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Estimates of landscape composition from terrestrial oblique photographs suggest homogenization of Rocky Mountain landscapes over the last century

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Abstract

While orthogonal (i.e., aerial or satellite) imagery has become the more conventional source of land cover data because it can yield spatially accurate land cover maps, terrestrial oblique photographs present a valuable, relatively untapped source of raw optical data for studies of land cover change. We present a case study contrasting how these two types of imagery sample landscape composition and using repeat oblique photographs to evaluate long-term land cover change in a remote region of the Canadian Rocky Mountains. We classified 46 historical oblique photographs and their corresponding modern repeats using the same discrete land cover classes employed in a Landsat-based map of the same area. We compared landscape-level composition estimates from both sources and regressed the land cover proportions from Landsat against the modern oblique images, hypothesizing a linear relationship for most classes. We found that the two sources sampled the landscape in broadly similar ways, with near-concordance for dominant land cover classes, yet that oblique photographs more frequently detected narrow landscape features and estimated higher proportions of rock compared to satellite imagery, possibly due to the higher spatial resolution of the oblique photographs, and to their angle of incidence against steep slopes. We then evaluated land cover change from corresponding historical and repeat photographs and found that the landscape has homogenized over the past century via increased coniferous forest cover. Our work shows that terrestrial oblique photographs can be used to estimate landscape composition, particularly in mountain environments. This is helpful for analyzing past landscape conditions in historical photographs, monitoring decadal-span landscape change and assessing habitat to model biodiversity through time.

Introduction

Land use and land cover change pose a global environmental challenge, impacting biodiversity, food systems and biogeochemical cycles (Brunsden and Thornes 1979; Vitousek et al. 1997; Lambin et al. 2003; Foley et al. 2005; United Nations, 2017). Monitoring the extent and rate of landscape change is useful for describing ecosystem structure and assessing biodiversity, for instance as part of the Essential Biodiversity Variable framework

(Pereira et al. 2013; Turner 2014; Pettorelli et al. 2016). Establishing reference conditions of historical landscape composition can help quantify change, understand landscape legacies and ecological memory (Schweiger et al. 2018), and respond to change with approaches such as ecological restoration (Keenleyside et al. 2012). While the predominant source of contemporary land cover data is remotely sensed orthogonal imagery – imagery approximately perpendicular to the Earth's surface – this imagery only became widely available in the 1940s for aerial photography and in the 1970s for satellites (Green 1983; Belward and Skøien 2015). Conversely, the first land-based landscape photographs were taken as early as the 1860s, predating even the earliest orthogonal imagery by several decades (MacLaren et al. 2005; Webb 2010). Thus, land-based photographs can offer greater temporal depth than their aerial counterparts, a significant opportunity for long-term landscape and biodiversity change research and monitoring.

Many studies have taken advantage of historical land-based photographs to examine long-term land cover change through the process of repeat photography (e.g., Hastings and Turner 1965; Butler and DeChano 2001; Byers 2008). These images, also referred to as "terrestrial oblique photographs" (henceforth "oblique photographs") because of the oblique angle of incidence from which they are taken, have numerous advantages over standard orthogonal images. First, oblique photographs can offer greater temporal depth. Second, oblique photographs present the landscape in a way that people (and terrestrial animals) are accustomed to seeing it – a human's eye view – as opposed to a bird's eye view, which is less intuitive (Grenzdorffer et al. 2008). Third, in mountainous landscapes with steep slopes and cliffs, the assumption that orthogonal images are perpendicular to the Earth's surface is violated. In such cases, oblique photographs may have a more appropriate angle of incidence, capturing a significant amount of detail on slopes that overhead images miss (Delaney 2008; Sanseverino et al. 2016). Fourth, oblique photographs often provide much greater resolution than typical satellite products (Chandler et al. 2002; Lefèvre et al. 2017). Fifth, photographs taken from the ground are abundant: Google Street View imagery, social media platforms and ground surveys are examples of widespread sources of oblique photographs. In recent years, numerous studies have sought to harness the enormous potential of these free or low-cost ground-level data for various applications such as urban planning, tree cataloging and land cover change detection (Li and Zhang 2016; Jiang et al. 2017; Lefèvre et al. 2017; Liang et al. 2017; Zhang et al. 2017), but this field is relatively new and rapidly evolving. As such, oblique photographs present a useful but relatively untapped data source for studies of landscape change, particularly around mountains (Kaim 2017).

Indeed, despite these advantages, oblique images are not used as frequently as orthogonal images for studies of land cover. Orthogonal images are typically favored because their basal unit, the pixel, is (sometimes wrongly) assumed to represent a constant area, making it easy to use orthogonal images as the basis of spatially consistent land cover maps of large areas. In contrast, oblique photographs are not spatially consistent; pixel size varies within an image and viewsheds include obscured areas (Fig. 1). Techniques exist to orthorectify oblique images to yield spatially referenced land cover data (e.g., Doytsher and Hall 1995; Corripio 2004; Bozzini et al. 2012). However, this process is nontrivial and time-consuming, particularly for large sample sizes, and entrains its own sources of error (Kolecka et al. 2015; Stockdale et al. 2015).

Another option is to estimate land cover by segmenting and classifying oblique images without orthorectification (Fig. 1). Land cover proportions can be estimated from these oblique images by computing pixel counts of various classes (Jean et al. 2015a). If, despite the variable pixel size in oblique photographs, these estimates of land cover proportions are found to be similar to those derived from spatially accurate imagery, many research questions could be answered using oblique photographs without requiring the orthorectification process and its associated error propagation. The data-rich world of oblique imagery could be leveraged to ask questions that span longer temporal periods and at greater spatial resolutions than possible with typical satellite products. A model of such oblique imagery is found in the Mountain Legacy Project in the mountains of western Canada.

The Mountain Legacy Project (MLP) is an ongoing repeat photography project based on over 120 000 historical terrestrial oblique photographs. The original photographs were taken systematically by surveyors from the late 19th to mid 20th centuries to create topographic maps of the Canadian mountain west (Deville 1895; Bridgland 1916, 1924). The photographs have been preserved on large format glass plates, mainly at Library and Archives Canada. Over the years, the MLP has repeated over 7000 of the historic images, and has built a suite of custom tools for classification and analysis of oblique images (Gat et al. 2011; Jean et al. 2015b; Sanseverino et al. 2016).

In this study, we took advantage of the MLP's vast collection of oblique landscape photographs and custom software tools to test whether the land cover proportions quantified by oblique photographs are similar to those quantified by land cover maps based on satellite imagery. Given that both types of imagery are optical representations of the same landscape, we expected land cover

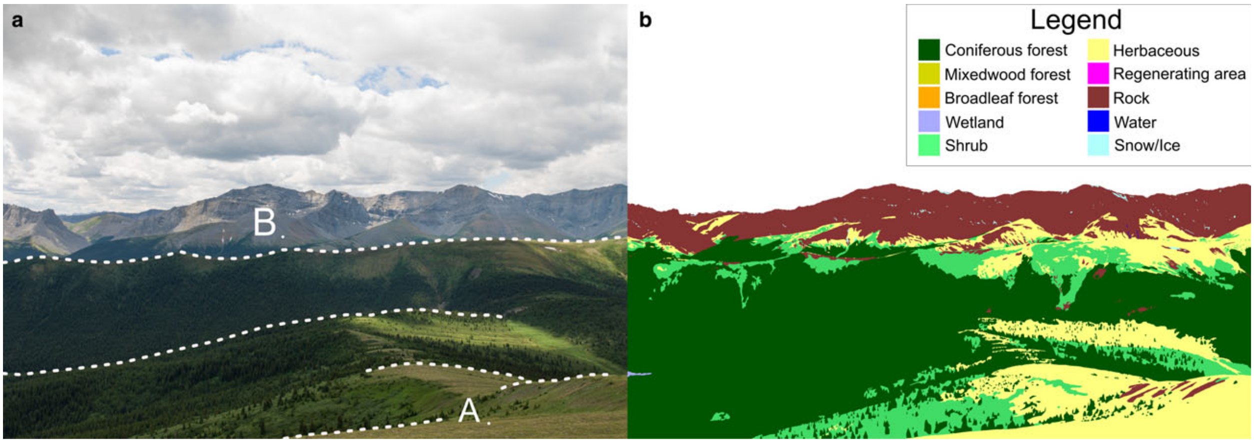

Figure 1. (a) An example of an oblique photograph, taken in 2014. A pixel at point A would represent a smaller area in the landscape than a pixel at point B, because point B is farther away from the camera. The dotted lines show subhorizon lines beyond which there are parts of the landscape that are obscured from view from this oblique viewpoint. (b) The classification associated with the photograph in (a).

composition to be fairly consistent between the two, with discrepancies reflecting inherent differences – but not necessarily biases – in the way the data sources sample the landscape. We hypothesized that: (1) there is a positive linear relationship between land cover proportions quantified by oblique photographs and those quantified by satellite images for most classes, although (2) classes characteristic of steep slopes would represent a higher proportion of the landscape in oblique images than in overhead images because of the different angles of incidence (Delaney 2008; Sanseverino et al. 2016), and (3) oblique images would capture a greater amount of detail in the landscape due to their higher resolution (Chandler et al. 2002). We further present an example analyzing long-term change in landscape composition in a mountain ecosystem using paired historical and repeat oblique photographs.

Materials and Methods

Acquisition of imagery

The historical photographs we analyzed are part of the MLP's much larger collection originally captured to create comprehensive topographic maps of western Canada (Bridgland 1916, 1924; MacLaren et al. 2005; Trant et al. 2015). Photographs in this analysis were taken between 1923 and 1953 with large format cameras on levelled tripods, on fine emulsion 4" by 6" glass plates. The glass plate negatives were preserved at Library and Archives Canada (Delaney 2008), and were digitized at 1800 pixels per inch and at 16-bit grayscale, using an Epson 10000XL Flatbed Scanner.

During summer months (June–August) since 1998, MLP field crews return to the vantage points from which the historical photographs were taken. Using prints of the historical photographs as a reference, crew members position their tripods by verifying the alignment of foreground and background features in the camera's viewfinder (Rogers et al. 1984; Webb 2010; Klett 2011). Repeat photographs are shot with high-resolution digital camera systems. The repeat photographs used in the present analysis date from 2007 to 2016. Appropriate software lens corrections were applied to adjust for optical distortion.

Historical and repeat photographs (Appendix A) were digitally aligned with one another using a custom-built MLP tool (Taggart-Hodge 2016).

The Landsat-based map used imagery from Landsat 5 TM acquired between mid-June and early September of 2002 and 2003 (McDermid 2006; McDermid et al. 2009).

Study area

Our study frame is the central Rocky Mountains of western Canada, a landscape heavily sampled by both oblique and satellite imagery. Within this frame, we sampled one of the least anthropogenically disturbed landscapes: the Willmore Wilderness Park, a 4568 km^2 mountainous wildland park in Alberta, Canada (Fig. 2). Topography in the park is rugged, with high peaks and steep ridge slopes (Fisher et al. 2011a). Vegetation is dominated by Engelmann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa)*, although alpine meadows of herb and shrub are common, and the eastern edge of the park supports more deciduous tree species (Hall et al. 2000; Fisher et al.

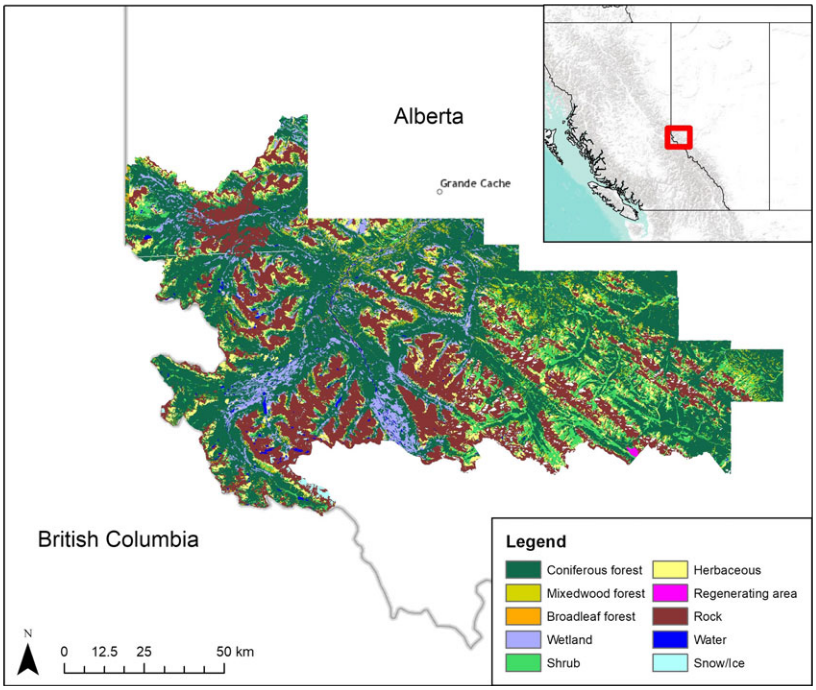

Figure 2. Landsat-based classified map, created with imagery from Landsat 5 TM acquired in the summers of 2002 and 2003, of the Willmore Wilderness Park in west-central Alberta, Canada.

2011a; Mucha 2013). We chose this study area for its relatively low human footprint (Fisher et al. 2014; Stewart et al. 2016); given that the repeat oblique photographs were taken between 4 and 14 years apart from when the satellite imagery was acquired, it was important to opt for a landscape that would not exhibit substantial changes between the time of acquisition of both sources of imagery. This way, differences observed between the two data sources more likely represented differences in the way they sampled the landscape rather than actual changes that occurred on the landscape in the time between image captures.

Sample selection

We selected 46 oblique photographs (Appendix B) from a total of nearly 500 in the Willmore Wilderness Park, according to the following criteria: (1) images were clear and sharp, with no exposure or focus issues, to facilitate classification. (2) Images consisted of 20% or less foreground, to maximize usable pixels. Foreground pixels were omitted from analysis as recommended by Rhemtulla et al. (2002), as pixels in the foreground of an oblique image represent a much smaller area than pixels in the background. By omitting disproportionately small pixels, land cover proportions are less affected by variable pixel size. (3) Images captured a view from valley to peak, to show the full range of possible land cover classes. (4) Images were geographically dispersed across the study area to capture climatic and topographic gradients.

Selected images showed no bias in any compass direction. In some cases, overlap between the viewsheds of multiple images occurred; this is sampling with replacement and there is no evidence this inflated degrees of freedom in our analysis.

Classification of oblique images

Initial tests with automated and semiautomated classification algorithms showed promising results with the modern photographs but poor performance with the historical black and white photographs, presumably due to limited spectral information (Caridade et al. 2008; Jean et al. 2015a). Manual classification, although slow and labor-intensive, can provide accurate land cover data (Cunningham 2006), and worked well with both grayscale and color photographs. As such, we deemed this method appropriate for our relatively small sample size for this proof-of-concept study. Future studies seeking to scale our approach to larger sample sizes could explore less time-intensive classification methods such as texture analysis (Haralick et al. 1973; Halounová 2003; Caridade et al. 2008) or deep learning (LeCun et al. 2015; Zou et al. 2015; Li and Zhang 2016; Zhang et al. 2016).

An expert familiar with the study area used a custom-built MLP software program to manually classify the oblique images (Jean et al. 2015a; Taggart-Hodge 2016), using a Wacom Intuos PTZ-930 pen tablet to delineate the land cover classes with great precision. The minimum mapping unit (MMU) was a 12-pixel polygon.

The 10-category classification scheme used on the oblique photographs was adapted from the classification scheme of the Landsat-based map to which the oblique photographs were compared (Table 1) (Fisher et al. 2011b). In some photographs, smoke and fog made classification of the background questionable; such areas with high uncertainty were omitted from analysis.

By means of this process, we created 46 pairs of oblique photograph-based land cover classifications ("oblique samples"; Appendix B), and estimated land cover proportions of each class by calculating pixel counts with respect to the total number of classified pixels in each photograph.

Extraction of Landsat samples

We digitally delineated polygons corresponding to the viewsheds of the oblique samples in Google Earth Pro using the Ruler tool (*Google Earth*, 2017). We opted for manual delineation because automated tools gave poor renderings of viewsheds due to insufficiently precise camera location and azimuth measurements for many photos, and because we could exclude portions of the landscape that were omitted from classification on a case-by-case basis. We then extracted land cover proportions within these polygons from a 16-category land-cover map generated from Landsat imagery (Fig. 2) (McDermid et al. 2009; Fisher et al. 2011b) using the Extract By Mask tool in ArcMap 10.4.1 (*ESRI*, 2015).

Table 1. Corresponding classes in the Landsat and oblique classification systems, with definitions used to classify the oblique photographs.

Landsat class	Corresponding oblique class	Definition used to classify oblique photographs
Dense conifer forest Moderate conifer forest Open conifer forest Treed wetland	Coniferous forest	>70% Conifer trees
Mixedwood forest	Mixedwood forest	Patches with 30–70% cover by broadleaf trees and the rest by coniferous trees
Broadleaf forest	Broadleaf forest	>70% Broadleaf trees
Open wetland	Wetland	Vegetation with a wet or aquatic moisture regime
Upland shrub	Shrub	Shrubby vegetation
Upland herbaceous	Herbaceous	Grasses and herbaceous vegetation
Regenerating area	Regenerating area	Visibly recently burned forest (charred trees)
Barren land	Rock	Bedrock, rubble, rocky outcrops
Water	Water	Lakes, rivers, ponds
Snow/Ice	Snow/Ice	Snow/ice
Agriculture	N/A	N/A
Cloud/No data	N/A	N/A
Shadow/No data	N/A	N/A

Regression analysis

We conducted data exploration on the land cover proportion estimates in the statistical software program R (R Core Team, 2015) to ensure that the assumptions of linear regression were upheld to avoid type I or type II errors (Zuur et al. 2010). Minor issues with nonlinearity, nonnormality and heteroskedasticity in some land cover classes prompted further investigation into data transformations. We found that transformations did not improve the measures of normality for most classes. Moreover, probability distributions for generalized linear models (Poisson, etc.) did not fit the data. Given that the purpose was not to find the best fit model for each class, but rather to test for a linear relationship between the two data sources, we computed simple linear regression in R on the untransformed data, for all classes, using the *lm* function in the STATS package (R Core Team, 2015).

Land cover change

To evaluate changes in landscape composition in the historical and modern oblique photographs, we directly compared land cover proportions of each class and ran paired t-tests using the *t test* function in the STATS package in R version 3.4.3 for each class (R Core Team, 2015).

Results

Characterization of the modern landscape

Across the entire study area, modern oblique samples and Landsat samples estimated similar mean proportions for most land cover classes (Fig. 3). Most classes were within 1% of one another, except for coniferous forest (within 5%), shrub (within 9%), rock and regenerating area (both within 3%).

Characterization of the modern samples

The three dominant classes – coniferous forest, herbaceous cover and rock, which together form over 86% of the total number of pixels in the oblique samples – exhibited relatively strong (r^2 = 0.319, 0.391, 0.589, respectively; all $P < 0.0001$) positive linear relationships between oblique and Landsat samples (Fig. 4). The slopes of the best fit lines for these land cover classes were all

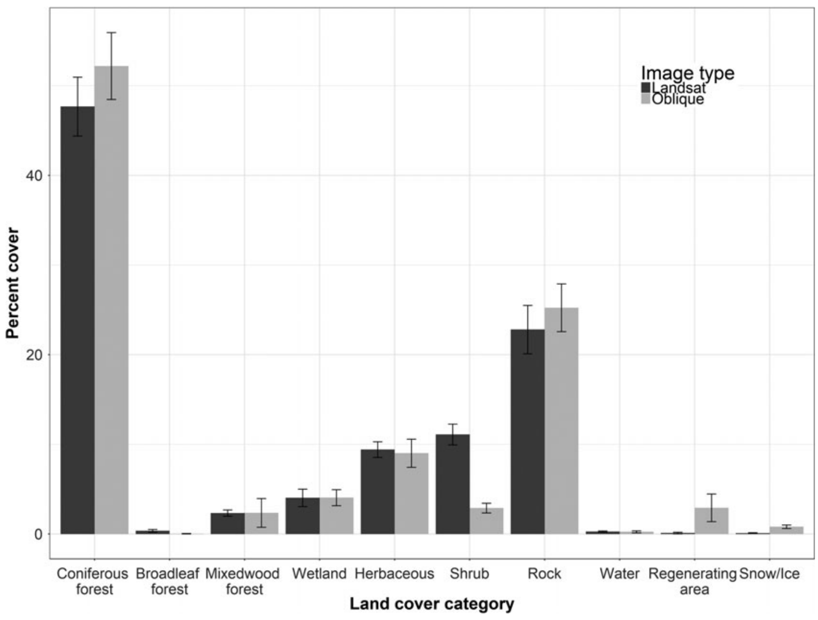

Figure 3. Mean per cent cover of each land cover class in both the Landsat and oblique classifications, with error bars (1 standard error).

less than 1 (slopes of 0.497, 0.347 and 0.777, respectively), suggesting that within individual images, oblique samples tend to assign a greater proportion of pixels to these classes than do Landsat samples.

Mixedwood forest and regenerating area also showed evidence of statistically significant relationships ($P < 0.0001$ and $P < 0.005$, respectively), but both were nearly null (slopes of 0.165 and 0.0256) as the relationships were driven by the large number of zeros observed for these classes by both data sources (Fig. 4).

The remaining classes (broadleaf forest, wetland, shrub, water and snow/ice) each consisted of less than 5% of the total number of pixels in the oblique samples. Many of these classes were entirely unrepresented in the majority of samples (Fig. 5), and did not exhibit evidence of a linear relationship between oblique and Landsat samples at $P < 0.05$.

Characterization of long-term land cover change

Overall the Rocky Mountain landscape became more homogeneous over the past century (Fig. 6). Coniferous forest cover increased significantly between the historical and modern photographs ($P < 0.05$), from 40.07% (standard error 3.14%) to 52.50% (SE 3.74%). Proportion of wetland decreased from 4.81% (SE 1.08%) to 4.14% (SE 0.91%), herbaceous cover from 15.50% (SE 2.15%) to 9.02% (SE 1.53%), and water from 0.30% (SE 0.12%) to 0.20% (SE 0.11%) (all $P < 0.05$). All other categories except mixedwood forest showed nonsignificant trends decreasing over time; mixedwood forest showed nonsignificant increase.

Resolution

On average, oblique samples were comprised of over 10 344 024 pixels (standard deviation 4 352 621), while the corresponding Landsat polygons comprised of 18 023 pixels (SD 13 082). Assuming an MMU of 12-pixel polygons for the oblique samples and of single pixels for the Landsat samples, this means that oblique samples had, on average, 48 times as many mapping units covering the same area. The mean areal coverage of an oblique sample, measured as the area of the corresponding viewshed polygon was approximately 17 km^2, with a total area of nearly 423 km^2 sampled by the aggregate collection of images.

Discussion

Oblique photographs and orthogonal Landsat imagery characterize mountain landscapes in broadly the same way, with some advantages and some drawbacks for rarer land cover classes characteristic of mountain environments. Applying analysis of repeat oblique photographs, we observed a clear signal of landscape homogenization – a significant increase in coniferous forest cover and concurrent declines in rarer land cover types – over nearly a century in this Rocky Mountain landscape.

Characterization of the modern landscape

At the landscape scale (i.e., when averaged across all samples), oblique and Landsat samples estimate similar proportions for most classes, as in Rhemtulla et al. (2002) (Fig. 3). The largest discrepancies between overall land

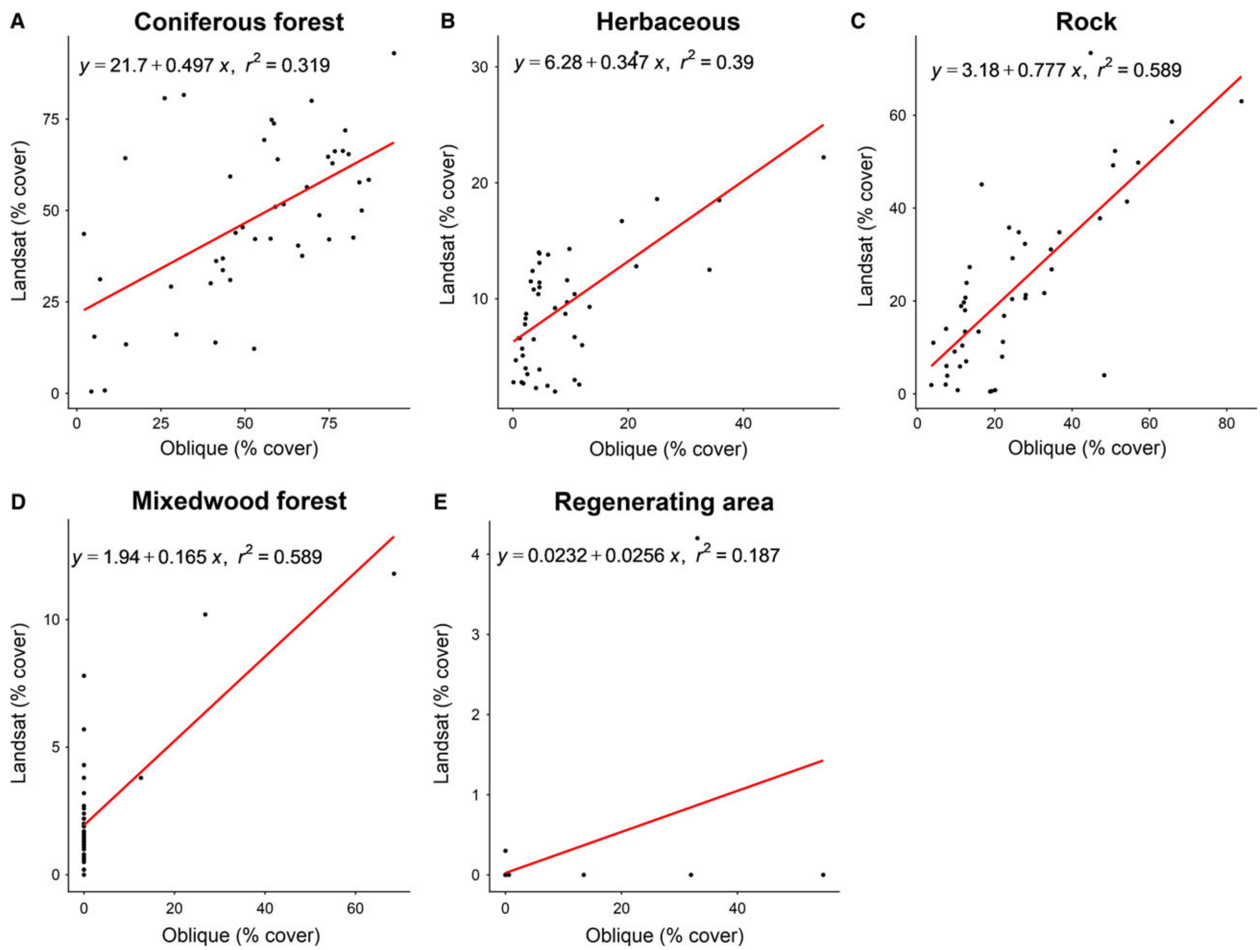

Figure 4. Per cent cover of (A) coniferous forest, (B) herbaceous cover, (C) rock cover, (D) mixedwood forest, and (E) regenerating area, in both the oblique classification and Landsat classification for each of the 46 sites.

cover proportion estimates are in the coniferous forest and shrub classes.

Coniferous forest dominates this region of the Rocky Mountains, with both oblique and orthogonal imagery predicting that it makes up approximately half of the landscape. However, on average, oblique photographs capture more coniferous forest than Landsat, by a small (<5%) margin. Conversely, oblique photographs capture less shrub cover than Landsat (2.9% vs. 11.1%, respectively) Several factors could explain these tendencies. (1) The variable size of pixels in the oblique photographs: 1 m^2 in the midground of an image is represented by more pixels than 1 m^2 in the background, so proportions based on pixel counts could be biased in favor of features that appear in the midground (typically forest). (2) Shrubs can be spectrally similar to (and thus confused with) other vegetation types (Castilla et al. 2014). (3) McDermid et al. (2009) reported an overall accuracy of 78.0% in the Landsat product, with confusion between shrub and herbaceous classes. Misclassifications of the Landsat product could result in disagreement between both data sources. (4) Temporal mismatch: shrubby vegetation in some areas could have made way for young forest in the 4–14 years between image acquisition.

Characterization of the modern samples

At the image scale (i.e., for each of the 46 pairs of samples), agreement was strong for dominant land cover classes, thus both types of imagery did a similar job of capturing the majority of the landscape. However, there was no linear relationship for rare classes due to lack of observations. Moreover, the oblique samples more frequently detected land cover classes that appeared as narrow or small patches (wetland, water and snow/ice) owing to the higher resolution of oblique photographs, as well as gave higher estimates of classes comprising steep terrain (rock) owing to the more appropriate angle of incidence.

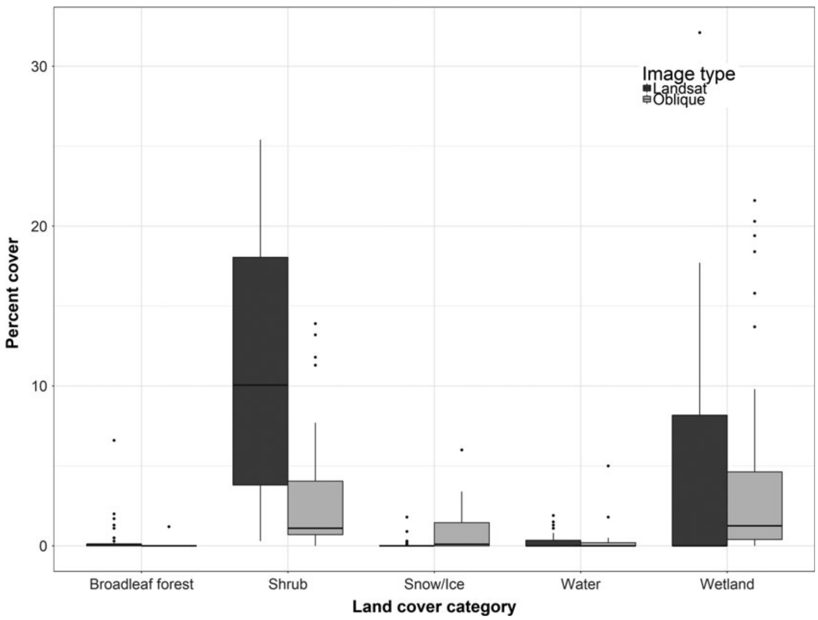

Figure 5. Boxplots representing the per cent cover of the more infrequent classes for both the oblique and Landsat classifications for all 46 sites.

Dominant categories

Oblique and Landsat samples generally predicted the same trends for coniferous forest, herbaceous cover and rock. However, there was a tendency for oblique samples to estimate higher proportions of these land covers compared to the Landsat samples (slopes all < 1; Fig. 4). First, coniferous forest may have been overrepresented in the oblique samples due to the issue with variable pixel size noted above. Second, some classes may have been better sampled by the oblique images due to their angle of incidence, particularly rock: it makes up the majority of steep terrain such as cliff faces, which are more visible from an oblique view than an overhead view. This implies that oblique photographs can be advantageous in that they provide information about the landscape that satellite images fail to capture in landscapes with rugged topography. Third, the confusion between herbaceous cover and shrubs in the Landsat product (McDermid et al. 2009) could be responsible for underestimations of herbaceous cover relative to the oblique samples.

Mixedwood forest

The near-null slope for mixedwood forest shows that Landsat samples quantify this class regardless of what is quantified by oblique samples. Indeed, mixedwood forest was observed in 45 of the 46 Landsat samples, but in only 3 of the 46 oblique samples. The three oblique samples that did detect mixedwood forest corresponded to three of the Landsat samples with the highest proportion of mixedwood forest, indicating that Landsat samples perhaps had perpetual noise in the mixedwood forest class or that oblique samples failed to detect mixedwood forest unless the signal was large. The discrepancy may also be attributable to the angled view in oblique photographs. Coniferous trees such as Engelmann spruce and subalpine fir seen in this park can reach heights of 30–40 m, whereas broadleaf species in the area do not often reach maturity and are smaller (Alexander 1987; Arsenault 2003). As such, it is possible that the broadleaf trees were obscured by taller coniferous trees in the oblique images but were observed from atop in the orthogonal images.

Regenerating area

Regenerating area was detected in only 5 oblique and 2 Landsat samples. Disagreement for this short-lived post-disturbance class could result from the temporal mismatch between oblique and Landsat image acquisition. For instance, the Rockslide Creek fire of 2015 (Finn and Gibos 2016) was captured in oblique samples 5 and 7 acquired in 2016 (Appendix B), but not in the corresponding Landsat samples because the Landsat imagery was acquired in 2002–2003, before the fire.

Rare categories

There was no relationship between oblique and Landsat samples for the remaining classes, suggesting that the two data sources sample or interpret broadleaf forest, shrub, wetland, water and snow/ice cover in different ways.

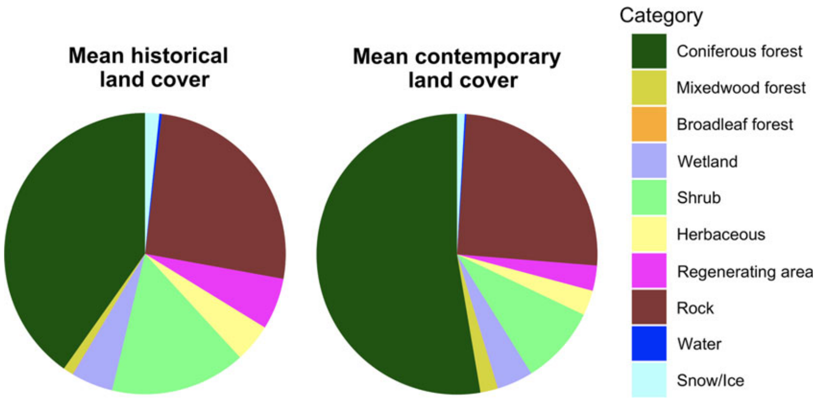

Figure 6. Mean land cover composition in the classifications of the historical and modern oblique photographs.

These classes either consistently represented small proportions of the landscape, or were unrepresented at a large number of sites, resulting in many "zeros" and many outliers in both oblique and Landsat samples (Fig. 5).

Broadleaf forest was observed in only one oblique sample. Similar to mixedwood forest, possible explanations include obstruction of broadleaf trees by coniferous trees in an oblique view, or misclassification of broadleaf forest. Shrub cover, conversely, was well represented across the samples, but was sampled or interpreted differently in both types of imagery (e.g., due to obstruction by taller trees or confusion with spectrally similar classes) (Castilla et al. 2014). Wetland was detected in twice as many samples in oblique photographs (42) compared to Landsat (21). Water was also included more frequently in oblique samples than in Landsat samples (20 and 16, respectively), as was snow/ice (26 oblique and 9 Landsat). Wetlands, rivers (water) and snow patches have the common characteristic of appearing as narrow features on the landscape. As such, it is possible that Landsat polygons failed to resolve these classes due to the large (30 m) grain size of Landsat imagery, but that they were captured in oblique samples due to their higher resolution.

Characterization of long-term land cover change

By quantifying contemporary and historical landscapes from oblique photographs, we observed a clear signal of landscape homogenization. Common coniferous forest increased through time, encroaching onto areas formerly occupied by rarer alpine meadows and valley bottom wetlands characteristic of mountain landscapes. Importantly, the high resolution of the oblique photographs likely allowed us to capture declines in rare classes, namely wetlands, more readily than we may have with typical satellite products.

Because the Willmore Wilderness Park has nearly no habitat loss from resource extraction, roading, and other development, we can infer that the changes are a result of climate change and shifts in wildfire suppression and fire cycle. Indeed, our observations were consistent with changes reported in other studies on Rocky Mountain systems (e.g., Brown et al. 1999; Rhemtulla et al. 2002; Stockdale 2017). Fuel accumulation resulting from a modified fire regime and lack of disturbance leads to densification of forests (Butler and DeChano 2001; Keane et al. 2002; Ryan et al. 2013). Furthermore, many studies have documented forest encroachment via "treeline creep" due to broad-scale warming (Lloyd and Fastie 2003; Walther et al. 2005; Coop and Givnish 2007; Roush 2009). Many factors, including changes in temperature and precipitation patterns, duration of growing season, and fire regime, are expected to be at play in our study area, and could explain our observed increase in coniferous forest cover (O'Neill 2011; Falk 2014).

These changes have probable implications on Rocky Mountain biodiversity. Habitat availability and suitability for multiple species has changed, which could entrain altitudinal range shifts (Parmesan and Yohe 2003), modified interspecific interactions (Heim et al. 2017; Pecl et al. 2017) and novel community assemblages (Hobbs et al. 2018). Given that the Rocky Mountains is an area of conservation importance for many species, monitoring of these land cover changes and resulting effects on biodiversity is essential to management efforts.

Homogenization also has consequences for wildfire potential in the park and adjacent landscapes. Given continued warming pressures, the trends we recorded could be amplified over the next century. Management of this landscape should consider actions to mitigate such risks, such as restoration or reintroduction of historical disturbance regimes (Grumbine 1994; Agee 1996).

Conclusion

Oblique photographs sample landscape composition in mountain environments differently from orthogonal satellite imagery. Oblique photographs can have much higher spatial resolution than Landsat products, and thus a better ability to detect narrow landscape features. Oblique photographs can also view cliffs and steep terrain from a more appropriate angle compared to the overhead imagery, a distinct advantage in mountainous areas. These distinctions notwithstanding, oblique photographs and Landsat imagery yield comparable estimates for broad-scale landscape composition.

Satellite-based thematic maps are generally accepted as reasonable models of landscape composition despite their uncertainties and errors. We argue that oblique photographs – even if not orthorectified to provide spatially accurate estimates – can also provide reasonable models of landscape composition, with key advantages: (1) high resolution oblique photographs can resolve narrow landscape features that may be of particular conservation interest (e.g., wetlands); (2) oblique photographs capture alternative and potentially more appropriate views of slopes in mountain environments; (3) oblique photographs are especially useful when seeking to understand past conditions from time periods before satellite imagery was available, in landscapes where historical photographs exist.

Systematic and comprehensive historical photographs are not necessarily widely available save for a few collections such as the Mountain Legacy Project. There are, however, many smaller collections or individual historical images that reveal significant landscape characteristics. Contemporary oblique images can also be important for analysis: immense quantities of oblique photographs exist via Google Street View, social media or citizen scientists. Our study points to the potential of harnessing land cover information from these data. As land cover is a useful variable for understanding ecosystem structure, local, regional and global monitoring initiatives could collect valuable information regarding habitat and biodiversity based on oblique photographs. This has implications for the cost, spatial resolution, spatial coverage and temporal frequency of data acquisitions that can contribute to biodiversity monitoring efforts such as the Essential Biodiversity Variable framework (Pereira et al. 2013; Pettorelli et al. 2016).

In order to realize the potential of these implications, future studies seeking to scale up our approach could benefit from a less time-consuming and labor-intensive image classification process; using automated or semiautomated classification techniques such as texture analysis or deep learning could allow for greater sample sizes and larger-scale geographic coverage. Furthermore, given the ability to generate linear relationships between per cent cover (from modern oblique photographs) and surface area (from satellite-based land cover maps), it would be possible to use those linear relationships in conjunction with per cent cover estimated from historical oblique photographs to "backcast" historical area coverage. We did not demonstrate this due to geographic overlap between many of our samples, but this could be a direction for further investigation. Additional future directions of this work could examine whether oblique photographs taken from different viewpoints but observing the same landscape predict similar landscape composition. This could give insight into the accuracy or potential biases present in oblique landscape views.

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Data Accessibility

All Mountain Legacy Project data is available freely under a Creative Commons license for non-commercial use at http://mountainlegacy.ca.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A: List of oblique photographs from Mountain Legacy Project.

Appendix B: Oblique photographs and associated land cover masks.

