

Visualizing Category-Specific Changes in Oblique Photographs of Mountain Landscapes

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Abstract

Our paper proposes a method for visualizing the spatial distribution of classes for a multi-class image segmentation problem. We apply this method for the case of mountain landscape images, where classes are defined by landscape categories. The proposed method builds class-specific distribution maps. Our contribution is two-fold. First, the class-specific distribution maps allow for the visualization of class-specific changes computed from pairs of images depicting the same landscape at different moments in time. Second, these maps enable us to calculate prior class probabilities for statistical scene segmentation purposes.

Categories and Subject Descriptors (according to ACM CCS): I.4.9 [Computer Graphics]: Image Representation—

1. Introduction

Monitoring changes in our bio-geophysical environment using remotely sensed data provides valuable information that can be used to improve resource and environmental management processes, as well as to better understand the human impact on ecological phenomena [LMBM04]. Visual change detection consists in identifying and localizing changes in the appearance and structure of relevant phenomena or objects over some temporal range.

For instance, remote sensing data have been used to detect changes that are relevant for climate studies, such as changes in land cover or land use, deforestation, regeneration and selective logging, forest fire and fire affected area, etc [PL01, JZL*12]. The development of automatic methods for change detection has received a lot of attention from the remote sensing and computer vision communities in the last decade [LMBM04]. This is due, of course, to the large amounts of data to be processed for the assessment of changes.

Very few works have explicitly addressed the topic of change visualization. In our opinion, this topic deserves an in-depth study, due to the fact that most climate-relevant changes tend to be complex in nature. Also, given the high socio-economical impact of climate change research, it is imperative to develop visualization methods that construct a complete, unbiased, data-driven picture of the changes of

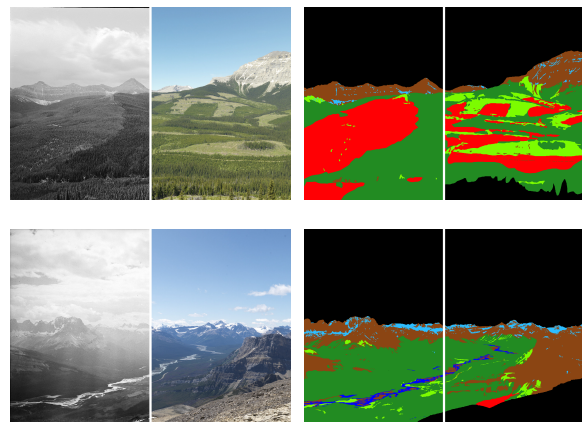


Figure 1: Examples of images from the MLP public dataset [JBC*14]. Historic and Repeat Images are presented side by side, as well as their manual segmentations into landscape categories. The colour code is given in Table 1.

interest. This is consistent with recommendations by Schneider [Sch11], who writes: “images picturing climate do not simply represent or illustrate information, but in the process actively produce and shape knowledge.” Our contribution lies therefore in the “nascent research area” of visual representations of climate change [OS14].

Meta-category	Category	Color
Forest(F)	broadleaf/mixedwood (B-MW)	orange
	coniferous forest (CF)	dark green
	regenerating areas (RA)	red
Non-forest (NF)	ice/snow (I-S)	light blue
	sand/gravel/rock (S-G-R)	brown
	upland herbaceous (UH)	light green
	water (WT)	blue
	wetland (WL)	turquoise

Table 1: Landscape categories and meta-categories.

Our paper proposes a method for visualizing the spatial distribution of classes for a multi-class image segmentation problem. We apply this method for the case of mountain landscape images, where classes are defined by landscape categories (see Table 1 and Figure 1). The proposed method builds class-specific distribution maps. Our contribution is two-fold. First, the class-specific distribution maps allow for the visualization of class-specific changes computed from pairs of images (historic and repeat) depicting the same landscape at different moments in time. Second, these maps enable us to calculate prior class probabilities for statistical scene segmentation purposes. The remainder of the paper is structured as follows. The following section presents the proposed approach for computing class-specific distribution maps. Next, we present and discuss results. The paper ends with conclusive remarks and an outline of future work.

2. Proposed Approach

2.1. Dataset

Unlike most related work on change detection in remote sensing (which use either aerial or satellite imagery), we work with high-resolution photographic images of mountain landscapes. While aerial photography and satellite imagery are relatively new technologies, oblique ground photography has been used since the late 19th century; thus, it enables us to study changes in landscape over a larger temporal range. Our database is a subset of the data acquired and managed by the Mountain Legacy Project (MLP) [Mou14], which hosts the world’s largest collection of historic mountain photographs (about 140,000), taken between 1888 and 1958. In addition, MLP contains a large number of high-resolution repeat photographs (about 5,000), which were manually aligned to their historic counterpart. The resulting image pairs have been studied for climate change detection, as well as for a variety of research and management-focused projects on fire history, vegetation change, human activity and ecological restoration [RHMM02, MHZM05].

A public database containing a subset of 60 image pairs (registered repeat and historic photographs), along with their manual segmentations, has been recently released [JBC*14, JBC*15]. The manually segmented images consist of labels assigned to every pixel in the image, where the label denotes the landscape category. This paper works with the manual

segmentations from this public database in order to build category-specific spatial distribution maps as well as prior probabilities. Only the bottom half of the manual segmentations has been considered in the computation process, as the top half contains some irrelevant information (i.e. a significant amount of sky).

2.2. Computation of spatial distribution maps and prior probabilities

Input data for the computation process consists of two sequences of images corresponding to manual segmentations for the historic and repeat images, with the top half of each image removed. The images in these sequences are denoted by $I_{t,\ell}(u,v)$, where t represents either historic (H) or repeat (R) images, and $\ell = 1, 2, \dots, L$, with $L = 60$. The value of image $I_{t,\ell}$ at location (u,v) is the label k of a certain landscape category, with $k = 1, 2, \dots, K$. The size of an image is denoted as $U_{t,\ell} \times V_{t,\ell}$. The total number of landscape categories is $K = 8$, as shown in Table 1 and Figure 1.

Let $\mu_{t,k,\ell}(i,j)$ denote the $S \times S$ spatial distribution map of category k for image $I_{t,\ell}$, where $i, j = 1, 2, \dots, S$. This map represents a division of the image $I_{t,\ell}$ into $S \times S$ blocks of pixels, and the map value for bin (i,j) is the number of pixels belonging to category k within the corresponding image block:

$$\mu_{t,k,\ell}(i,j) = \sum_{u=a(i,U_{t,\ell})}^{b(i,U_{t,\ell})} \sum_{v=a(j,V_{t,\ell})}^{b(j,V_{t,\ell})} \delta_{t,k,\ell}(u,v), \quad (1)$$

where

$$\delta_{t,k,\ell}(u,v) = \begin{cases} 1 & \text{if } I_{t,\ell}(u,v) = k \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

and

$$a(x,Z) = \left\lfloor \frac{Z(x-1)}{S} \right\rfloor, \quad b(x,Z) = \left\lfloor \frac{Zx}{S} \right\rfloor. \quad (3)$$

Here, the Kronecker delta $\delta_{t,k,\ell}(u,v)$ allows for a compact expression of the fact that only pixels belonging to category k and located inside the block corresponding to the map bin (i,j) will contribute to $\mu_{t,k,\ell}$. The functions $a(x,Z)$ and $b(x,Z)$ define respectively the starting and the ending index of an image block along one dimension of the image with respect to bin index x and image dimension length Z .

Let $M_{t,k}(i,j)$ denote the total spatial distribution map, which is computed by summing up image-specific distribution maps $\mu_{t,k,\ell}$ over the entire dataset ($\ell = 1, 2, \dots, L$) for images of type t :

$$M_{t,k}(i,j) = \sum_{\ell=1}^L \mu_{t,k,\ell}(i,j). \quad (4)$$

Using the total spatial distribution map for historic images $M_{H,k}(i,j)$ and the total spatial distribution map $M_{R,k}(i,j)$

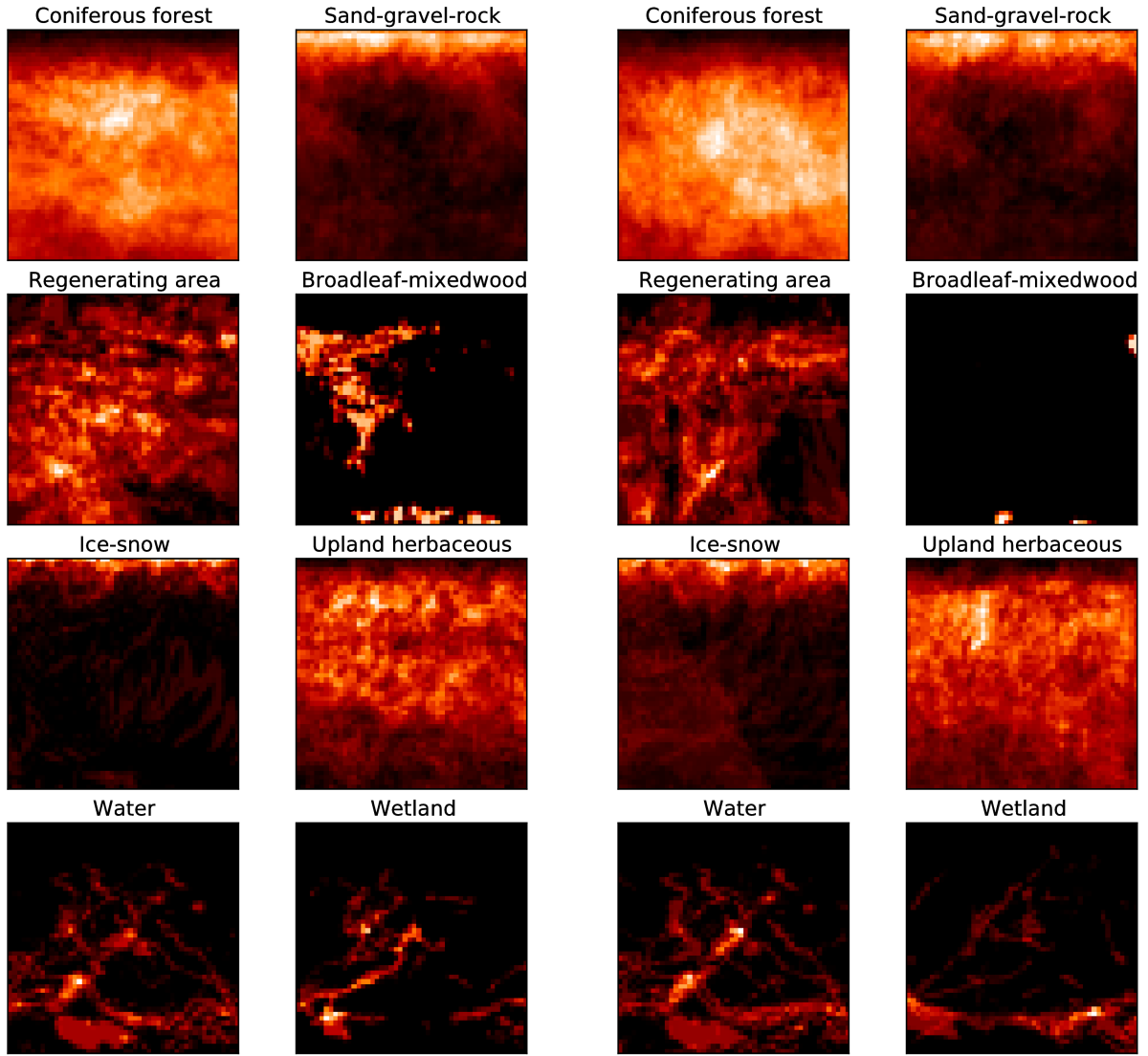


Figure 2: Category-specific heat map for repeat images

for repeat images, it is possible to compute a difference map of spatial distribution for category k as follows:

$$D_k(i, j) = M_{R,k}(i, j) - M_{H,k}(i, j). \quad (5)$$

Subtracting the historic map from the repeat map allows for representing the changes for a category k at spatial location (i, j) as a negative value if there are less repeat pixels for that category than historic pixels, and as a positive value if there are more repeat pixels than historic pixels.

The spatial distribution maps also allow for a straightforward computation of prior probabilities for every category k

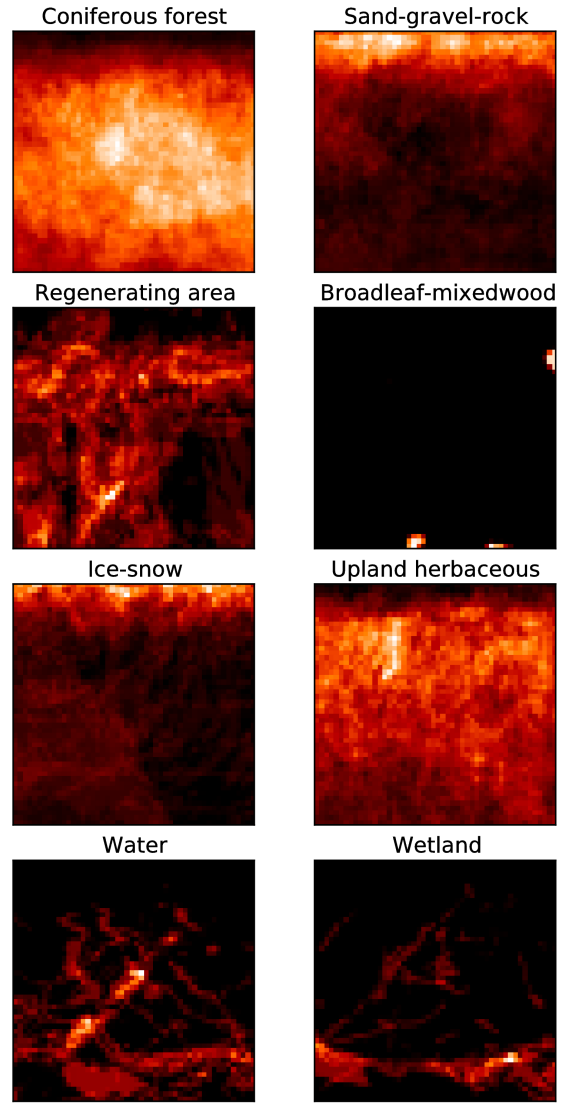


Figure 3: Category-specific heat map for historic images

in function of the image height i and image type t :

$$P_{t,k}(i) = \frac{1}{N_{t,k}} \sum_{j=1}^S M_{t,k}(i, j), \quad (6)$$

where $N_{t,k} = \sum_{i=1}^S \sum_{j=1}^S M_{t,k}(i, j)$. The summation occurs along the horizontal axis because the most significant variations in landscape occur as a function of altitude (vertical axis).

3. Results

The category-specific spatial distribution maps computed with $S = 50$ for the repeat and historic images in the MLP public dataset are shown in Figure 2 and 3, respectively;

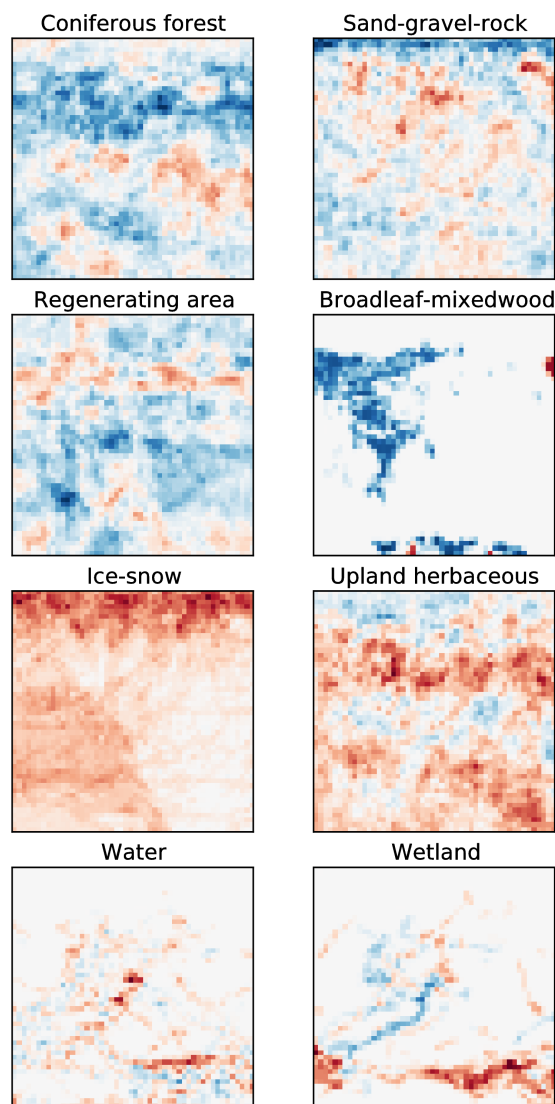


Figure 4: Spatial distribution map of intra-category differences. Blue means more pixels in repeat images than in historic images, and red means less pixels in repeat images. White means nothing has changed.

a heat map is used for visualization purposes. A simple pixel-wise difference process allows for the computation of the difference map in Figure 4, which illustrates category-specific changes using a blue-red colormap. While this map is generated for the purpose of visualization by experts in environmental studies, earth sciences, climate etc. the non-expert viewer may also observe some salient characteristics of these maps. For instance, the ice-snow category shows no blue, therefore one may state that the amount of ice and snow has clearly decreased in all repeat images with respect to their historic counterparts. Another difference map which

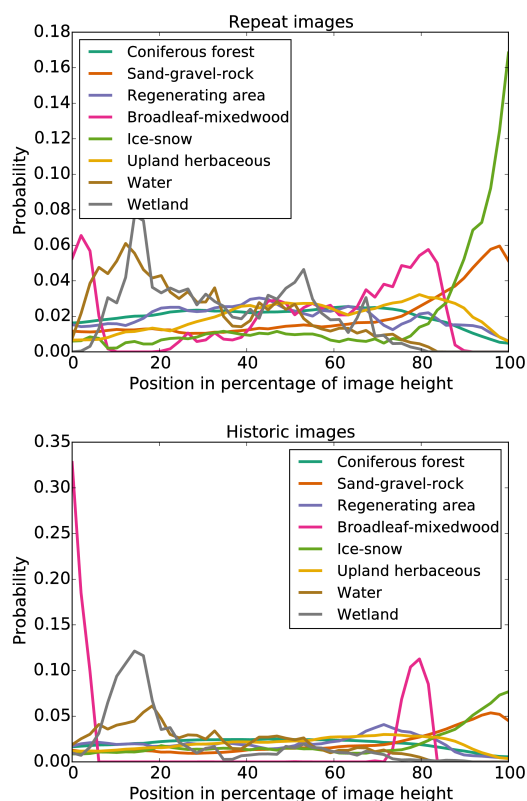


Figure 5: Category-specific prior probabilities

is easy to interpret is the one corresponding to the coniferous forest; the deep blue regions in its upper part show that the tree-line has advanced towards the summit, which is an indicator of climate change according to [GBN02].

Landscape categories occur with variable frequency in our database. The coniferous forest is one of the most frequent, while the broadleaf-mixedwood, water, and wetland might be completely missing from some images. To design automatic segmentation methods of these categories based on statistical models, one needs to take into account prior probabilities for all categories. These prior probabilities are computed with Equation 6 and shown in Figure 5.

4. Conclusion

This paper proposes a novel visualization method for changes occurring within mountain landscape images photographed at two different moments in time. The mountain landscapes represent complex scenes, so changes need to be assessed for each landscape category. Using a new public dataset, we build category-specific spatial distribution maps, and derive prior probabilities for each category. The difference of the distribution maps is useful for the qualitative evaluation and visualization of changes, while the prior

probabilities serve to design robust automatic segmentation methods based on statistical models. Future work will focus on the design of such automatic segmentation algorithms that will outperform the baseline segmentation algorithms proposed in [JBC*15].

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