



A method for considering the evolution of the visible landscape

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Abstract

The visible landscape represents an important consideration within landscape management activities, forming an inhabitants' perception of their overall surroundings and providing them with a sense of landscape connection, sustainability and identity. The historical satellite imagery archive can provide key knowledge of the overall change in land use and land cover (LULC), which can inform a range of important management decisions. However, the evolution of the visible landscape at a terrestrial level using this information source has rarely been investigated. In this study, the Landsat archive is leveraged to develop a method that depicts changes within the visible landscape. Our method utilises other freely available data sources to determine the visibility of the landscape, and LULC composition, visible from road networks when the imagery was captured. This method was used to describe change in the visible landscape of a rural area in Ñuble, Chile, in the period from 1986 to 2018. Whilst native forests on the slopes of the mountains within the study area provide a natural backdrop, because of the flat topography of most of the area, the foreground dominates the overall landscape view. This has resulted in a visible transition from a landscape visibly dominated by agricultural use in 1986 to one of equal agriculture and plantation forestry in 2018. It is hoped that the method outlined within this study can be applied easily to other regions or at larger scales to provide insight for land managers regarding the visibility of LULC.

Keywords Landscape · Satellite imagery · Visibility · Time series · LULC · Perception

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1 Introduction

Historical satellite imagery provides a rich source of information that can be used to depict temporal change that occurs upon the surface of the Earth (Hemati et al. 2021). Descriptions of these changes, derived from satellite imagery, present a range of land use and land cover (LULC) processes, including; urban growth and industrialization (Chen et al. 2020), deforestation (Nguyen et al. 2020), desertification (Bezerra et al. 2020) and wildfire intensification (Hislop et al. 2018) among others. The process of these aforementioned change events have had profound influence on the characteristics of landscapes across the world (Song et al. 2018).

An important development in the proliferation in the use of satellite imagery for mapping change within landscapes is the increased availability of open data (Hermosilla et al. 2022). Open data, like that captured by the Landsat series of satellites, has provided continuous imagery in some areas since 1972 (Wulder et al. 2018). In combination with modern computational power and processing techniques, the current openness and availability of satellite imagery has allowed analysis across extensive areas and throughout the entire period of the image archive (Wulder et al. 2018). Studies which utilise change analysis from open satellite imagery, either over discrete dates or time-series analysis, have provided insight into a range of current environmental, cultural and social issues; including the effects of climate change (Bannari and Al-Ali 2020), environmental disasters (Deliry et al. 2020) and food production dynamics (Kafy et al. 2021).

Satellite imagery analysis provides an opportunity to investigate change across the entire two-dimensional extent of a landscape (Hermosilla et al. 2022). This complete description provides important information that is currently used in many landscape decision-making and planning processes (Wulder et al. 2018). It is understood that the composition of LULC plays an important role in the overall aesthetic values that landscape holds and how the public, at both small and larger scales, may perceive or preference it (Ren 2019). Therefore, understanding how change in LULC may alter this aesthetic landscape value is important within the process of landscape management (Tveit et al. 2006). For example, some LULC types (such as natural land covers or those linked to local livelihood) may be preferred by the general public within local populations, and the exposure to more continuous land covers provides a sense of openness (Ode et al. 2009; Lee and Cho 2016). As such, it is important to understand how change in the composition of landscapes translates to the visible landscape, and in turn, how this affects public perceptions (Tveit et al. 2006; Roe et al. 2013).

In order to understand the visible composition of a landscape, viewshed analysis is often employed. This approach utilises spatial data to determine the areas visible from any single point within the landscape (Sahraoui et al. 2018). Analysis of viewshed outputs has been used to determine the scenic properties of an area from one or more vantage points. This includes determining the impact of proposed LULC change on the visible landscape (Jeung et al. 2018), determining how prevalent preferable landscape qualities are (Labib et al. 2021) and what role certain landscape features play in visibility (Garré et al. 2009). Whilst, viewshed analysis provides an

indication of what is visible from a specific point (both spatially and temporally), further information describing the composition of that visible area is required for many applications. As such, the combination of viewshed analysis with satellite imagery and its derivatives (such as LULC maps or greenness indicators) has proven to be a strong combination in these assessments.

Whilst several studies have utilised single date satellite imagery to analyse the visual landscape (Van Berkel et al. 2018; Hilal et al. 2018), to date, historical satellite imagery has rarely been used to map the evolution of the visible landscape. Examples of studies which do utilise historical satellite imagery for this purpose have often used it as an auxiliary datasource (Schirpke et al. 2020) or to provide a static LULC map (Schirpke et al. 2021). Schirpke et al. (2020) for instance, utilised LULC mapping along with other land cover information (some of which was derived from satellite imagery) at five distinct time points to analyse the changes in Italian Alps over the last 150 years. Through the inclusion of visibility analysis from manual digitisation of road and path networks, Schirpke et al. (2020) showed that increased access to the landscape can result in distinct changes (both positive and negative) in aesthetic value. Schirpke et al. (2021) extended this study to include selected points within the European Alps utilising a similar method, however, in this case the LULC derived from satellite imagery was held constant for three time points.

This study aims to develop a workflow to monitor LULC changes within the visible landscape utilising open geospatial data. The method is demonstrated within a case study area in Chile, in which historical records as used in similar previous studies were unavailable. As such the method aims to primarily rely on satellite data and be transferable to wherever that imagery exists.

2 Materials and methods

2.1 Study area

The municipality of Yungay, Chile, was selected as the study area for this paper (Fig. 1). The Yungay municipality covers 824 km² and contains significant areas of relief including a plateau in west, with an altitude between 105 m and 200 m Above Sea Level (ASL), and the Andes mountain range in the East reaching > 2000 m ASL. The current LULC within the West of Yungay is comprised primarily of plantation forestry (Eucalyptus and pine species) and Agriculture (consisting of primarily grain crops and stone fruit); conversely, LULC on the slopes in the East of Yungay is primarily native vegetation (forests and grasslands). Yungay was chosen for this study as, like the remainder of Chile, it has undergone significant economic development. As such, it was expected that the road network and the LULC will have undergone some change during the study period (1986 to 2018) (Fig. 1). This includes the effects of increases in commercial forestry operations, a reduction of land used for agricultural practice, as well as the region suffering from several natural disasters, such as the Chilean Earthquake in 2010 and wildfires in 2017.

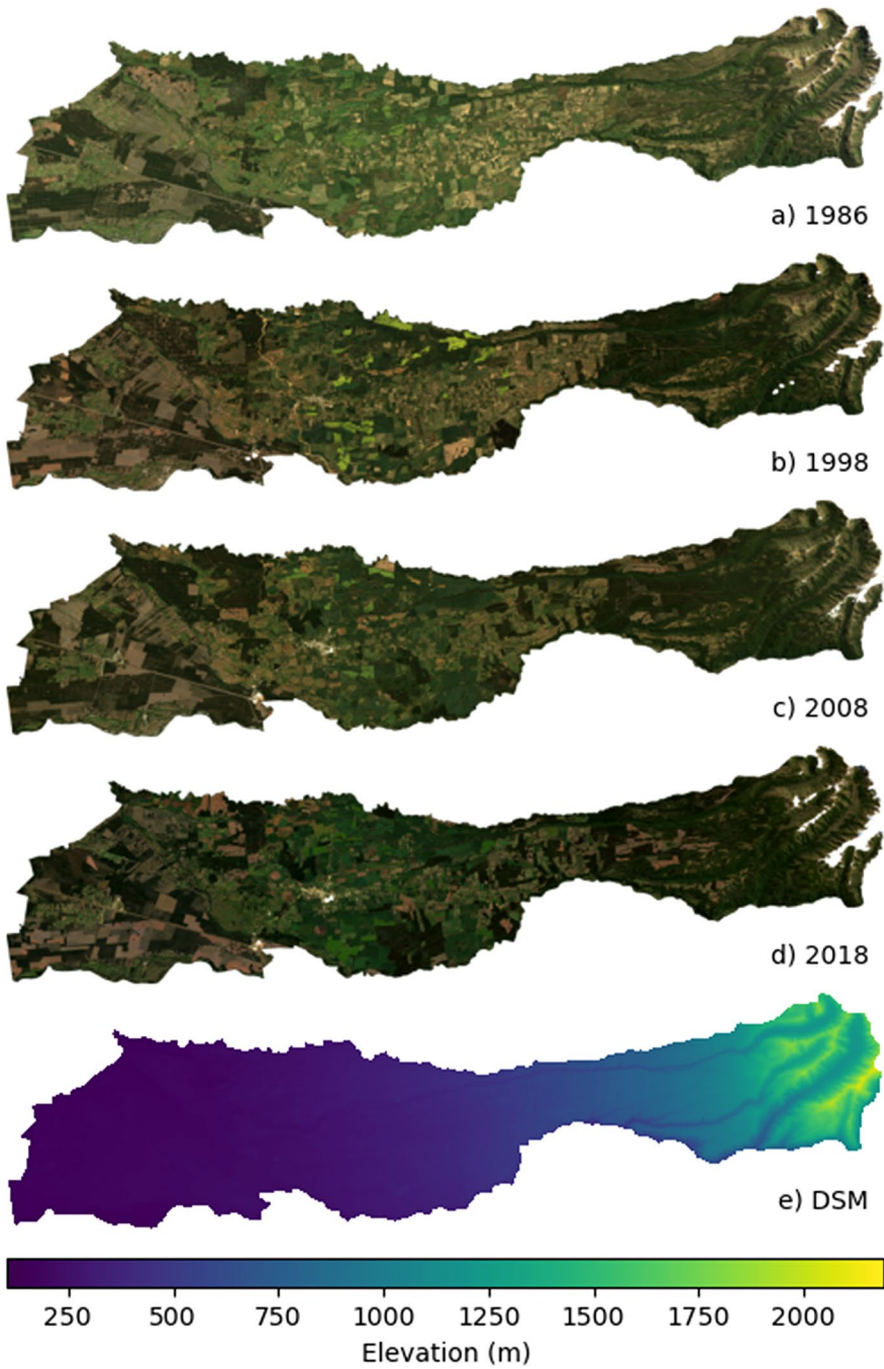


Fig. 1 Red, Green and Blue composites of the Yungay region in the years **a** 1986, **b** 1998, **c** 2008 (Landsat-5) and **d** 2018 (Landsat-8). **e** the ALOS3D Digital Surface Model

2.2 Data

2.2.1 Satellite imagery

Satellite imagery from the United State Geological Service Landsat series, retrieved from Google Earth Engine, was used in this study. Landsat-8 Surface Reflectance (SR) Level 2, Collection 2, Tier 1 data was used for 2018 and Landsat-5 SR Level 2, Collection 2, Tier 1 data for 2008, 1998 and 1986. Noting the year 1986 was substituted for 1988 due to it being the closest year with at least one Landsat image with < 30% cloud cover from the same period available. Following, Phan et al. (2020) a median image was generated based on all cloud free pixels from between 1 August and 31 October in each year. Each band was re-sampled to a spatial resolution of 30 m before classification.

Nine indices and entropy (a measure of image texture) commonly used in LULC classification methods were generated from the Landsat images taken for each year. These indices include the Normalized Difference Vegetation Index, Enhanced Vegetation Index, Soil Adjusted Vegetation Index, Modified Soil Adjusted Vegetation Index 2, Normalized Difference Water Index, Modified Normalized Difference Water Index, Normalized Difference Water Body Index, Normalized Difference Built-up Index and simple ration.

2.2.2 Digital surface model

A Digital Surface Model (DSM) provides a representation of the height of the top most surface within an area. In this study an ALOS World 3D (ALOS3D) DSM was used (Tadono et al. 2014). This DSM has a spatial resolution of 30 m and is a freely available dataset that is an upscaled version of the commercially available 5 m resolution DSM (Caglar et al. 2018). The ALOS3D DSM has a reported vertical error of up to 1.8 m at 1σ (Jain et al. 2018; Caglar et al. 2018). The DSM was resampled to coincide with the LANDSAT imagery.

2.2.3 Road network

The road network was downloaded as a shapefile from (https://www.bcn.cl/siit/mapas_vectoriales/index_html). This file contained the primary road network within the Yungay region as of 2019. The roads were segmented into 300 m lengths. Each segment was then compared to a true colour composite made from each years Landsat image. If there was no evidence that a road was present within a satellite image it was removed from the network for that year and all preceding years. Evidence used to determine the presence of a road included, the road being visible in the image, buildings evident along the extent of the road, and the road being visible in any image prior to the current year. This approach is similar to the one taken by Nascimento et al. (2021) who found it to be 98% accurate.

2.3 Training and validation data

Training data, consisting of attributed LULC class at each location, were determined based on visual interpretation of the Landsat image from each year. Where possible a multiple lines of evidence approach was used. This included high resolution satellite imagery in interpreting the 2018 data, other Landsat images captured in different seasons within a year of the image date and local knowledge. This process was completed for 645 points at each date. The points were chosen within a regular grid covering the bounding box of the Yungay municipality buffered by 5 km.

A further 143 validation points were collected in 2018. These points were visited in the field with the LULC class and GNSS location recorded as well as images captured in four cardinal directions. The location of the in situ validation sites was determined by randomly distributing 60 points within each LULC class (based on an initial classification of the imagery). The locations were then visited until a minimum of 20 points from the four main classes (agriculture, plantation forestry, native forests and urban areas) were recorded. Any points that were inaccessible or close to a LULC boundary were not used in the study.

2.4 Land cover classification

Broad LULC classes describing the whole of the Yungay landscape and surrounds within the land cover classification were used for this study (as provided in Table 1). These broad classes were chosen to correspond to the major LULC classes within Yungay and to those that can be understood by a local lay person with minimal explanation.

Following Phan et al. (2020) a random forest classifier was used to provide land cover classification for each year. Similar to Phan et al. (2020) 100 trees ($n_{tree} = 100$) were used and the number of variables selected at each split was set to the square root of the total number of features. The SR images (composed of the twelve Landsat-8 and five Landsat-5 bands), derived indices and texture metrics and surface elevation (from the DSM) were used as features describing the properties of each pixel. All pixels within 5 km of the Yungay border were considered in the

Table 1 The definition of the LULC classes used in this study

LULC class	Composition
Agriculture	Areas used for grain and canola crops, stone-fruit and for grazing.
Plantation forestry	Pine and eucalypt plantations
Native vegetation	Areas consisting undisturbed or regeneration native vegetation. Including forests and shrub and grass lands.
Built-up Areas	Urban areas and areas for the processing of timber and agricultural goods.
Water	Rivers, lakes and canals
Bare ground	Areas of bare soil where future land use can not be determined
Snow	Snow cover

classification. The random forest was trained on 70% of the training data with 30% held out for validation.

2.5 Visible landscape determination

Two viewshed methods were used to determine the properties of the visible landscape from each location; planimetric analysis and tangential analysis. The implementation of these viewsheds within PixScape 1.2 was used (Sahraoui et al. 2018).

Planimetric analysis determines the area (via a count of the pixels) visible from a view point (Sahraoui et al. 2018). This type of analysis was used to determine the total area of the landscape visible from each location along the road network. Tangential analysis uses the vertical angle of the view of each pixel to provide it a weight in determine the visible area (Sahraoui et al. 2018). This analysis was used to provide the visible LULC class proportion from each view point. Tangential analysis was preferred over planimetric analysis for this purpose as it provides a better correspondence to the view of an observer (Sahraoui et al. 2018; Nutsford et al. 2015)

In both cases, view points were set at the centre of each Landsat pixel that contained any part of the road network for each year and an observer height of 1.6 m was used. Analysis was computed to determine metrics and visible areas at 1400 m, 5000 m and infinity. These distances were used as distances to the foreground, mid ground and background. 1400 m was chosen as it is the distance at which recognition of individual features is no longer possible (Garré et al. 2009) and 5000 m as it has been shown to be the distance at which background, foreground and mid views separate (Martín et al. 2018).

2.6 Analysis

The accuracy of the LULC maps calculated for each year was summarised through overall accuracy, users accuracy (a measure of commission) and producers accuracy (a measure of omission) which were calculated from the confusion matrices. For the 2018 LULC classification accuracy was determined against both the in-field collected validation points and the 30% of the manually determined points held out from the training set. Only the manually determined points held out from the training set were available for determining accuracy in 1986, 1998 and 2008.

The overall landscape was summarised by percent cover of each class and Shannon's diversity index. Percent cover provides an indication of the abundance of each LULC class. While Shannon's diversity index quantifies landscape diversity based on the number and proportional cover of different patch types. Shannon's diversity index is a measure of fragmentation with higher values representing a more fragmented landscape (Plexida et al. 2014).

The visible landscape determined by the tangential viewshed was summarised by the mean proportion of each LULC class visible from each viewpoint as well as the mean Shannon's diversity index of the projected view. Qualitative comparisons were made between the overall landscape metrics and those of the visible landscape.

3 Results

3.1 Changes in landscape visibility

The road network within Yungay increased in length from 229 to 339 km during the study period (1986 to 2018). The majority (61 km or 55% of the total increase) of the road development occurred between 1986 and 1998. Smaller increments in road development, mainly around the two population centres (Yungay and Campanario), were seen from 1998 to 2008 (38 km), and then again between 2008 and 2018 (11 km) (Table 2).

According to the planimetric viewshed analysis 635 km² (76%) of the Yungay region was visible from at least one point on the road network in 1986. With a further 1351 km² visible from the road network but outside of Yungay. This increased in each of the subsequent analysis years as road networks increased in length Table 2. With the smallest increase observed between 2008 and 2018 corresponding to lower road development. Without restricted viewing distances the mountainous east of Yungay was the most visible area in each year, with some areas being visible from more than 50% of the road network.

Increases in landscape visibility occurred primarily adjacent to the road network within the topographically flat areas Fig. 2. This is indicated as the newly visible areas also occurring in the planimetric viewsheds of the restricted viewing distances. When viewing distances were restricted, the most visible landscape areas were those around the urban and industry centres of Yungay (in all years), Campanario and Cholguan (from 2008).

3.2 LULC classification

The LULC classification of the 2018 Landsat-8 image achieved an overall accuracy of 86% when compared to the ground truth data. The water class had the lowest users accuracy (20% with one of five observations being correctly classified) and was often misclassified as being either a cell containing plantation or agriculture

Table 2 Length of the road network and the associated visible area from roads at each of the study dates

Year	Road network Length (km)	Visible area					
		1.4 km		5 km		Infinity	
		Yungay	All	Yungay	All	Yungay	All
1986	229	320	365	455	637	635	1986
1998	290	390	444	522	732	672	2049
2008	328	440	496	573	789	699	2093
2018	339	446	581	582	804	703	2100

Area within the municipality of Yungay and including the surrounding area (all) are provided for each viewing distance. Note that the 'infinity' viewing distance is calculated to the edge of the imagery set at bounding box of Yungay buffered by 5 km

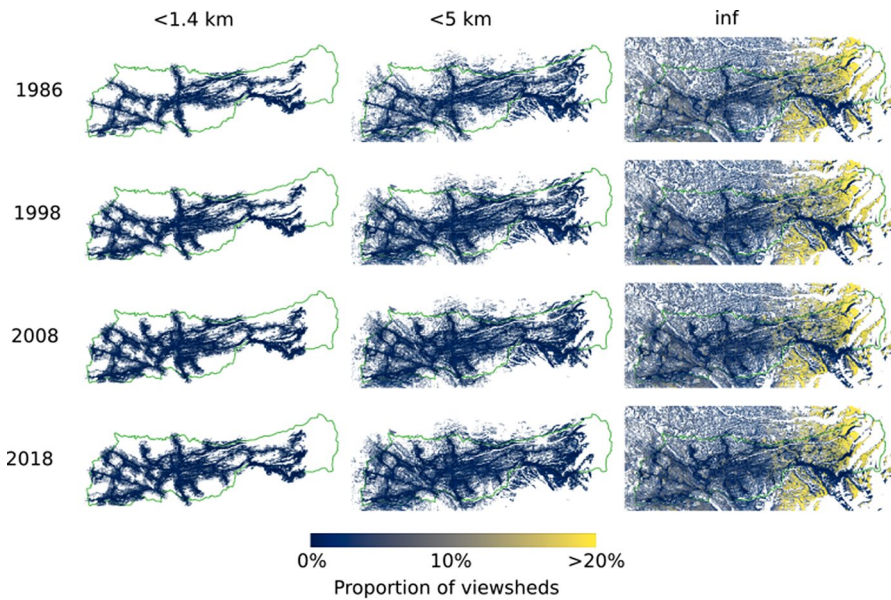


Fig. 2 Proportion of road vantage points from which an area was visible 1986 (4817 vantage points), 1998 (9263 vantage points), 2008 (10464 vantage points) and 2018 (10,814 vantage points)

cover (Table 3). Confusion also occurred between plantation and native forests resulting in a user accuracy of 77% for plantations and a producer accuracy of 78% for native forests.

When compared to the held-out manually interpreted data, an overall accuracy of 84% in 1986, 82% in 1998, 89% in 2008 and 90% in 2018 was achieved for the respective years. The greatest source of error was misclassification occurring between the Agricultural, Plantation and Native Vegetation classes in all years (Table 3). The 1998 classification had the lowest overall accuracy. This could be attributed to a greater area classified as bare ground and misclassification between this class (indicated lower producers and user accuracy than other years) and Agriculture and Plantation forestry.

3.3 Change in the overall landscape

The landscape in 1986 was dominated by agricultural land use (52%, see Fig. 3). Native vegetation cover (28%) occurred primarily in the east and Plantation forestry (13%) interspersed with agriculture in the west. By 2018 plantation forestry cover had grown by 22% (to 35%) with corresponding decreases in agricultural land use (by 19% to 33%) throughout, and Native Forests (by 6% to 22%) at the foot of the mountains. The urban areas in Yungay also increased from 0.1% in 1986 to 0.3 % of

Table 3 Users (UA) and producers (PA) accuracy of the LULC classification for each year

Class	1986		1998		2008		2018		2018*	
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA
Agriculture	88	92	80	92	88	97	91	94	91	98
Plant. forestry	82	74	86	73	90	89	87	91	78	84
Native Veg.	78	85	81	85	92	84	94	86	88	79
Urban	100	100	100	100	67	100	75	100	100	71
Bare ground	100	56	80	63	82	90	89	89	70	100
Water	100	25	100	33	–	0	67	67	100	20
Snow	100	100	100	100	100	100	100	88	100	100

1986 to 2018 data are evaluated against manually interpreted points held out from training set. The 2018* are evaluated against validation data collected infield

the area by 2018. Water, snow and bare ground all varied in cover across the study period. However, an overall decrease in water cover (0.8 to 0.3%) was notable.

The changes in cover corresponded to a more fragmented landscape indicated by an increase in Shannon's diversity index from 0.59 in 1986 to 0.68 in 1998. However, only minor differences were observed between 1998, 2008 (0.65) and 2018.

3.4 Change in the visible landscape

The change in the proportion and fragmentation of each LULC classes visibility from the road network followed a similar trend to the overall landscape composition (Fig. 4). Notably, the overall view is dominated by the foreground composition (Fig. 4 columns 1 and 4). This is because of Yungay's terrain being composed of a flat plain, with the mountains to the East providing the only background view. This is further indicated by the high proportion of Native vegetation (> 50%) visible in the background in each year. A steady decline in the visibility of native vegetation in the background is noticeable (by 1% every four years to 52% in 2018). This decrease is accompanied by an increase in the Plantation class (from 4% in 1986 to 23% in 2018) in the background. Further, native vegetation is the only class to have lower visibility in all years in comparison to its overall cover (by between 1% and 4%). This is due to the lower road density in the denser areas of native vegetation.

Change in urban visibility follows a similar trend to urban cover. However, urban areas are between 3 and 6% more visible than the urban cover in all years. This is due to the increased road density in urban areas, as the visible proportion of these areas was highly bimodal. Views from roads in urban centre of Yungay containing > 90% urban cover and views from the other roads containing very little urban LULC. This is further highlighted by a low prevalence in the background view. Bare ground was significantly more visible in 1998 (21% compared to a maximum of 6% in the other years) as the areas close to roads appear to have been under transition from agriculture to plantation forestry. This corresponded to a decline in both Agricultural and plantation visibility between 1986 and 1998. Whilst this decline was

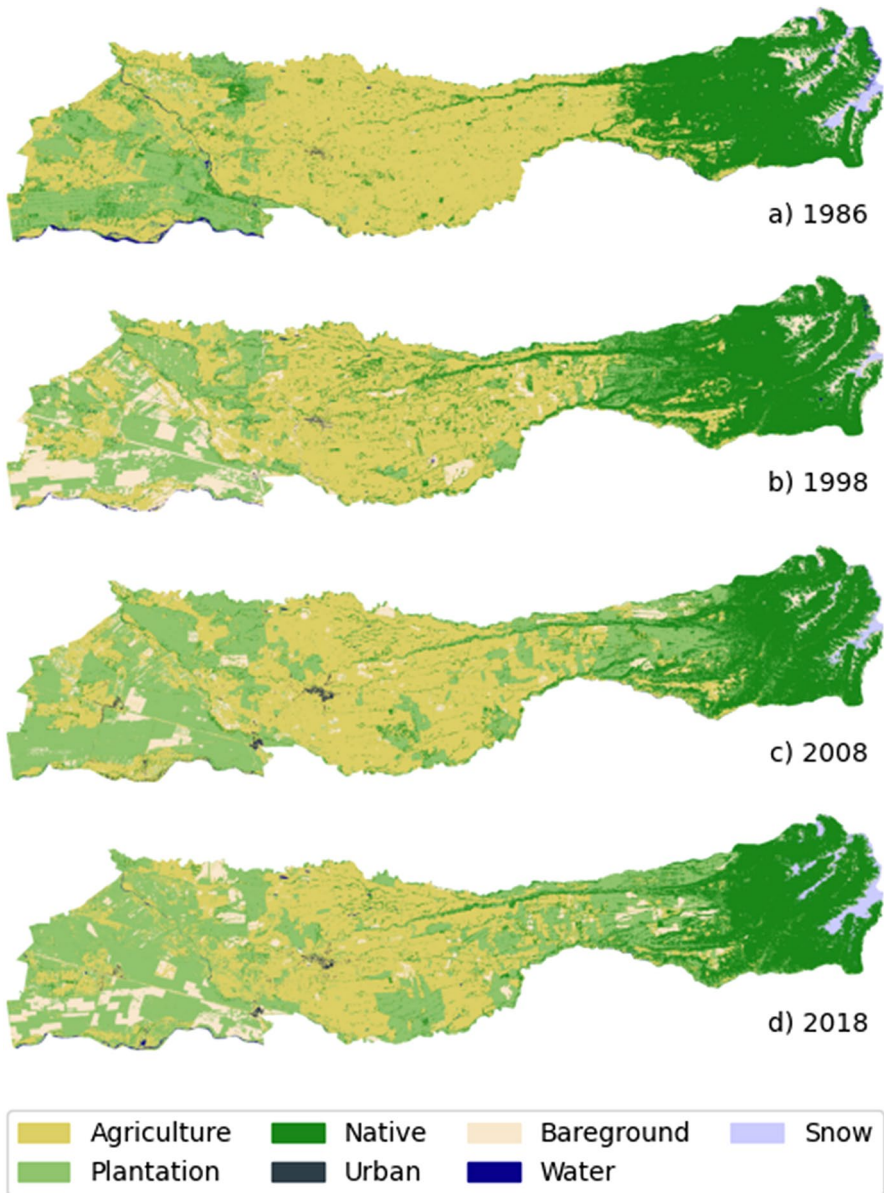


Fig. 3 LULC maps generated from Landsat images from **a** 1986, **b** 1998 **b** 2008 and **c** 2018

present in agricultural cover, it was not seen in the overall landscape contribution of the plantation class.

Agriculture dominates the visible landscape in 1986, with a mean proportion of visibility of 64%. This class then follows a similar trend to the overall landscape decreasing to a proportion of visibility of 40% in 2018. Agricultural visibility in the

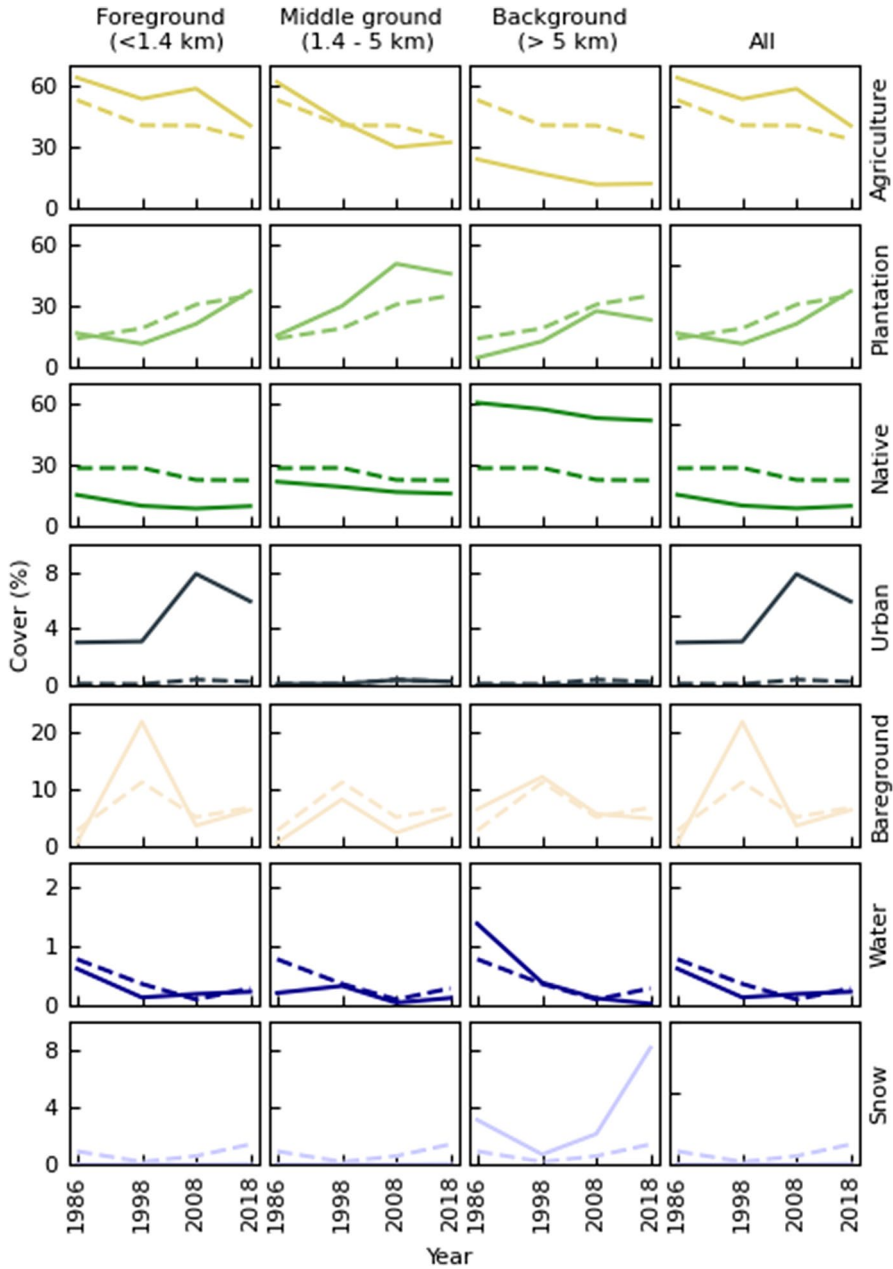


Fig. 4 The mean visible proportion (solid lines) for each of the seven LULC classes within the foreground, middle ground and background. LULC cover for all of Yungay is provided for reference (dashed line)

foreground increased between 1998 and 2008 due to the establishment of new roads, indicated by an increase in Agricultural cover (from 53% to 55%). The visibility of the plantation class increases between 1986 and 2018. By 2018 this class makes up a similar proportion of the overall view to agriculture. Whilst agriculture is more visible from the roads than its overall cover in all years, plantation forestry is represented similarly in 1998 (11% visible and 11% cover) and 2008 (21% visible and 17% cover) and only becomes highly visible in 2018 (37% visible and 19% cover).

Fragmentation of the visible landscape increased, similarly to the overall landscape during the study period. Mean Shannon's diversity index increased from 0.06 in 1986 to 0.9 in 1998, 2008, 2018. This index was observed to be higher in roads surrounding urban centres, with only minimal changes in the connecting roads. The overall increase was therefore primarily a result of the expansion of Yungay and Campanario urban areas.

4 Discussion

4.1 Evolution of the visible landscape

Despite the study only covering a 32-year time-span widespread changes in the overall landscape composition were observed. Visibility analysis from the road network also suggests that the changes seen in the visible landscape follow the same trend as changes in the overall LULC. Due to Yungay, for the most part, being located on a flat plain the foreground is dominated by near road landscapes. This leads to LULC centralised around road networks dominating the visible proportion of the landscape calculated from the tangential viewshed analysis. As such, early in the study period (1986), and as new roads were built to accommodate the growing plantation timber industry in the area (Uribe et al. 2020), agriculture was the dominant LULC class. However, by 2018 plantations had reached the same visibility from the road network.

Given the increased proximity of plantations to road networks, this gradual transition over time would have profound effects on the visible landscape of Yungay. The seasonal variations in the crop intensive agriculture in the region would have presented inhabitants with a seasonally changing landscape, which would now not be the case in areas where visibility is dominated by slow growing plantation species (both pine and eucalyptus). Further, a completed survey undertaken in the area in 2018 by San Martín Saldías et al. (2021) showed that Plantations were the most unappreciated land cover type. This suggests that the landscape transition to one that is equally dominated by agriculture and plantation has not been viewed favourably by the residents.

Some loss of native forest—from 28% (1986) to 26% (2018)—was observed within the study period. Areas of native forest over time primarily transitioned to plantation forest Fig. 3. Notably, this transition occurred within the background of landscapes visible from the majority of the road network. The distances chosen when delineating the back, middle and foreground views were based on literature review, with the 1400 m threshold indicated to be the distance at which individual

objects could be distinguished (Garré et al. 2009). It is unclear as to whether this transition of native forest to plantation was evident to residents who frequent the areas where they occurred. Whilst observers would be unlikely to perceive individual trees, this transition may be evident due to the linear patterns often present in plantation forests. For example, the interpretation of these forest types from satellite imagery utilises larger landscape patterns; such as abrupt transitions in land cover, configuration of stands and trees, and potentially the colour of plantations in comparison to the irregular growing patterns in native forests.

Satellite imagery is able to capture cyclical temporal events. For example in this study the water levels in the 1998 imagery suggested a very dry year, indicated low water levels in the Bio-Bio river. Such fluctuations would also play a role in the lived experiences of the residents.

4.2 Data and analysis

A key point of differentiation of this work to similar prior studies is the use of locally trained classifiers, in the context of both time and space. Schirpke et al. (2021), for example, utilised the CORINE land cover map that was generated for the whole of Europe (outlined in Bossard et al. (2000)) and choose to keep this constant throughout the study period (1950 to 2010) due to classifier error within the study area. The use of a locally trained classifier was designed to minimise errors within the region of interest. However, it is important to recognise that any land cover map is dependent on choices made by the producers in order to reconcile information needs and the end user applications (Comber et al. 2005). In this case, we consider the accuracy achieved in each year, for the broad LULC classes chosen, to be easily interpreted by laypeople suitable for the analysis performed. However, a choice was made not to analyse local changes (i.e. transition of individual pixel classes) in LULC as the methods employed and the localised classifier likely makes this analysis unsuitable.

In terms of underlying data, a key goal of this study was to utilise open geospatial data to conduct the desired analysis. For this purpose, the publicly available Landsat archive represents an excellent resource for the analysis similar to that completed in this study. This archive provides imagery throughout the data period with similar characteristics and at spectral and spatial resolutions high enough to determine the LULC classes of interest when considering landscape perception. Whilst the satellite imagery used within this study was able to capture some of the water features in the area, such as the Bio-Bio river flanking the Yungay border to the south (see Fig. 3a), many of the smaller rivers are represented only by the natural landscape buffer in place to protect the water source from plantation forestry operations. In these cases, higher resolution data (such as freely available sentinel imagery or commercial imagery) may provide better discrimination of these features. Further, vertical features such as water falls (of which there are several in the area), cliffs or

building facades cannot be well represented in satellite imagery. These features are still important however, as studies have clearly shown that natural features such as rivers and waterfalls are more likely to be perceived and appreciated by the public and therefore must still be considered Schirpke et al. (2021). As such, even minimal representation of such features from a vantage point may enhance the perceived quality of that landscape.

Importantly, for the analysis performed, the temporal and spatial resolutions of the underlying satellite imagery should be matched by the resolutions of the underlying data where possible. For example, the ALOS3D DSM used here provided similar resolution to the Landsat imagery. It is likely that abrupt changes in surface height, such as from a plantation or building, are not captured at this resolution. Therefore, it is likely that the visible proportion of plantations, native forests and urban classes—within scenes with mature trees and buildings close to the road—are underestimated in this study. Furthermore, the DSM (captured in 2018) was considered static throughout the study period. This means that changes in top surface elevation due to developments such as the construction of a road or water course through previously forested area or a plantation being grown or harvested were not represented within this study. Such changes may have significant impact on the visible landscape. For example, with a large plantation likely to represent a larger portion of the visible area when directly adjacent to one side of a road.

In this study we used a manually edited road network. Whilst the method we used indicated high accuracy, due to the absence of historic datasets, it is likely errors of omission and commission were present using this approach. This manual approach was also laborious and restricted the study area and number of time points that could be compared. Having access to historically accurate road networks, including the date of road establishment, may facilitate more in depth analysis across space and time. Further, whilst this analysis suggested there was only a small amount of public road network development in the area. Comparatively, significant private road development was observed including a range of roads corresponding with the expansion of the plantation land use. These roads were not included in the analysis as they were not indicated in the public road network and thus the degree of usage and/or whether the public could use them was unclear. An indication of usage would have enhanced this study as it would allow views from heavy usage roads to be weighted more highly as these are the most likely used by the public.

This study demonstrates that the LULC change when viewed from all roads in Yungay follow a similar pattern to the overall landscape change. However, it is unlikely that individuals access all roads within the area, nor use the roads they access equally. The amount of usage of a road is likely to be dependent on a number of factors. For example, whilst Chile had a relatively low car ownership before 1990 (Lee and Rivasplata 2001), the number of cars increased by 4% per year in the period between 1991 and 2001 (Zegras and Hannan 2012). A similar

trend is likely to be observed in Yungay, suggesting that Yungay's occupants had lower mobility. With lower mobility in 1986 it is likely that landscapes in the local area surrounding people's homes and places of work had more influence on how the landscape of Yungay was perceived than in 2018. Road usage data is now routinely collected through smartphones, in car navigation apps or through simulations (Lana et al. 2018). Such data could be integrated into future landscape perception analysis through the use of weights when generating these summary statistics.

5 Conclusion

Understanding the perception of landscapes by local populations is critical for the effective communication and planning by landscape managers. Geospatial data have shown the potential to assist in the analysis and understanding of this perception over different time periods. This study further highlights the role geospatial data can play in understanding landscape perception through the development of a methodology using open source satellite imagery for describing the visibility of LULC change from public road networks. We demonstrate this method within Yungay, Chile, between the years from 1986 to 2018 over four time periods. The results we have presented show the transition over time, with a large proportion of the landscape originally being used for agriculture in 1986 now used for plantation forestry. Furthermore, the method we have designed is able to show the difference between the landscape visible and ground level and the overall landscape composition visible from satellite imagery. However, for the case of Yungay, this difference between perspectives was shown to be minimal. As this method utilises data sources that are largely freely available at a global scale, it is hoped that it may be applied easily over larger scales and within other regions to provide land managers with information regarding the visibility of landscape use and cover.

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Data availability Data for replication purposes are available at 10.25439/rmt.21202007.

Declarations

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