ensure consistency in phenology and in vegetation states. UAV imagery used for the analysis was however not readily available and was scheduled and collected personally using a Sequoia_4.9_4608 x 3456 camera model with RGB features. The Average Ground Sampling Distance (GSD) for the UAV imagery was 3.37 cm /1.32 in and an approximate processing time of 5 hours was used on 1221 geolocated images.

Table 1: Satellite imagery used for analysis.
All the images were acquired in November to ensure more effective comparisons devoid of vegetation phenological differences due to time of year.

Satellite Image	Acquisition Date	Spatial Resolution (meters)
Landsat Thematic Mapper	11/15/2017	30 × 30
Sentinel 2	11/18/2017	
Band 2		10 × 10
Band 3		10 × 10
Band 4		10 × 10
Band 5		20 × 10
Band 6		20 × 10
Band 7		20 × 20
Band 8		10 × 10
Band 8A		20 × 20
Band 11		20 × 20
Band 12		20 × 20
NAIP	11/30/2017	0.25 × 0.25
Unmanned Aerial Vehicle (UAV)	11/08/2017	0.03 × 0.03

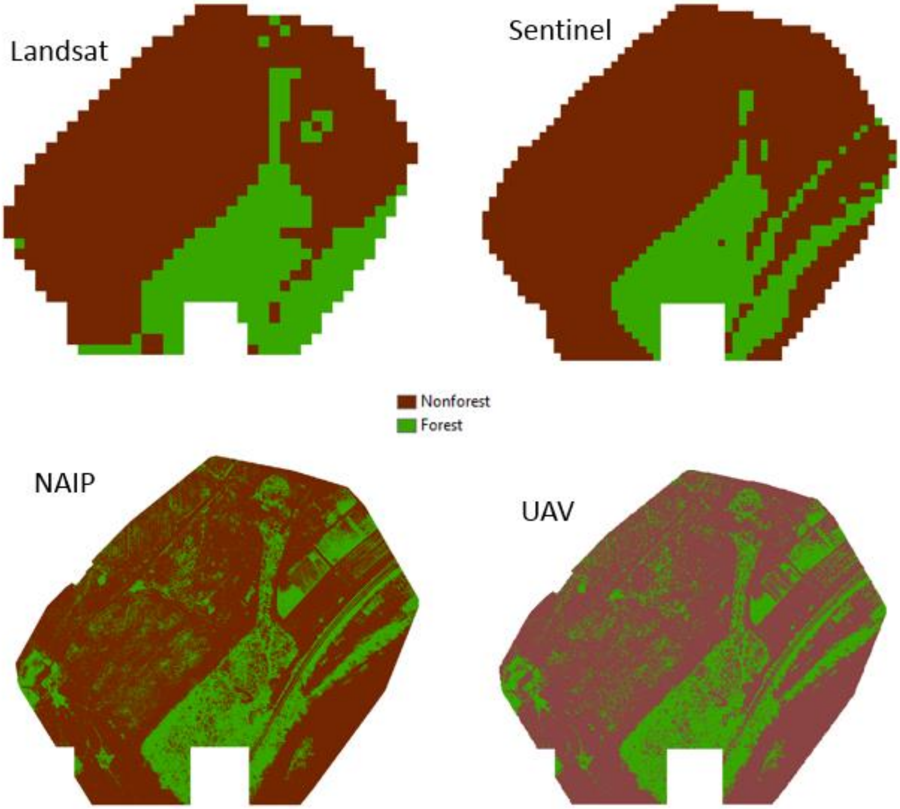
Methodology

Across the study area, 60 points were randomly selected to serve as training samples for classification. These 60 random points were field-verified on-site to confirm that their classification as either forest or non-forest, is accurate. Using ArcGIS, we assigned each point to a land cover class; forest or non-forest. These 60 locations were used for classification of Landsat, Sentinel, NAIP and UAV images, by selecting training data polygons around the points, with the same reflectance characteristics, as the point location. Classification accuracy was assessed for all images based on 500 stratified random points.

ArcGIS was used to conduct a supervised classification of the images. The 60 training data locations used to generate signature files were used to classify each of the images into either forested or non-forested areas. Pixels in each image were compared numerically and algorithmically with the training data by the ArcGIS software via the 'Maximum Likelihood' tool, to allocate the two classes.

Raster outputs from the classification of the 4 images (Figure 3) were used as inputs in FRAGSTATS to calculate patch metrics. In ArcGIS, all the non-forest areas were reclassified to have NODATA values before the raster images were analyzed in FRAGSTATS. This change was done so that, patch metrics calculated in FRAGSTATS, reflected only the forest regions in the raster images.

Fig. 3: Classified raster images of the satellite imagery analyzed in FRAGSTATS. Between the NAIP and UAV imagery, there is only little difference visually but the number of pixels in the two classes are significantly different.



Patch metrics such as patch density, total edge distance, perimeter-area ratio and shape indices were calculated for each of the images (Table 2). The Patch Density metric has the same basic utility as number of patches as an index, except that it is more effective for comparison because it expresses the number of patches on a per unit area basis. Patch Density is calculated by dividing the number of patches by the total landscape area and is useful in determining the number of subpopulations in a spatially-dispersed population for species exclusively associated with that habitat type e.g. forests. Patch density in FRAGSTATS is greater than 0 and has no maximum limit.

Table 2: Patch metrics calculated in FRAGSTATS (McGarigal and Marks, 1995).
These patch metrics are important indicators of fragmentation and connectivity

Patch Metric	Description
Patch Density	The number of patches divided by total landscape area measured per 100 hectares. • Images with high patch density indicates a higher number of patches identified and is thus, considered to be more fragmented.
Largest Patch Index	The area of the largest patch divided by the total landscape area, multiplied by 100 (to convert to a percentage)
Edge Density	The sum of the lengths (m) of all edge segments, divided by the total landscape area (m^2), converted to reflect every 100 hectares.
Landscape Shape Index	The sum of the landscape boundary and all edge segments (m) within the landscape boundary, divided by the square root of the total landscape area
Radius of gyration	The mean distance between each cell in the patch and the patch centroid
Cohesion	Measures the physical connectedness of the patches

The Largest Patch Index (LPI) metric quantifies the percentage of the total landscape comprised by the largest patch. It is therefore a measure of dominance showing the degree of variability within the landscape (Vizzari & Sigura, 2013). This metric identifies the largest forest patch within a specific landscape and therefore, determines the health of species with respect to competition and interactions between species since the size of patches have a direct impact on species population dynamics. LPI is different from the Landscape Shape Index (LSI) which is a measure of aggregation, measuring perimeter-area ratio for the landscape, calculated by dividing the total length of patch edges by the minimum measured edge length.

The Edge Density (ED) metric reports total patch edge length within a landscape on a per unit area basis. It equals the sum of the lengths, in meters, of all edge segments in the landscape, divided by the total landscape area. In this study, edge areas is defined as the area 300ft away from a patch boundary. Radius of gyration (a patch metric affected by both patch size and patch aggregation or connectivity), was also measured in meters for each image by calculating the mean distance between each cell in a patch and the patch centroid. Radius of Gyration is a measure of how far across the landscape a patch extends its reach.

The patch Cohesion metric measures physical connectedness of the patch type in the landscape under study. Cohesion increases as patches in the landscape become more aggregated and has a range between 0 and 100 in FRAGSTATS. Total Core Area (TCA) (a measure of the aggregation of the core areas in each patch), was also measured for each image. Metric results for each of the four images were subsequently compared, to note any differences.

RESULTS AND DISCUSSION

Considerable differences were found between the metric values of Landsat, Sentinel, NAIP and UAV images from FRAGSTATS. Contrary to our initial hypothesis that differences between the four images, might be subtle, if any, the case is not so for fragmentation metrics. Fragmentation metrics such as number of patches or patch density, Largest Patch Index, Landscape Shape Index, Edge Density and Radius of Gyration, showed similarities between Landsat and Sentinel Imagery compared with NAIP and UAV images (Table 3). The similarity of results of Landsat and Sentinel and then, NAIP and UAV, were to be expected because Landsat and Sentinel sensors have similar spatial resolutions compared with NAIP and UAV imagery.

Table 3: Patch Metric Values from FRAGSTATS.

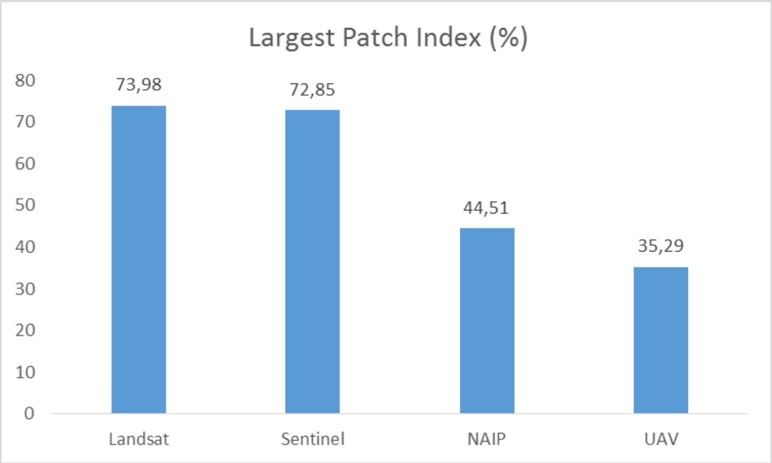
There is a lot of similarity between metric values of Landsat and Sentinel and another cluster of similar values for NAIP and UAV metric values. This trend is because of comparable spatial resolutions

PATCH METRICS					
IMAGE	Patch Density (patches/100ha)	Largest Patch Index (%)	Edge Density (per 100ha)	Landscape Shape Index	Radius of Gyration (m)
Landsat	0.10	73.98	0.55	2.52	84.0259
Sentinel	0.14	72.85	0.69	2.86	71.4634
NAIP	734.37	44.51	259.99	77.93	0.093
UAV	1321.66	35.29	346.97	120.96	0.091

Patch Density affects the stability of species interactions and opportunities for coexistence among different species. Patch Density, is however, constrained by the spatial resolution of the image used, since it is measured when every cell is a separate patch. This constraint is evident in the results reported in Table 3, as Patch Density differed considerably depending on the spatial resolution of the images used. Careful consideration of spatial resolution is important because if Patch Density is used as the only metric of comparison between images of varying spatial resolution, investigators will reach erroneous conclusions, given the differences in results reported in Table 3. This means that in a given area, depending on the spatial resolution of the satellite imagery used for the analysis, patch density value can either be lower or higher than the actual ground information. Hence, it is important for conservationists to consider the spatial resolution of images used in a fragmentation analysis before making decisions based only on Patch Density.

The significant differences between LPI metric values for the four images was not expected since this metric is thought to be independent of spatial resolution (Aithal *et al.*, 2012). Our results, however, show that, images with lower spatial resolution (such as Landsat and Sentinel) have the tendency of skipping small patches within larger patches and therefore aggregating smaller patches as individual larger patches. With increasingly finer spatial resolution, the distinction between smaller patches is more easily recognizable, as is seen in Table 1 and therefore, LPI declines (Figure 4). This result serves as an important factor for conservationists and policy makers as it shows the value of using higher resolution imagery.

Fig. 4: Largest Patch Index (LPI) reduces with increasing spatial resolution.
Although the same area at the same time is analyzed, the spatial resolution of the satellite imagery used, results in differences in the calculations of the LPI. There is a significant reduction in LPI values obtained from fine resolution imagery (NAIP and UAV) compared with coarse resolution imagery (Landsat and Sentinel).



Edge Density, like Patch Density, is very sensitive to the spatial resolution of images used (McGarigal & Marks, 1995). In higher resolution imagery where the smallest patches can be identified and distinguished, it is reasonable that Edge Density will be higher as more edges are identified and quantified. For many landscape ecological studies, the presumed importance of spatial pattern is related to edge effects. For instance, one of the most significant consequences of forest fragmentation is an increase in edge effects and adverse effects of this phenomenon on core sensitive species. With so much importance placed on edge effects in forest fragmentation studies because of the significance of edges on the species present in the area, it is important to note that, measurements of edge density are highly variable within a single landscape. Variation in edge density measurements depends on the spatial resolution of the imagery used for the analysis (Figure 5). Figure 5 shows that Edge Density values for Landsat and Sentinel are very different from those of NAIP and UAV images because of differences in spatial resolution. The increased capture of small forest patches by high resolution imagery, and therefore the increased ED values captured by NAIP and UVA images, demonstrates the value of high resolution imagery. However, given that differences between resolutions of NAIP and UAV imagery are not vast, the relatively large difference in their corresponding ED values, raises questions about effects of canopy shadow (Asner & Warner, 2003).

Fig. 5: Increasing Edge Density values with increasing spatial resolution. This means that there is a correlation between spatial resolution and edge density metric values

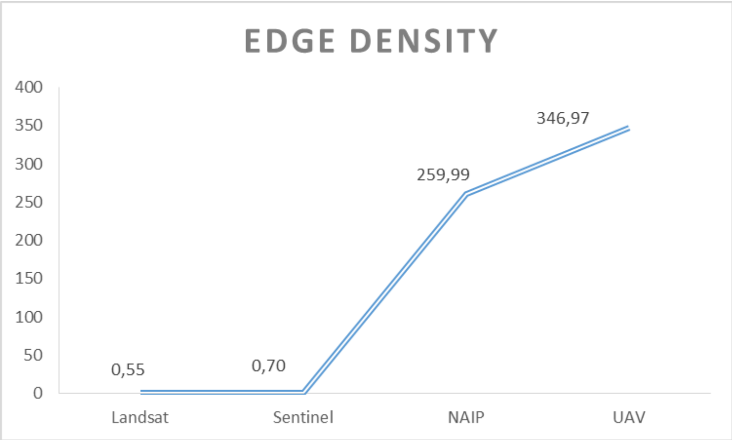


Table 4: Classification Accuracy Assessment. Created using randomly selected points in the forest (250 points) and non-forest (250 points) areas of the classified NAIP, UAV, Sentinel and Landsat images.

CLASSIFICATION

	REFERENCE			
CLASS	Forest	Non- Forest	Row Total	Overall Accuracy
NAIP				
Forest	207	40	247	
Non-Forest	14	189	203	0.792
Column Total	221	229	500	
UAV				
Forest	183	62	245	
Non-Forest	81	174	255	0.714
Column Total	264	236	500	
SENTINEL				
Forest	179	79	258	
Non-Forest	74	168	242	0.694
Column Total	253	247	500	
LANDSAT				
Forest	163	108	271	
Non-Forest	71	158	229	0.64
Column Total	234	266	500	

Canopy shadows, higher in forested regions, refer to reflectance of vegetation. With fine resolution imagery, canopy shadows become increasingly easily detected and can be erroneously categorized as part of the forest structure by computer algorithms such as the 'Maximum Likelihood' classification tool in ArcGIS, that was used for this analysis. This is why a closer look at the NAIP and UAV images show a decrease in classification accuracy of the UAV imagery (Table 4). Thus, it is important for ecologists and policy makers to be prudent in the use of high resolution imagery, especially with regard to edge density values from fragmentation analyses.

LSI measures the overall shape of the landscape with values close to 0 indicating that the landscape has a simple shape with higher aggregation. Values that are far from 0, like those of the NAIP and UVA (Table 1), show that the landscape has a complex shape with dispersed patches, and not as aggregated as indicated by the values of the Landsat and Sentinel images. This result is contrary to the findings of Aithal *et al*. (2012) suggesting that fragmentation metrics based on shape like the LSI, are not sensitive and behave similarly across all spatial resolutions. From our results, LSI varies significantly across resolutions and should therefore be interpreted cautiously. LSI is dependent on spatial resolution because more patches, within the same landscape, are identified with higher resolution imagery, exposing the dispersion within the landscape (Boyle *et al*., 2014).

The radius of gyration is a measure of the average distance an organism can move within a patch before encountering the patch boundary from a random starting point. It is therefore a measure of landscape connectivity important in conservation studies for assessing health of species populations. Results from Table 1 show that, the radius of gyration is very sensitive to spatial resolution. Between the two high-resolution images used (NAIP and UAV), the difference in this metric is not significant but can pose a problem if conclusions are drawn from images of very different spatial resolutions such as between a Landsat image and an UAV image. Given the subtle difference in values for the NAIP and UAV imagery but the stark difference between coarser resolution Landsat and Sentinel images, conservationists can use the relatively cheaper NAIP imagery in connectivity studies involving inference from this metric, compared to the more expensive UAV imagery. This is important for connectivity studies that determine the abundance of species within an area as the more readily available and cheaper NAIP imagery, gives similar results as the more expensive UAV imagery.

An important part of our results lies in the values of the *Cohesion* metric. A Cohesion value of 100 is an indication of clumpiness or connectivity of the landscape patches. Values close to 0 indicate highly unconnected fragmented landscapes. Our results show that the Cohesion values in the landscape were 78.11, 78.39, 79.05 and 78.64 for Landsat, Sentinel, NAIP and UAV images respectively. A trend cannot be identified in the measurement of these values with respect to spatial resolution. Given that there is no significant difference in the metric values, it can be concluded that Cohesion is not sensitive to spatial resolution. This result is consistent with the findings of Aithal *et al*. (2012) who found that Cohesion results were similar irrespective of spatial resolution and therefore concluded that Cohesion is independent of spatial resolution. Given this result, the use of Cohesion as a metric of aggregation is useful since the result is independent of the spatial resolution of the satellite imagery used. It should be noted, however, that other metrics indicated higher fragmentation in the landscape, especially the high-resolution metric values from NAIP and UAV images. Thus, an average Cohesion value of 78, an indication of aggregation, is not a good representation of the level of fragmentation in the area.

CONCLUSION

Our results highlight the fact that differences in satellite image resolution used in fragmentation analyses are not trivial, and can reliably assess significant differences in patch metrics. Consequently, these differences are likely to influence interpretations of fragmentation metrics, which can directly impact populations of species within an ecosystem. Our results have shown that it is critical for every researcher to tailor spatial imagery needs according to objectives of the research and that higher resolution images do not always guarantee higher accuracy and better interpretations. It is important that future research identify specific threshold resolutions, above which high image resolution ceases to be useful for those specific objectives.

Assessment of the classification accuracy of remote sensing images remains very important. It is important that remote sensing researchers not assume that high resolution images automatically imply high classification accuracies. Different studies have found different effects of spatial resolution on image classification. Perhaps, it is important for future studies to accurately identify effects of spatial resolution on classification accuracy, on the premise of the field of interest such as for either marine, coastal, or terrestrial studies. Differences in effects of spatial resolution on classification accuracy might be more apparent if specific study areas are characterized.

In our study, NAIP imagery proved to have a higher classification accuracy compared to the higher resolution UAV imagery. The classification of the area based on the NAIP imagery was a better representation of the state of the area, given that ground data had been verified. Whereas the UAV imagery misclassified certain non-forest areas, NAIP imagery more accurately classified forests and non-forest areas. This effect shows the tendency of very high resolution imagery to produce canopy shadows that lead to false classifications. It is important for conservationists to do ground studies in order to produce better training data for forest classifications of high resolution imagery.

Despite high costs of high-resolution imagery, our results show its significance in detection of smaller patches. For measurements of connectivity within landscapes where small patches serve as stepping stones for most species within the larger ecosystem, it is important for conservationists to consider the spatial resolution of images used in the analysis. Also, in studies where forest loss detection is a primary aim, it is important to consider the resolution of images used in fragmentation analysis as they influence results. Preferably, high resolution images should be used in such studies.

Our study, based on 30 m, 20 m, 10 m, 0.25 m and 0.03 m spatial resolution images, missed some important intermediary information. Considering the poor performance of the coarse resolution images (30 m and 20 m) and improvement of the accuracy of 0.25 m over 0.03 m resolution images in identifying forest patches, it will be expedient to know if an image of between 5 m and 10 m spatial resolution, can perform even better. The inclusion of an image with spatial resolution between 5 and 10 m, will be helpful in illuminating this research interest.

The study area for this research consists of agricultural, forest and low density residential areas. With agricultural and forest areas having similar reflectance spectra, but vastly different from the reflectance spectra of non-vegetation, our study area might be missing some important spectral information. Higher resolution imagery might be more convenient in areas with relatively denser residential constructions, compared to our study area. Moving forward, it is important for this research to be replicated in other areas with differing vegetation and non-vegetation combinations, to assess the accuracies of high and coarse resolution imagery.

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