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A REVIEW OF ASSESSING THE IMPACT OF UAV IMAGES FOR LAND COVER ANALYSIS

Srijit SHARMA[1]* Paul NOVAK[1]

[1] University College, University of Denver, CO, USA.

*Corresponding Author: S. Sharma, srijit.sharma@du.edu 0000-0002-1702-8304

ABSTRACT

Land cover maps are an important tool to understand global change and various landscape analyses. Accurate land cover maps are important for their precise application in forest conservation and snow-melt analysis. Satellite images are used as a data source for preparing land cover maps. This review evaluates the use of Unmanned Aerial Vehicles (UAV) as an alternative technology to produce a more accurate land cover map. Throughout the comparative study it is found that higher spatial resolution of the images generally leads to improved overall accuracy of the land cover product. UAV images are found to have the highest overall accuracy compared to other satellite imagery. The review also highlighted that UAV images are not feasible from an economic perspective if the land cover analysis needs to be carried out over a large area. Therefore, it is concluded that UAVs are a good alternative tool for high-precision, local-scale land cover mapping, but satellite imagery is suitable for regional and global monitoring.

Keywords: UAV, Land Cover, Remote Sensing, High Resolution Imagery, Spatial Resolution, Land Cover Classification.

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1. INTRODUCTION

Land cover maps are widely considered a tool to monitor global change (Verburg et al. 2011). The land cover map represents the region by forest, wetlands, impervious surfaces, agriculture, water, and other land types. A series of land cover maps over time can be used to monitor the various changes in the land. The changes in land cover are rapid and significantly impact people, the economy, and the environment (National Ocean Service 2024). Such land cover change data have many applications; they are mostly used in climate change modeling, flood modeling, agricultural drought analysis, monitoring environmental changes, and forest change detection (Mora et al. 2014).

Providing a highly accurate land cover map is still a challenge in today's world. So far, satellite images are being used to determine the land cover maps, whose resolution is very low compared to that of UAV images. The most used satellite image, Landsat 7, has a spatial resolution of 30m (Dewitz and USGS 2021), and MODIS imagery has a spatial resolution of 250m, 500m, and 1km according to data type (NASA 2026). The National Land Cover Database (NLCD), created by the US Geological Survey, used Landsat 30m resolution images (Dewitz and USGS 2021). The land cover output from these images may not provide an accurate result of the places where there are drastic changes in land cover types. Many components, such as the amount of glacier melt and change in river pattern, are subject to annual changes between a few inches and a few meters each year (Lindsey 2020). Landsat and MODIS imagery with a pixel spatial resolution of 30m and 250m will not be able to monitor the change of 1-2 meters. The understanding of change in river pattern is important to estimate the flood probability. Understanding the flood probability would help people prepare for land erosion and several other losses. Furthermore, approximately 1.2 trillion tons of ice are melting each year, resulting in rising sea levels (Mooney and Freedman 2021). An accurate land cover map can be used to correctly monitor such ice melt. To address such issues, it is important to determine land cover change using imagery with high spatial resolution.

Unmanned Aerial Vehicles (UAVs) are also capable of monitoring land cover change. The UAV images are captured at low elevation, which provides high-resolution images. Satellite image issues, such as cloud cover or lack of data on the desired date, can be addressed using UAV imagery (Jumaat et al. 2018). In recent days, the UAVs have advanced from the experimental phase to ultra-high resolution mapping, driven by the integration of diverse technologies such as radar, RF sensors, acoustic detectors, and optical imaging systems. The integration of Machine Learning and Artificial Intelligence in this technology has enabled more accurate and reliable systems (Semenyuk et al. 2025). The integration of LiDAR in airborne systems has allowed a new dimension toward the classification feature space, where distinguishing elevated features (such as buildings, trees) from ground features is not possible using a single satellite remote sensing image. Further, LiDAR intensity data collects the backscattered laser energy at the NIR wavelength, which allows for the differentiation of the land cover types. This allows for differentiating man-made features and ground features (Yan et al., 2015). Thus, this review aims to use high-resolution UAV images over satellite images to provide a more accurate land cover map for forest conservation and various climate change analyses.

The accurate land cover map can be used as a key component to determine the global change (Ge et al. 2007). It can be used to analyze the change in land cover, hydrography, and snowmelt over time. The accurate map will help government bodies to engage in good land planning, determine the snowmelt, understand the pattern of land cover change, and predict the future landscape in a particular area. It helps the nation to control problems like rapid urbanization, uncontrolled development, loss of forest and wildlife, and decreases in agricultural land.

1.1. Problem Statement

While numerous studies have been carried out to study the use of UAVs for land cover analysis, the accuracy of UAVs, a comprehensive synthesis comparing UAV and satellite imagery in terms of their relative accuracy, cost, and scalability is still lacking. Previous studies have focused on generating accuracy assessments for UAVs through confusion matrices or have emphasized their applications. Others have concentrated on single case studies or specific sensor comparisons. Furthermore, the economic trade-off between these technologies has not been evaluated across different project scales.

2. APPROACH

A narrative literature review approach is adopted to understand the impact of UAVs on land cover classification. The existing literature on land cover mapping is highly heterogeneous in terms of classification methods, number of classes, sensor spectral/radiometric properties, and scale of the project. This makes it difficult to conduct a systematic review with standardized criteria and directly comparable quantitative metrics.

Literature was identified through targeted searches using the keywords “landcover”, “Remote Sensing”, “UAV”, and “Accuracy assessment”. Rather than cataloging all available studies, the available journal articles and conference papers were manually screened. Priority was given to papers that include classification accuracy metrics (e.g., overall accuracy, confusion matrices, and kappa index) and also discuss other constraints such as cost, processing time, and project scale, and studies after 2000 were given more preference.

3. LITERATURE REVIEW

3.1 Land Cover, Land Use, and Resolution

The Food and Agriculture Organization (FAO) defines land cover as the observed (bio) physical cover on the earth’s surface (Di Gregorio and Jansen 2000). The different types of physical coverage could be forest, grassland, cropland, lakes, wetland, etc. Land use is the second important term that is mostly used together with land use. The ocean services describe land cover as the representation of the physical land type, such as forest or open water, whereas land use documents how people are using the land, whether for development, conservation, or mixed uses (National Ocean Service 2024). The report of Environment (ROE) published by the United States Environmental Protection Agency describes land use as the representation of economic and cultural activities such as agricultural, residential, industrial, mining, and recreational uses that are practiced in a given map (US Environmental Protection Agency 2008).

Land cover maps can be used for various purposes such as environmental monitoring, land management, and policy making. Land cover datasets are a tool for decision-making and shaping policies worldwide (Kovacic 2025). The land cover data and maps are also used by coastal managers to understand the current landscape. The land cover map helps coastal managers to assess urban growth, model water quality issues, predict and assess impacts from floods and surges, track wetland losses, determine impacts of sea level rise, prioritize areas for conservation, and compare the land cover changes (National Ocean Service 2024).

Resolution refers to the smallest size at which an object or detail can be represented in an image. Higher-resolution images have a smaller pixel size, which provides more details, while lower-resolution images have a larger pixel size, which provides fewer details (Setyawan, 2019). There are four types of resolutions for satellite imagery (Navulur 2006):

i. Spatial resolution: It represents the length of the side of the pixel. The greater spatial resolution allows precise identification of features. The use of spatial resolution can be considered depending on the application. For large area change detection, it is economical to use medium resolution imagery, and for planimetric applications, it is recommended to use imagery with the highest possible resolution that can be used to extract various features such as pavements, roads, etc.

ii. Spectral resolution: This represents the number of spectral bands of the given sensor. For most GIS applications where images are primarily used as a backdrop, three-band natural color imagery in RGB format is commonly used. For extracting information such as impervious surfaces and vegetation classification, visible and near-infrared (VNIR) bands are utilized, whereas applications like mineral exploration and forest species classification rely on multispectral or hyperspectral data.

iii. Radiometric resolution: This represents the number of gray levels that can be recorded for a given pixel. The higher radiometric resolution gives better discrimination of variations in reflectance.

iv. Temporal resolution: This represents the time frequency at which the sensors cover the same area of interest (AOI). Issues such as cloud cover can be minimized by using satellites with higher temporal resolution (Navulur 2006).

Table 1 briefly describes the representation and characteristics of the four types of resolutions discussed.

Table 1. Types of Resolution for satellite imagery (Navulur 2006).

Resolution Type	Representation	Characteristics
Spatial	Length of the side of a pixel	Spatial Resolution is defined by Ground Sampling Distance (GSD). Commonly, Low resolution is defined as pixels with a GSD of 30 m or greater resolution, medium resolution is GSD in the range of 2.0–30 m, high resolution is GSD 0.5–2.0m, and very high resolution is pixel sizes < 0.5m GSD. The smaller the pixels, the more details are visible.
Spectral	Number of bands of the given sensor	Multispectral sensors have fewer than ten bands, superspectral sensors have bands greater than ten, and hyperspectral sensors usually have bands in hundreds. With higher spectral resolution, one can extract better information, such as impervious surfaces, vegetation classification, etc.
Radiometric	Number of gray levels that can be recorded for a given pixel	A radiometric resolution of 8 bit radiometric resolution can capture DN values ranging from 0 to 255. The value can be calculated using the equation $N = 2^R$, where N is the range, and R is the radiometric depth.
Temporal	Time frequency at which the sensors cover the same AOI.	The sensor that visits the AOI every day has higher temporal resolution than the sensor that revisits the AOI monthly. Temporal resolution is important for change detection.

3.2 History of Land Cover Maps

The era of land cover mapping started in the early 1970s. Civil space-based remote sensing came into the age in the early 1970s. The 1970s are the foundational period for space-based land cover mapping. The 1970s era was influenced by two major events of the mid-1960s. First, William Pecora (Director of the US Geological Survey) proposed an idea about a civilian remote sensing satellite program to collect information about the natural resources of the Earth. Second, NASA conducted a series of remote sensing investigations using an image-capturing infrastructure mounted on an aircraft. These two events resulted in the launch of NASA's Earth Resources Technology Satellite in 1972, which is now known as Landsat. Later, a draft 'A Land Use and Land Cover Classification System for use with remote sensor data' was published in 1976, which provided a classification legend that defined land use and land cover categories to be derived from remote sensing images (Anderson et al. 1976). The launch of Landsat and the framework for land cover mapping today serve as a framework for land cover mapping using satellite images, even though it was a manual approach rather than a computer-assisted method (Giri 2012).

The 1980s were the point where the rapid growth of land cover mapping methods and projects happened. Three major factors influenced this decade in land cover mapping. First, computer-assisted methods were developed for land cover mapping. Second, Landsat data quality was improved with the Thematic Mapper instrument, and Landsat was commercialized, which made a heavy impact on the land cover initiative. The spatial details obtained from Landsat needed some improvement to gain efficiencies through the digital imagery. Anderson from USGS recognized this need and led his team in the initial research of land cover classification. He tried to provide an accurate land cover map with Landsat data and developed an automated classification method (Anderson et al. 1976). In the late 1970s and early 1980s, many land cover mapping programs were initiated across the United States in Arizona, Kansas, Nebraska, North Dakota, South Dakota, and Texas. The land cover mapping again boosted in 1982 when Landsat launched a new sensor called 'Thematic Mapper (TM)', which improved the accuracy of the data with spatial and multispectral capabilities. The Landsat resolution was improved from 79 meters to 30 meters (Giri 2012).

The 1990's is when the start of national to global land cover mapping happened. The Advanced Very High-Resolution Radiometer (AVHRR) based land cover project was started in this global land cover mapping era. The 1990s can also be called the end of the commercial Landsat era, which contributed to the growth of national-scale Landsat-based land cover mapping and allowed investment in land cover programs. The use of the time-series dataset and derived seasonal metrics excluded the limited coarse-resolution imagery. The seamless dataset was available, which reduced the problem of scene boundaries. The use of ancillary data and stratification helped increase classification accuracy. The data were available for new satellite missions like the India Remote Sensing satellite, which increased the innovation in the land cover mapping (Giri 2012).

The first decade of the twenty-first century was when operational mapping became more mature, and researchers' emphasis on land cover change studies increased. The land cover monitoring matured in this period with the launch of NASA Terra and Aqua Terra with the Moderate Resolution Imaging Spectroradiometer (MODIS). The accuracy assessment was less common, but the accuracy standards for land cover products were established and matured significantly. Most land cover practices started to include validation as a standard practice (Giri 2012).

During the second decade of the twenty-first century, the European Space Agency's (ESA) Copernicus program introduced the launch of Sentinel Satellites. The first of the Sentinel series, Sentinel-1A, was launched on 3 April 2014, followed by Sentinel-1B on 25 April 2016. For land monitoring, Sentinel-2A was launched on 23 June 2015, followed by Sentinel-2B on 7 March 2017. Sentinel-2 is a polar-orbiting, multispectral high-resolution imagery at spatial resolutions from 10m to 60m across 13 spectral bands, with its core applications including land cover classification and forest monitoring. On 5 September 2024, Sentinel-2C was launched into orbit to ensure the continuous provision of high-resolution data from the mission (ESA, n.d.).

Similarly, the use of Very High Resolution (VHR) satellite imagery has significantly advanced in land cover mapping. DigitalGlobe's QuickBird was launched on 18 October 2001, which was the first commercial satellite to offer sub-meter imagery, collecting data at 0.65m resolution. The QuickBird satellite was switched off on January 27, 2015, after completing 70,000 trips around the globe and capturing around 636 million sq km of high-resolution imagery. WorldView-1 was launched on 18 September 2007, with a resolution of 0.50 m and has a daily collection capacity of up to 750,000 square kilometres (Satellite Imaging Corporation, n.d.).

Under the French-Italian ORFEO programme, Pléiades-1A was launched on 17 December 2011, followed by Pléiades-1B on 2 December 2012, both operating at 0.5 m resolution with daily revisit capability over any point on Earth. (CNES, 2025) Concerning the history, it is assumed that the land cover technology will lead towards innovation in the future, and the remote sensing satellite imagery will be much cheaper (Giri 2012).

3.3 Accuracy in the land cover map

Unlike the satellite image, the land cover map is not the perfect representation of reality. In remote sensing, the term accuracy means the degree of correctness of the map. No map is 100% perfect, and to determine the degree of correctness, it is necessary to conduct an accuracy assessment. The result of the accuracy assessment gives the overall accuracy of the whole map as well as the accuracy of each class in the map (Horning 2004). There is no accepted standard method of accuracy assessment. However, the confusion matrix is the most popular method for accuracy assessment. The confusion matrix will determine the confusion between each class within the map. In the confusion matrix, commonly, the data is represented in percentage cases, as it is easy to interpret. The confusion matrix provides a summary of two types of thematic error present: omission error (producer's accuracy) and commission error (consumer's accuracy). Producer's accuracy determines how well the reference pixels from the ground are classified in the map, and consumer's accuracy determines how well the classified category in the map represents the ground. However, the non-thematic error is not represented in the confusion matrix, which may be large and could have a larger effect. The problems, like mixed pixels and misregistration of the data set, may not be incorporated (Foody 2002).

Liang et al. (2019) studied the accuracy evaluation and consistency analysis of different land cover products. The study was conducted in the Arctic Region. Land cover products from four different sensors - Climate Change Initiative Land Cover (CCI-LC), GlobeLand30, Global Land Cover by the National Mapping Organization (GLCNMO), and Moderate Resolution Imaging Spectroradiometer

(MODIS) were utilized. The land cover product was refined to nine different classes: Shrub, sparse vegetation, Wetland, Snow/Ice, Trees, Herbaceous, Cropland, Artificial Surface, and Water. For accuracy assessment, validation point data were collected, and a confusion matrix was prepared. The accuracy assessment proved CCI-LC to be the most accurate product with an overall accuracy of 63.5%. GlobeLand30 and GLCNMO were found to have an overall accuracy of 62.2% and 48.8%, respectively. The MODIS land cover product was found to have the lowest overall accuracy of 29.5%. The spatial resolution of Globe30 is highest at 30m, followed by CCI-LC and MODIS with 300m for both. GLCNMO has the lowest resolution of 1 km. CCI-LC was found to have the highest overall accuracy and has good accuracy for the forest, shrubs, sparse vegetation, snow/ice, and water bodies. GlobeLand30 and CCI-LC have a good output for the classification of the shrub. MODIS and GLCNMO product having a very low resolution are omitted for classification in the Arctic region. CCI-LC and GLCNMO have comparatively better accuracy, but the author believes the current land cover products are not ideal in terms of accuracy for classification studies in the Arctic Region (Liang et al. 2019). The comparison of accuracy of the selected land cover products in Arctic region is presented in Table 2, where CCI-LC with resolution of 300m demonstrates the highest overall accuracy among the datasets.

Table 2. Land Cover Products accuracy in the Arctic Region.

Study	Objective	Sensors	Resolution	Accuracy	Conclusion
Liang et al. (2019)	Accuracy evaluation and consistency analysis of different land cover products in the Arctic Region	CCI-LC	300m	63.5%	Land cover products are not ideal in terms of accuracy for classification studies in the Arctic Region
		Globe-Land30	30m	62.2 %	
		GLCNMO	1 km	48.8%	
		MODIS	300m	29.5%	

3.4 Impact of Spatial Resolution on Map Accuracy

The spatial resolution of the image is a basic characteristic of a remote sensing image, which makes a heavy impact on the accuracy of the image classification. The improper selection of spatial resolution may lead to an ambiguous interpretation of the products. Land use, land cover classification using a single sensor may result in limitations like low classification accuracy and adaptability. Mishra et al. (2016) evaluated the land use, land cover classification accuracy using 3 different sensors. LISS IV with 5.8 meters, Landsat 8 with 30 meters, and AWiFS with 56 meters spatial resolution were used for the study. Images were imported to ENVI (remote sensing image processing software) for classification and were classified into seven different classes as Agriculture land, Dense vegetation, Sparse vegetation, fallow land, built-up, water bodies, and sand. For the accuracy assessment, 438 sample points with 30-43 points for the individual class were checked. The overall accuracy of 83.28%, 77.93%, and 74.61% was determined for LISS IV, Landsat 8, and AWiFS sensors. The result indicates a slight increase in overall accuracy with an increase in spatial resolution from 56m to 5.8m. The study concludes that better spatial resolution reduces mixed pixel problems, which helps in providing a greater extent of information from land use/land cover data sets. Thus, the increase in spatial resolution results in an increase in the overall accuracy of the land use/land cover map (Mishra et al. 2016).

Fisher et al. (2018) project has researched to determine the impact of satellite imagery resolution on land use classification to model the water quality. The objective of their study were:

To assess the influence of the spatial resolution of satellite images on the accuracy of the land cover classification and the estimated sediment load at the plank intake.

To evaluate the technical and economic trade-offs associated with using two images of different resolutions.

DigitalGlobe's Quickbird and Worldview 2 satellites of spatial resolution 0.6m and 0.5m, respectively, and Landsat of 30m were considered for the study. The DigitalGlobe images were resampled to 1m, as the DEM used for the study was 1 m. Land use classification was conducted via ArcGIS feature analyst and on the total suspended solids (TSS) load estimates from the Soil and Water Assessment Tool (SWAT). The study was conducted for the Camboriu watershed in southeastern Brazil. The land use accuracy from DigitalGlobe with 1m spatial resolution was determined 82.3%, and for Landsat data with 30m spatial resolution was calculated as 75.1%. For annual and peak TSS load in the whole study area, however, Landsat data with 30m resolution predicted better only in the sub-watershed. (Fisher et al. 2018)

There have been lots of investments to obtain the accuracy of land cover datasets. However, the accuracy may not hold the same importance when the products are on different scales. It is important to understand the relationship between map error, the scale of observation, and scene spatial structure to understand the scaling issues and their implication of accuracy in land cover data. Moody and Woodcock (1994) have tried to develop an understanding of the factor of scale in errors in the estimation of land cover proportions for the implications of the global land cover dataset. The authors tried to develop an understanding of the size and spatial pattern of vegetation classes, which influenced errors in estimating cover type proportions as the classified scene was progressively aggregated to coarser resolutions. The purpose of the study is to understand the relationship of the proportional error to scale or spatial resolution. The study focuses on the use of land cover data at various scales using remotely sensed data, and the subsequent use or further aggregation of the datasets. The study area was in the western part of the Plumas National Forest in the Sierra Nevada, California. The images were collected from Landsat Thematic Mapper imagery, which is of 30m resolution, and an unsupervised image classification approach was used to produce a land cover map. The research deals with vegetation classes, so the land cover classes for the study include barren/grass, brush, hardwood, meadow, conifer, and water. The 30m resolution per pixel land cover map of the Plumas National Forest study was used as a base data to compare it with coarser resolution maps. Resolutions of 30, 90, 150, 240, 510, 1020, 3000, and 6000 meters were considered for the study. The 240-, 510-, and 1020- meter resolution is roughly close to the MODIS spatial resolution. Each resolution of interest was created using a polygon grid as a sampling frame. It was seen that the proportional errors in a forested area (such as conifer class) increased as the resolution exceeded 90 meters. Classes that are characterized by highly clumped distribution but small in size decreased in size as the resolution was increased. Small classes with fragmented units disappeared as they were dominated by large cover types through the aggregation procedure. The author considers that these errors may pose difficulties for the use of land cover products derived from coarse resolution sensors such as MODIS (Moody and Woodcock 1994). Table 3 summarizes the studies from Mishra et al. (2016), Fisher et al. (2018) and Woody and Woodcock (1994), highlighting imagery with higher spatial resolution has more accuracy.

Table 3. Impact of spatial resolution on map accuracy.

Study	Land Cover Classes	Imagery Source (Resolution)	Accuracy Result	Conclusion
Mishra et al. (2016)	7 classes (Agri, Dense/Sparse Veg, Fallow, Build-up, Water, Sand)	LISS IV (5.8m)	83.28%	Higher resolution reduces the "mixed pixel" problem, leading to better accuracy and more detailed information.
		Landsat 8 (30m)	77.93%	
		AWiFS (56m)	74.61%	
Fisher et al. (2018)	Not specified (used for TSS Load modeling)	DigitalGlobe - QuickBird (0.6m) and WorldView 2 (0.5m) Resampled to 1m	82.3%	High resolution is more accurate
		Landsat (30m)	75.1%	

Moody & Woodcock (1994)	6 classes (Barren/Grass, Brush, Hardwood, Meadow, Conifer, Water)	Landsat, Coarser Resolution Land Cover Map of Plumas National Forest (30m to 6000m aggregated)	Errors increased significantly once the resolution exceeded 90m.	Coarse resolution causes small or fragmented land classes to "disappear" as they are absorbed by larger, dominant cover types.

3.5 Operational and Technical aspects of Satellite Image and UAV

In Fisher et al. (2018)'s research, the authors determined that the cost of using 1m high-resolution data from DigitalGlobe is $6969, whereas there is no cost for a 30m resolution Landsat image. Using high-resolution images takes extra storage and a longer processing time. The author evaluates that it takes 4 times longer to process for land-use classification using the same hardware device. In terms of technical and economic tradeoff, it is beneficial to work on low-resolution images rather than high-resolution images (Fisher et al. 2018).

Foster et al. (2024) and team discuss the cost-effectiveness of remote sensing technology for spruce budworm monitoring in Maine, USA. The study analysed comparing remote sensing data and ground sampling techniques, with an integrated monitoring approach that combines remote sensing change detection with field sampling. For the remote sensing technique, Sentinel-2 imagery, PlanetScope imagery, and UAV images were taken. The study presented that Sentinel 2 is the most cost-effective option, with costs ranging from US $33 to $63 per sq km to accomplish the task. PlanetScope ranged from US $ 77 to US $ 241 per sq km, and UAV imagery had a great variation from US $9,220 to US $58,481 per sq km. The integrated approach ranges from $144 to $213. The integrated monitoring approach proposed in this study costs range from US $144 to US$213 per sq km. It was found that labour costs accounted for the highest for remote sensing analysis, making up about 30% of the total cost, while in field sampling, the labour cost accounts for nearly 80% of the total cost (Foster et al. 2024).

Sozzi et al. (2021) and team conducted an economic comparison of satellite, plane, and UAV-acquired NDVI images to define a decision-making process for site-specific nitrogen application. The study was carried out in Italy, where the price of satellite, plane, and UAV were considered to acquire vegetation indices. The result was compared to the economic benefit resulting from variable-rate nitrogen application. The results showed that the medium resolution satellite (10m to 15m) is profitable for a minimum field size of 2.52 ha. The high-resolution satellite imagery becomes profitable from 13.2 ha, while the very high-resolution satellite imagery becomes profitable after 76.8 ha. Similarly, an airplane-acquired NDVI is profitable after a field size of 66.4 ha. The UAV was not found economically profitable for variable rate nitrogen fertilization of grains, as the average price per hectare was higher than the average economic benefits resulting from their use. The break-even costs were found at €83.1 for medium-resolution satellites, €434 for high-resolution satellites, €2,191 for aircraft imagery, and €2,536 for very high-resolution satellite imagery, while UAV imagery did not reach a profitable break-even point (Sozzi et al. 2021). Table 4 summarizes the studies from Fisher et al. (2018), Foster et al. (2024), and Sozzi et al. (2021), where UAVs are generally not economically viable, and satellite or aircraft imagery are found cost-effective only for larger field sizes.

Table 4. Economic aspect of Satellite imagery and UAV.

Study	Data used	Findings	Conclusion
Fisher et al. (2018)	DigitalGlobe's - QuickBird and WorldView 2, and Landsat	**Cost:** DigitalGlobe: $6,969 and Landsat: $0 **Processing:** High resolution image takes higher storage and 4 times more processing time than lower resolution images	Purchasing and processing high-resolution imagery is costly.
Foster et al. (2024)	Sentinel -2, PlanetScope, UAV imagery, and integrated monitoring with field sampling	Sentinel-2: $33-$63 per sq km PlanetScope: $77-$241 per sq km UAV: $9,220 - $58,481/ sq km Integrated approach: $144 - $213 per sq km	The operational cost of UAV is very high than using satellite imagery. Labour cost accounts 30% for remote sensing cost and 80% for field sampling cost

Sozzi et al. (2021)	Satellite (medium, high, very high resolution), aircraft imagery, and UAV	**Break-even costs:** Medium-resolution satellite: €83.1 High-resolution satellite:€434 Aircraft €2,191 Very high-resolution satellite €2,536 UAV: not profitable **Profitability on field size:** Medium-resolution satellites: 2.52 ha High-resolution: 13.2 ha Aircraft: 66.4 ha very high-resolution satellites: 76.8 ha UAV: not profitable	UAV imagery was not economically profitable

3.6 Comparing the satellite image and the UAV image

There are numerous benefits of using UAVs over satellite images for landscape analysis, such as the study of land use and land cover. The major disadvantage of using satellite data is cloud cover, which makes it difficult and sometimes impossible to detect and analyze the land under the cloud. Although numerous high-resolution satellites are available, such as GeoEye and WorldView, their output may contain less visible and analyzable scene due to cloud cover (Sanga et al. 2012).

Iizuka et al. (2018) conducted a study to demonstrate the advantage of drone photogrammetry for collecting more detailed and useful local landscape information than satellite data. The postmining site in Indonesia was selected as a study area considering its complex topography and landscape. For the UAV image, considering flying height regulations, the study area was further divided into two sites, where Site 1 is in the south-central part of the island, and Site 2 is in the eastern part of the island. The satellite remote sensing data were obtained from the Advanced Land Observation Satellite-2 (ALOS-2) Phased Array L-band Synthetic Aperture Radar-2 (PALSAR-2). SAR sensor data was used to avoid cloud cover. Another dataset used was drone-based aerial photos with a DJI Phantom 4 quadcopter. Two products of land use land cover maps were generated by Satellite image (SAR) based and UAV-based data. Then, a conventional accuracy assessment was conducted with random sample points. The result of the accuracy assessment of satellite images was found to be 78.1%. Further, for

UAV image processing, 655 drone images were captured in site 1 and 517 images in site 2. Photoscan Pro software was used to generate an orthophoto. The land cover map was then generated considering four land cover classes: water bodies, vegetation, bare soil, and houses. Accuracy assessment was carried out using the ground truth points collected through imagery. The overall accuracy result was 89.9% and 94.7% for site 1 and site 2, respectively. The land cover map generated from each source has a distinct difference. The spatial resolution is the main factor, as the SAR satellite image is 7.5 and the drone image is 0.05 m. The accuracy of SAR satellite data is specifically low due to the scattering mechanism of the microwave, depending on land objects, moisture content, topography, etc. Therefore, the author believes that conventional accuracy assessment does not make sense. To compare the two maps, the Kappa index of agreement (KIA) was computed to quantify the reliability of the SAR map to the drone map. The drone Land cover map was resampled to 7.5 m using the nearest neighbor algorithm with a 3x3 mode filter. The resulting KIA value was 0.42 and 0.33 for site 1 and site 2, respectively. According to the benchmarks established by Landis and Koch (1977), a value between 0.21 and 0.40 is classified as 'fair', while 0.41 to 0.60 is considered 'moderate'. The overall result of this study falls within a fair range. Consequently, Iizuka et al. (2018) conclude that drone technology serves as a superior alternative for high-resolution local landscape analysis. Hence, the author concludes by describing drone Technology as the alternative for local landscape analysis (Iizuka et al. 2018).

Jumaat et al. (2018) studied the capability of high-resolution satellite images and UAVs to study the change in land cover patterns in Cameron Highlands, Malaysia. Further, the land cover change pattern is also studied for the time frame of 12 years. Two satellite images from IKONOS imagery acquired in March 2001 and QuickBird imagery acquired in March 2007 were used for the study. 591 UAV images acquired in November 2013 were used to produce an orthophotography and hence for classification. The image classification was conducted in ArcGIS software with an object-based classification approach. A total of seven classes were defined as follows: agriculture, water body, forest, bare soil, grass, urban area, and landslide. After the classification, accuracy assessment was carried out in each class based on overall accuracy, kappa coefficient, commission errors, and omission errors. The overall accuracy has resulted as 86.67%, 83.89%, and 93.80% for the IKONOS satellite image, Quickbird satellite image, and UAV-developed orthophoto, respectively. The author concludes that all three images are an effective way for mapping land cover. However, the overall accuracy of the result from the UAV image is highest, so there is an advantage of flying UAVs for more accurate data. UAV images can collect precise information even in hilly terrains, which makes the overall accuracy higher (Jumaat et al. 2018).

Duke et al. (2022) studied the comparison of crop classification using UAV and SAR data using machine learning algorithms. The study was conducted in experimental plots using high-resolution multispectral 12cm UAV data (resampled to 50cm for efficient data handling) with the Sentinel 1A

SAR dataset. The Support Vector Machine (SVM) classifier produced an overall accuracy of 94.78% for the UAV and 81.72% for the SAR dataset. However, with Random Forest (RF), SAR performed 92.58% and became comparable to UAV 93.84%. The author suggests that this study would be useful in mapping small farm holdings and for precision agriculture. In contrast, SAR only data provides large area coverage, making it more suitable for larger fields. Further, the study also highlighted that spatial resolution has a strong influence on classification accuracy. The finer resolutions (50 cm) produced higher accuracies, while coarser resolutions (1–10 m) led to a decline in performance, although some classes, lake and mucuna, were less affected. Moderate resolutions (around 2–5 m) still provided acceptable results, but very coarse resolution significantly reduced classification accuracy (Duke et al. 2022). Table 5 summarizes studies by Iizuka et al. (2018), Jumaat et al. (2018), and Duke et al. (2022) that compare satellite imagery with UAV data, clearly showing that UAV imagery provides higher accuracy than satellite images.

Table 5. Comparing satellite imagery with UAV imagery.

Study	Objective	Data Source	Accuracy	Conclusion
Lizuka et al. (2018)	Compare Drone vs. Satellite (SAR) for local landscape analysis in complex topography.	UAV: DJI Phantom 4 (0.05 m)	Site 1: 89.9% (KIA: 0.42) Site 2: 94.7% (KIA: 0.33)	UAVs can be considered an alternative technology for local landscape analysis. Conventional accuracy assessment is flawed for SAR due to the scattering mechanism
		Satellite: ALOS-2 PALSAR-2 (SAR) (7.5m).	78.1%	
Jumaat et al. (2018)	Analyze LULC change over a 12-year timeframe using Satellite and UAV data.	UAV: Fixed wing Helang	93.80%	Overall accuracy of UAVs is highest, hence there is an advantage of flying UAVs for more accurate data.
		Satellite: IKONOS (1m)	86.67%	
		Satellite: QuickBird (0.65m)	83.89%	

Duke et al. (2022)	Comparison of UAV and SAR performance for Crop type classification using machine learning algorithms	UAV (12cm, resampled to 50cm)	RF Classifier: 93.84% SVM Classifier: 94.78%	UAV is more accurate due to finer resolution, but SAR can still achieve competitive accuracy with robust algorithms like RF
		Sentinel 1A SAR (10m)	RF Classifier: 92.58% SVM Classifier: 81.72%	

4. SYNTHESIS OF REVIEWED STUDIES

Land cover mapping technology has evolved from 1970 to the present day. In this time, various classification systems and satellite systems have been developed, which have helped to obtain great accuracy. With time, the availability of satellite images will be easier and less costly. With the help of a land cover map, one has been able to determine the change in the forest, agricultural, and urban land, which has helped the community to preserve the forest.

The spatial resolution of the image makes a great impact on the accuracy of land cover products. The higher spatial resolution makes it easy for a user to identify the object in the image, through which the user can provide a correct spectral signature for image classification. It is found that the increase in spatial resolution increases the overall accuracy of the land cover map. The classified image scale is equally important to maintain accuracy. For land cover classification using images from the coarse resolution satellites like MODIS, pose difficulties like the disappearance of small classes and an increase in proportional error in forested area classes. It is important to analyze the original spatial resolution of the image and the product scale of the classified image. The coarse satellite images should not be used to represent the large-scale classification maps.

The use of UAVs is becoming popular and can serve as an alternative technology for landscape analysis, including land cover classification. UAVs fly at a lower height and achieve a greater ground sampling distance, which enables the capture of finer details from the image. With UAVs, there are no issues with cloud cover, poor image quality, or difficulty collecting images on a desired date. Further, UAV image resolutions are very high compared to satellite images. UAVs are capable of capturing images in any landscape, which plays a great role in increasing the overall accuracy of the land cover product. The SAR sensor satellite omits the cloud cover issue, but its accuracy is found to be low compared to the UAV image. The accuracy of SAR images is highly sensitive to land objects, moisture contents, topography, and the scattering mechanism of the microwave, which can be avoided by UAV images.

High-resolution satellite images, like Quickbird and Worldview 2, can also be used to increase the overall accuracy. Considering the technical and economic tradeoff, low-resolution satellite images can be considered much more reliable. The use of images from DigitalGlobe is very expensive compared to that of freely available, low-resolution, commonly used satellite images like Landsat and MODIS. Processing a high-resolution image requires additional processing time and hardware storage. The overall accuracy can be achieved with high-resolution images, but it is not reliable from the technical and economic points of view.

The economic tradeoff for using UAV images over satellite images depends on the scale of the project. The use of UAV images are found to be very costly for large-scale projects (eg, national-level land cover classification or state-level land cover classification) (Fisher et al., 2018; Foster et al., 2024; Sozzi et al., 2021). They are more economical for small projects covering a smaller area, such as local-level or municipal-level projects. UAV images require additional processing before classification. Initially, an orthomosaic must be developed using dedicated UAV processing software, which requires extra technical resources. Collecting UAV images demands extra fieldwork, skilled human resources and time. The UAV images are larger in size and need extra storage capacity. From a technical point of view, using high-resolution satellite images can be much more reliable compared to UAV images.

5. HYPOTHETICAL ACCURACY ANALYSIS

From the literature review, a large set of data was found, discussing accuracy across different study areas, sensors, classification methods, and the number of classes. A hypothetical accuracy analysis is carried out to address the lack of a unified quantitative comparison across the cited literature. The accuracy values compared here are drawn from studies with variation in numbers of classes, geographies, and classification algorithms. Across the cited literature, the geographies span tropical Indonesia, highland Malaysia, temperate Italy, and the Arctic, etc., and the classification algorithms include object-based, pixel-based, Support Vector Machine, and Random Forest approaches, etc. Each of these factors independently influences the overall accuracy. This analysis presents the descriptive summary in broad trends rather than a statistical benchmark, hence, the result should be interpreted considering these limitations.

5.1 Data Extraction

An overall accuracy across the sensors are collected from the cited literature. The sensors are then classified as per their category: Very High Resolution (≤1 m), High Resolution (> 1 m and ≤ 10 m), Medium Resolution (> 10 m and ≤ 30 m), Low Resolution (>30 m), SAR Satellites, and UAV. Table 6 consolidates the overall accuracy values found across various literature cited in this paper.

Table 6. Overall accuracy as per sensors from cited studies.

Study	Sensor	Resolution	Sensor Category	Accuracy
Liang et al. (2019)	CCI-LC	300m	Low resolution	63.5%
	GlobeLand30	30m	Medium resolution	62.2 %
	GLCNMO	1 km	Low resolution	48.8%
	MODIS	300m	Low resolution	29.5%
Mishra et al. (2016)	LISS IV (5.8m)	5.8m	High Resolution	83.28%
	Landsat 8 (30m)	30m	Medium resolution	77.93%
	AWiFS (56m)	56m	Low Resolution	74.61%
Fisher et al. (2018)	DigitalGlobe - QuickBird (0.6m) and WorldView 2 (0.5m) Resampled to 1m	1m	Very High Resolution	82.3%
	Landsat (30m)	30m	Medium Resolution	75.1%
Lizuka et al. (2018)	DJI Phantom 4 (Site 1)	0.05m	UAV	89.9
	DJI Phantom 4 (Site 2)	0.05m	UAV	94.7
	ALOS-2 PAL-SAR-2 (SAR)	7.5m	High Resolution / SAR	78.1
Jumaat et al. (2018)	Fixed wing Hel-ang	Not mentioned	UAV	93.80%
	IKONOS	1m	Very High Resolution	86.67%
	QuickBird	0.65m	Very High Resolution	83.89%

Duke et al. (2022)	UAV (Using SVM Classifier)	12cm	UAV	93.84%
	UAV (Using RF Classifier)	12cm	UAV	94.78%
	Sentinel 1A SAR (Using SVM Classifier)	10m	High Resolution / SAR	81.72%
	Sentinel 1A SAR (Using RF Classifier)	10m	High Resolution / SAR	92.58%

5.2 Hypothetical Analysis Summary

A group of 17 data were re-classified in Table 6 as per the sensor category, to provide a descriptive accuracy performance. Three observations were considered in SAR as well as high-resolution imagery. Table 7 presents the number of observations, minimum overall accuracy, maximum overall accuracy, and mean overall accuracy as per the sensor category.

Table 7. Hypothetical Analysis of Sensor Accuracy.

Sensor Category	No. of Observations	Minimum Overall Accuracy (%)	Maximum Overall Accuracy (%)	Mean Overall Accuracy (%)
UAV	5	89.9	94.78	93.40
SAR	3	78.1	92.58	84.13
Very High Resolution (≤1 m)	3	82.3	86.67	84.29
High Resolution (> 1 m to ≤ 10 m)	4	78.10	92.58	83.92
Medium Resolution (> 10 m to ≤ 30 m)	3	62.20	77.93	71.74
Low Resolution (> 30 m)	4	29.50	74.61	54.10

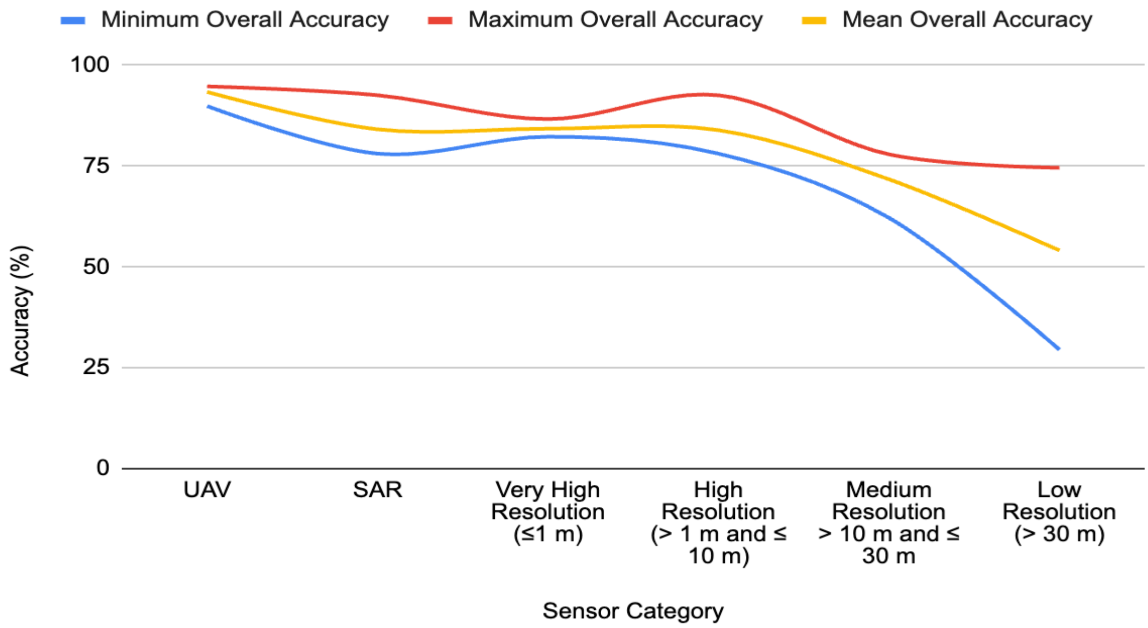

Figure 1. Hypothetical Analysis Chart of Sensor Accuracy.

The analysis presented represents the accuracy trend discussed from the literature review. Among all of the sensor types, UAV consistently achieved the highest mean overall score with 93.40%, followed by Very High resolution imagery with 84.29% and SAR imagery with 84.13%. The high resolution imagery was found with an overall accuracy of 83.92%, while medium resolution decreased to 71.74%, and low resolution with 54.10%. The SAR satellite category shows a wide range (78.10% to 92.58%), representing a wide range of sensitivity as per the classification algorithm choice (Duke et al. 2022).

The trend highlights that UAV has the highest overall accuracy, and it can be understood that the image resolution plays an important role in obtaining the overall accuracy. As UAV has the highest resolution, it can be considered as an alternative technology for high accuracy land cover classification. The 3 SAR imagery, which all being high resolution, the SAR imagery has higher mean overall accuracy than the accuracy of very high resolution imagery. It can be understood that SAR imagery can obtain higher

The trend indicates that UAV data achieves the highest overall accuracy, which can be understood as spatial resolution plays a crucial role in obtaining classification accuracy. Due to its very high resolution, UAV imagery can serve as an alternative technology to achieve highly accurate land cover maps. Among the three high-resolution SAR datasets, the mean overall accuracy is higher than that of very high resolution optical imagery. This implies that SAR imagery can provide comparatively strong classification performance; however, the hypothetical analysis shows that its overall accuracy still remains lower than that achieved by UAV data.

6. DISCUSSION

6.1 Impact of resolution and other factors on accuracy

The studies in the literature review gave in-depth information about the importance of spatial resolution and its impact on the accuracy of land cover classification products. Most literature highlighted that an increase in spatial resolution gives better accuracy; the UAV imagery was found to have the highest accuracy compared to that of satellite imagery. It is understood that with an increase in spatial resolution, one could identify the objects clearly in the image. With this, the user can provide a better spectral signature that would correctly classify the image.

However, studies from coarse resolution products in the Arctic Region indicate that spatial resolution cannot guarantee the accuracy of the classification. Liang and team (2019) showed that the accuracy of GlobeLand30, having 30m resolution, was lower than that of CCI-LC, having 300m resolution, in the Arctic. This suggests that landscape homogeneity, spectral signature, and sensor characteristics can outweigh the resolution advantage.

Further, the literature suggests that several factors—such as the number of classes selected, the choice of classification approach, the nature of the landscape, and data quality, also influence the overall accuracy. It is necessary to apply atmospheric correction to an image before classifying, as this will determine the true surface reflectance value, removing the atmospheric effect. (Themistocleous and Hadjimitsis 2008). A study has shown that there is a decrease in 0.77% of maps' overall accuracy with an increase in class (Thinh et al. 2019). There are two classification methods in remote sensing: Pixel-Based Image Analysis (PBIA) and Object-based image analysis (OBIA), with supervised and unsupervised classification approaches; these classification methods make a heavy impact on the overall accuracy of the product.

Spectral resolution also plays a vital role in classification accuracy. Navulur (2006) suggested that for most GIS applications where satellite images are used as a backdrop, three-band natural color imagery in RGB format is commonly used. For vegetation classification, visible and near - infrared can be used, and for more detailed applications such as mineral exploration and forest species classification, multispectral or hyperspectral data can be used. The finer the radiometric resolution, the more it can detect small features through the reflected or emitted energy. It can therefore be assumed that a finer radiometric resolution increases classification accuracy. However, a detailed study is necessary to understand the role of radiometric resolution for the overall accuracy of the land cover product.

6.2 Comparison of Sensors: Optical, SAR, and UAV

Optical sensors are considered a standard for monitoring global change; however, it is frequently compromised by atmospheric conditions. UAVs can be considered as an alternative technology to address this gap, considering their capability of flying in lower elevations and avoiding the cloud cover, and their ability to integrate sensors. Using a UAV, one can collect images on the desired date, and there are no issues of cloud cover, weather, or bad image results. Fisher et al (2018) had to merge two images from different dates to eliminate the cloud cover in the image. Such issues can easily be omitted using UAVs. UAVs offer a greater ground sampling distance, which enables them to distinguish the smallest element in the image. With high resolution and greater ground resolving distance, it makes a great impact to increase the overall accuracy of the land cover classified image.

Synthetic Aperture Radar (SAR) sensors are capable of omitting cloud cover from the satellite images. However, the literature found their accuracy of land cover products from SAR sensors is still low compared to that of UAV imagery. Duke et al. (2022) found that SAR can still achieve competitive accuracy with robust algorithms like Random Forest, but its accuracy is still low compared to UAV images. The SAR sensors are not capable of interpreting the complex variable and are very sensitive to land objects, moisture contents, topography, and the scattering mechanism of the microwave. Iizuka et al. (2018) mentioned that SAR maps give an average KIA of 0.375, which is not a satisfying result for landscape analysis. UAV devices can capture an image in any type of landscape. The UAV is equipped with a 360-degree movable camera, this allows pilots to capture images from any angle. This capability enables effective imaging across diverse landscapes and topographies, while the integration of sensors further enhances accuracy.

6.3 Scalability, Technical and Economic Trade-off

The reviewed literature presents the idea on technical and economic tradeoff for using UAV over satellite images, where it is found that the decision factor is to be made by the scalability of the project (Fisher et al., 2018; Foster et al., 2024; Sozzi et al., 2021).

Image acquisition with UAV images in a small area would require less time and manpower, but in a large area, it would require many UAV devices, manpower, and powerful computers to process the images and prepare land cover maps. UAV images need additional processing before classifying an image. The orthomosaic needs to be developed from a separate UAV image processing software, which will later be used for land cover classification. Fisher et al (2018), determined that land use classification time for high-resolution images was 4 times longer than using a low-resolution image. The literature also evaluated the cost of using high-resolution satellite images with low-resolution images. The operational cost of UAV is much higher than the satellite imagery. It can be suggested that using UAVs over satellite images will require additional manpower and powerful computers, which is not economical.

Considering the technical tradeoff, to collect data from a UAV, a licensed UAV pilot is necessary to fly UAVs. Then, a separate processing software needs to be installed. Processing a UAV image is very time-consuming, which requires a hardware device with a better computer processor and RAM. The image size is very large; this may require an additional storage device.

Therefore, from the technical and economic perspective, UAV-based land cover mapping is typically feasible for the local level project covering a small area. For a national or state-level project, the economic challenge, computational demands, and longer processing time make the satellite imagery a more practical choice.

6.4 UAV as an alternative technology

The literature suggests that UAV images can be used by local bodies to evaluate their landscape (Iizuka et al. 2018). Highly accurate, high-resolution land cover imagery would help to determine an accurate change in land pattern. It can be used to understand the change in the forest, agricultural land, and urbanization growth. The climate change researchers need to work on the accuracy of inches to determine the glacier melt, change in river pattern, etc. Even the high-resolution satellite will not be able to capture the images to determine the change in inches. The use of UAVs would be a great benefit for researchers to determine such a change.

To study climate change, determining the ice melt in the Arctic region, it is important to correctly assess the land cover of the Arctic Region. Liang et al. (2019) came up with a conclusion stating there is no ideal land cover product in terms of accuracy for studying land cover change in the Arctic Region. The issue with the Arctic region is its divided and unevenly distributed surface, which is difficult to analyze with satellite imagery. UAV is capable of capturing images on any landscape surface. UAV being able to capture an image, adjusting its flying height, and having a better ground sampling distance, UAV can be taken as an alternative technology to assess the land cover of the Arctic region. It is important to find out the capabilities of UAV images over satellite images to access the Arctic region.

The major threat of using UAV imagery over satellite imagery is the availability of old data. A series of old satellite imagery data can be found on the web, which is ready for analysis. UAV is capable of capturing data in the future date, but old data cannot be found. The change in landscape analysis for past years cannot be determined using UAV images. For example, there will be no data to analyze the glacier melt for the last 5 years, but the same analysis for the next 5 years can be conducted, with more accurate data. It is necessary to store the safe for a long time for later use. Satellites keep moving on their own, and no extra effort is necessary to capture data from the satellite. Using a UAV, one needs to go to the field on the desired date and should be able to collect data.

6.5 Application of an accurate land cover map

The review also highlights various purposes of an accurate land cover map. Dalle et al. (2006) used it to monitor the impact of forest conservation. Dalle's research is evidence of how the land cover map can be used to solve real-world challenges like the conservation of a forest. Dalle has an overall accuracy of 81%. The research used a series of Landsat images from 1976, 1988, 1991, 1997, and 2000, whose spatial resolution is 30m. Regarding Varun Narayan Mishra et al. (2016) and Iizuka et al. (2018) research, we can understand that the use of high-resolution UAV images would produce more accurate land cover maps. Dalle's research, which monitors the change in the loss of forest land, can be analyzed using UAV images for more accurate results. This would increase the overall accuracy, and the result will help the community and conservationists to understand the impact and make necessary decisions.

Land cover classification technology has evolved with time. The accuracy of the land cover map and availability of the satellite imagery have been the things to be most important. The current trends indicate that the availability of data has been much easier, as most data can be ordered and downloaded from the web. The development of new sensors and high-resolution satellites has been able to provide good resolution imagery, which has made a great impact in improving the overall accuracy of the land cover products. With the end of commercialization of Landsat imagery in the 1990s, we can predict that satellite imagery will become much cheaper and eventually all satellite images will be freely available.

6.6 Limitations and Recommendations

This review is limited to a small number of manually selected literature; the findings of this review contain narrative analysis but are limited mostly to classification accuracy. Future research should prioritize a systematic review to statistically analyze classification methods, the number of land cover classes, and the choice of different sensors. Such an analysis would allow quantitative comparison and strengthen the review.

This review does not incorporate the temporal analysis and has limited information about the technological advancement of UAVs for land cover analysis. Future research can examine temporal resolution and determine how the accuracy of landcover analysis has been strengthened with the advancement of UAV technology.

While this review touches on the potential of SAR imagery, this does not prioritize the nuances of satellite imagery fusion, SAR fusion, and individual SAR bands. To strengthen the understanding of SAR alongside UAV imagery, incorporating these factors in future systematic reviews would provide a more definite roadmap for selecting accurate and cost-effective tools for landcover mapping.

7. CONCLUSION

This review analyzed the findings from various existing literature to understand the impact of UAV images for an accurate land cover map, with a focus on comparing UAV and satellite imagery on classification accuracy, operation cost, and scalability. The reviewed studies indicate that spatial resolution has a great impact on the accuracy. UAVs can achieve higher accuracy than most satellite imagery, with a mean overall accuracy of 93.40% in the hypothetical study. For comparison, very high-resolution satellite imagery reached a mean overall accuracy of 84.13%, high-resolution SAR imagery achieved 84.29%, high-resolution imagery reached 83.92%, and medium- and low-resolution imagery achieved 71.74% and 54.10%, respectively.

The reviewed literature also discusses the economic and technical tradeoff. UAVs offer high accuracy and are found flexible for local scale mapping, with advantages of their sensor's high resolution, sensor integration, and cloud cover constraints. However, UAVs are found most costly, which demands a licensed pilot, high processing time, and processing software. It is suggested that satellite imagery is indispensable for global applications due to its coverage, temporal continuity, and scalability of the project. Low-resolution satellite imagery is identified as the most cost-effective, but it has low classification accuracy. High-resolution commercial satellites bridge the accuracy gap, but the financial cost and processing time are high. In summary, it can be understood that UAVs can be preferred as an alternative technology for local-scale land cover mapping where great detail and accuracy are required, whereas satellite imagery remains the practical and economic solution for large-scale global monitoring.

This study is limited to a few manually selected literature sources, and the findings are limited to the selection criteria adopted. The future research should focus on a systematic review with defined inclusion and exclusion criteria, a comparative analysis that enables evaluation of sensor performance and classification accuracy. Further, examining temporal trends can provide insights into the technological advancement of landcover analysis with UAV technology.

This review also recommends an understanding of other factors like the number of classes, classification methods, and sensor types, which have an important impact on the accuracy of land cover classification.

REFERENCES

Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E. (1976). A land use and land cover classification system for use with remote sensor data (Geological Survey Professional Paper 964). U.S. Department of the Interior. https://doi.org/10.3133/pp964

CNES (Centre National d'Études Spatiales). (2025). Pléiades. Last modified September 19, 2025. https://cnes.fr/en/projects/pleiades

Dalle, S. P., de Blois, S., Caballero, J., & Johns, T. (2006). Integrating analyses of local land-use regulations, cultural perceptions and land-use/land cover data for assessing the success of community-based conservation. Forest Ecology and Management, 222(1–3), 370–383. https://doi.org/10.1016/j.foreco.2005.10.052

Dewitz, J., & USGS. (2021). National Land Cover Database (NLCD) 2019 products (ver. 3.0, February 2024). U.S. Geological Survey data release. https://doi.org/10.5066/P9KZCM54

Di Gregorio, A., & Jansen, L. J. M. (2000). Land cover classification system (LCCS): Classification concepts and user manual. Environment and Natural Resources Service, Africover–East Africa Project & Soil Resources, Management and Conservation Service.

Duke, O. P., Alabi, T., Neeti, N., & Adewopo, J. (2022). Comparison of UAV and SAR performance for crop type classification using machine learning algorithms: A case study of humid forest ecology experimental research site of West Africa. International Journal of Remote Sensing, 43(11), 4259–4286. https://doi.org/10.1080/01431161.2022.2109444

ESA. (n.d.). The Sentinel missions. European Space Agency. Retrieved March 1, 2026, from https://www.esa.int/Applications/Observing_the_Earth/Copernicus/The_Sentinel_missions

Fisher, J. R. B., Acosta, E. A., Dennedy-Frank, P. J., Kroeger, T., & Boucher, T. M. (2018). Impact of satellite imagery spatial resolution on land use classiŞcation accuracy and modeled water quality. Remote Sensing in Ecology and Conservation, 4(2), 137–149. http://doi.org/10.1002/rse2.61

Foody, G. M. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment, 80(1), 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4

Foster, A., Rahimzadeh-Bajgiran, P., Daigneault, A., & Weiskittel, A. (2024). Cost-effectiveness of remote sensing technology for spruce budworm monitoring in Maine, USA. Forests Monitor, 1(1), 66–98. https://doi.org/10.62320/fm.v1.i1.14

Fu, P., & Weng, Q. (2015). A time series analysis of urbanization induced land use and LC change and its impact on land surface temperature with Landsat imagery. Remote Sensing, 7(12), 16671–16698. https://doi.org/10.3390/rs71215844

Ge, J., Qi, J., Lofgren, B. M., Moore, N., Torbick, N., & Olson, J. M. (2007). Impacts of land use/cover classification accuracy on regional climate simulations. Journal of Geophysical Research: Atmospheres, 112(D5), Article D05120. https://doi.org/10.1029/2006JD007404

Giri, C. P. (2012). Remote sensing of land use and land cover: Principles and applications. CRC Press; Taylor & Francis Group.

Guha, S., Govil, H., Gill, N., & Dey, A. (2020). Analytical study on the relationship between land surface temperature and land use/land cover indices. Annals of GIS, 26(2), 201–216. https://doi.org/10.1080/19475683.2020.1754291

Horning, N. (2004). Overview of accuracy assessment of land cover products (Version 1.0). American Museum of Natural History, Center for Biodiversity and Conservation. Retrieved May 1, 2021, from http://biodiversityinformatics.amnh.org

Iizuka, K., Itoh, M., Shiodera, S., Matsubara, T., Dohar, M., Watanabe, K., & Bhardwaj, A. (2018). Advantages of unmanned aerial vehicle (UAV) photogrammetry for landscape analysis compared with satellite data: A case study of postmining sites in Indonesia. Cogent Geoscience, 4(1), Article 1498180. https://doi.org/10.1080/23312041.2018.1498180

Jumaat, N. F. H., Ahmad, B., & Dutsenwai, H. S. (2018). Land cover change mapping using high resolution satellites and unmanned aerial vehicle. IOP Conference Series: Earth and Environmental Science, 169(1), Article 012076. https://doi.org/10.1088/1755-1315/169/1/012076

Kovacic, L. (2025). Open land cover maps – Validation from the user perspective (Master's thesis, University of Zagreb). https://urn.nsk.hr/urn:nbn:hr:256:657876

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. Biometrics, 33(1), 159–174.

Liang, L., Liu, Q., Liu, G., Le, H., & Huang, C. (2019). Accuracy evaluation and consistency analysis of four global land cover products in the Arctic region. Remote Sensing, 11(12), Article 1396. https://doi.org/10.3390/rs11121396

Lindsey, R. (2020). Climate change: Glacier mass balance. Climate.gov. Retrieved April 4, 2021, from https://www.climate.gov/news-features/understanding-climate/climate-change-glacier-mass-balance

Markham, B. L., & Barker, J. L. (1985). Spectral characterization of the Landsat Thematic Mapper sensors. International Journal of Remote Sensing, 6(5), 697–716. https://doi.org/10.1080/01431168508948492

Mishra, V., Rai, P. K., Kumar, P., & Prasad, R. (2016). Evaluation of land use/land cover classification accuracy using multi-resolution remote sensing images. Forum Geografic, 15(1), 45–53. https://doi.org/10.5775/fg.2016.137.i

Moody, A., & Woodcock, C. E. (1994). Scale-dependent errors in the estimation of land-cover proportions: Implications for global land-cover datasets. Photogrammetric Engineering and Remote Sensing, 60(5), 585–594.

Mooney, C., & Freedman, A. (2021, January 25). Earth is now losing 1.2 trillion tons of ice each year. And it's going to get worse. The Washington Post. https://www.washingtonpost.com/climate-environment/2021/01/25/ice-melt-quickens-greenland-glaciers/

Mora, B., Tsendbazar, N. E., Herold, M., & Arino, O. (2014). Global land cover mapping: Current status and future trends. In I. Manakos & M. Braun (Eds.), Land use and land cover mapping in Europe (Remote Sensing and Digital Image Processing, Vol. 18, pp. 11–23). Springer. https://doi.org/10.1007/978-94-007-7969-3_2

NASA. (2026). MODIS specifications. MODIS Web. Retrieved January 9, 2026, from https://modis.gsfc.nasa.gov/about/specifications.php

National Ocean Service. (2024). What is the difference between land cover and land use? National Oceanic and Atmospheric Administration. Retrieved January 12, 2025, from https://oceanservice.noaa.gov/facts/lclu.html

Navulur, K. (2006). Multispectral image analysis using the object-oriented paradigm. CRC Press. https://doi.org/10.1201/9781420043075

Purevdorj, T. S., Tateishi, R., Ishiyama, T., & Honda, Y. (1998). Relationships between percent vegetation cover and vegetation indices. International Journal of Remote Sensing, 19(18), 3519–3535. https://doi.org/10.1080/014311698213795

Sanga-Ngoie, K., Iizuka, K., & Kobayashi, S. (2012). Estimating CO2 sequestration by forests in Oita Prefecture, Japan, by combining LANDSAT ETM+ and ALOS satellite remote sensing data. Remote Sensing, 4(11), 3544–3570. https://doi.org/10.3390/rs4113544

Satellite Imaging Corporation. (n.d.). QuickBird satellite sensor. Retrieved March 8, 2026, from https://www.satimagingcorp.com/satellite-sensors/quickbird/

Semenyuk, V., Kurmashev, I., Lupidi, A., Alyoshin, D., Kurmasheva, L., & Cantelli-Forti, A. (2025). Advances in UAV detection: Integrating multi-sensor systems and AI for enhanced accuracy and efficiency. International Journal of Critical Infrastructure Protection, 49, Article 100744. https://doi.org/10.1016/j.ijcip.2025.100744

Setyawan, E. (2019, May 25). Satellite imagery: Resolution vs. accuracy. Intermap Blog. https://www.intermap.com/blog/satellite-imagery-resolution-vs.-accuracy

Sozzi, M., Kayad, A., Gobbo, S., Cogato, A., Sartori, L., & Marinello, F. (2021). Economic comparison of satellite, plane and UAV-acquired NDVI images for site-specific nitrogen application: Observations from Italy. Agronomy, 11(11), Article 2098. https://doi.org/10.3390/agronomy11112098

Themistocleous, K., & Hadjimitsis, D. G. (2008). The importance of considering atmospheric correction in the pre-processing of satellite remote sensing data intended for the management and detection of cultural sites: A case study of the Cyprus area. 14th International Conference on Virtual Systems and Multimedia (VSMM 2008), 125–132.

Thinh, T. V., Duong, P. C., Nasahara, K. N., & Tadono, T. (2019). How does land use/land cover map's accuracy depend on number of classification classes? SOLA, 15, 28–31. https://doi.org/10.2151/sola.2019-006

U.S. Environmental Protection Agency. (2008). EPA's 2008 report on the environment (Report No. EPA/600/R-07/045F). National Center for Environmental Assessment. http://www.epa.gov/roe

Verburg, P. H., Neumann, K., & Nol, L. (2011). Challenges in using land use and land cover data for global change studies. Global Change Biology, 17(2), 974–989. https://doi.org/10.1111/j.1365-2486.2010.02307.x

Yan, W. Y., Shaker, A., & El-Ashmawy, N. (2015). Urban land cover classification using airborne LiDAR data: A review. Remote Sensing of Environment, 158, 295–310. https://doi.org/10.1016/j.rse.2014.11.001