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Landscape classification with deep neural networks.

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Abstract: The application of deep learning, specifically deep convolutional neural networks (DCNNs), to the classification of remotely sensed imagery of natural landscapes has the potential to greatly assist in the analysis and interpretation of geomorphic processes. However, the general usefulness of deep learning applied to conventional photographic imagery at a landscape scale is, at yet, largely unproven. If DCNN-based image classification is to gain wider application and acceptance within the geoscience community, demonstrable successes need to be coupled with accessible tools to retrain deep neural networks to discriminate landforms and land uses in landscape imagery. Here, we present an efficient approach to train/apply DCNNs with/on sets of photographic images, using a powerful graphical method, called a conditional random field (CRF), to generate DCNN training and testing data using minimal manual supervision. We apply the method to several sets of images of natural landscapes, acquired from satellites, aircraft, unmanned aerial vehicles, and fixed camera installations. We synthesize our findings to examine the general effectiveness of transfer learning to landscape scale image classification. Finally, we show how DCNN predictions on small regions of images might be used in conjunction with a CRF for highly accurate pixel-level classification of images.

Keywords: image classification; image segmentation; land use; land cover; landforms; deep learning; machine learning; UAS; aerial imagery; remote sensing

1. Introduction

1.1. The growing use of image classification in the geosciences

There is a growing need for fully automated pixel-scale classification of large datasets of color digital photographic imagery, to aid analysis and interpretation of natural landscapes and geomorphic processes. The task of classifying natural objects and textures in images of landforms is increasingly widespread in a wide variety of geomorphological research [1-7], providing impetus for the development of completely automated methods to maximize speed and objectivity. The task of labeling image pixels into discrete classes is called object class segmentation or semantic segmentation, whereby an entire scene is parsed into object classes at a pixel level [8-9].

There is a growing trend in studies of coastal and fluvial systems for using automated methods to extract information from time-series of imagery from fixed camera installations [10-16], UAVs [17-19] and other aerial platforms [20]. Fixed camera installations are designed for generating time-series of images for assessment of geomorphic change in dynamic environments. Many aerial imagery datasets are collected for building digital terrain models and orthoimages using Structure-from-Motion (SfM) photogrammetry [21,22]. Numerous complementary or alternative uses of such imagery and elevation models for the purposes of geomorphic research include facies description and grain size calculation [23,24], geomorphic and geologic mapping [25,26], vegetation structure description [27,28], physical habitat quantification [29,30], and geomorphic/ecologic change detection [31-33]. In this paper, we utilize and evaluate two emerging themes in computer vision research, namely deep learning and structured prediction, that, when combined, are shown to be extremely effective in application to pattern recognition and semantic segmentation of highly structured, complex objects in images of natural scenes.

1.2. Application of deep learning to landscape scale image classification

Deep learning is the application of artificial neural networks with more than one hidden layer to the task of learning and subsequently recognizing patterns in data [34,35]. A class of deep learning algorithms called deep convolutional neural networks (DCNNs) are extremely powerful at image recognition, resulting in a massive proliferation of their use [36,37], across almost all scientific disciplines [38,39]. A major advantage to DCNNs over conventional machine learning approaches to image classification is that they do not require so-called 'feature-engineering' or 'feature extraction', which is the art of either transforming image data so that they are more amenable to a specific machine-learning algorithm, or providing the algorithm more data by computing derivative products from the imagery, such as rasters of texture or alternative colorspaces [40,6,12]. In deep learning, features are automatically learned from data using a general-purpose procedure. Another reputed advantage is that DCNN performance generally improves with additional data, whereas machine learning performance tends to plateau [41]. For these reasons, DCNN techniques will find numerous applications where automated interpretation and quantification of natural landforms and textures are used to investigate geomorphological questions.

However, many claims about the efficacy of DCNNs for image classification are largely based upon analyses of conventional photographic imagery of familiar, mostly anthropogenic objects [42,6], and it has not been demonstrated that this holds true for image classification of natural textures and objects. Aside from the relatively large scale, images of natural landscapes collected for geomorphological objectives tend to be taken from the air or at high vantage, with a nadir (vertical) or oblique perspective. In contrast, images that make up many libraries upon which DCNNs are trained and evaluated tend to be taken from ground level, with a horizontal perspective. In addition, variations in lighting and weather greatly affect distributions of color, contrast and brightness; certain land covers change appearance due to changing seasons (such as deciduous vegetation); and geomorphic processes alter the appearance of land covers and landforms causing large intra-class variation, for example, still/moving, clear, turbid, and aerated water. Finally, the distinction of certain objects and features may be difficult against similar backgrounds, for example groundcover between vegetation canopies.

The most popular DCNN architectures have been designed and trained on large generic image libraries such as Imagenet [43], mostly developed as a result of international computer vision competitions [44] and primarily for application to close-range imagery with small spatial footprints [42], but more recently have been used for landform/land use classification tasks in large spatial footprint imagery such as that used in satellite remote sensing [45-49]. These applications have involved design and implementation of new or modified DCNN architectures, or relatively large existing DCNN architectures, and have largely been limited to satellite imagery. Though powerful, DCNNs are also computationally intensive to train and deploy, very data hungry (often requiring millions of examples to train from scratch), and require expert knowledge to design and optimize. Collectively, these issues may impede widespread adoption of these methods within the geoscience community.

In this contribution, a primary objective is to examine the accuracy of DCNNs for oblique and nadir conventional medium-range imagery. Another objective is to evaluate the smallest, most lightweight existing DCNN models, retrained for specific land use/land cover purposes, with no retraining from scratch and no modification or fine-tuning to the data. We utilize a concept known as 'transfer learning', where a model trained on one task is re-purposed on a second related task [35]. Fortunately, several open-source DCNN architectures have been designed for general applicability to the task of recognizing objects and features in non-specific photographic imagery. Here, we use existing pre-trained DCNN models that are designed to be transferable for generic image recognition tasks, which facilitates rapid DCNN training when developing classifiers for specific image sets.

Training is rapid because only the final layers in the DCNN need to be retrained to classify a specific set of objects.

1.3. Pixel-scale image classification

Automated classification of pixels in digital photographic images involves predicting labels, y, from observations of features, x, which are derived from relative measures of color in red, green and blue spectral bands in imagery. In the geosciences, the labels of interest naturally depend on the application but may be almost any type of surface land cover (such as specific sediment, landforms, geological features, vegetation type and coverage, water bodies, etc) or description of land use (rangeland, cultivated land, urbanized land, etc). The relationships between x and y are complex and non-unique, because the labels we assign depend nonlinearly on observed features, as well as on each other. For example, neighboring regions in an image tend to have similar labels (i.e. they are spatially autocorrelated). Depending on the location and orientation of the camera relative to the scene, labels may be preferentially located. Some pairs of labels (e.g. ocean and beach sand) are more likely to be proximal than others (e.g. ocean and arable land).

A natural way to represent the manner in which labels depend on each other is provided by graphical models [50] where input variables (in the present case, image pixels and their associated labels) are mapped onto a graph consisting of nodes, and edges between the nodes describe the conditional dependence between the nodes. Whereas a discrete classifier can predict a label without considering neighboring pixels, graphical models can take this spatial context into account, which makes them very powerful for classifying data with large spatial structure, such as images. Much work in learning with graphical models has focused on generative models that explicitly attempt to model a joint probability distribution $P(x,y)$ over inputs, x, and outputs, y. However, this approach has important limitations for image classification where the dimensionality of x is potentially very large, and the features may have complex dependencies, such as the dependencies or correlations between multiple metrics derived from images. In such cases, modeling the dependencies among x is difficult and leads to unmanageable models, but ignoring them can lead to poor classifications.

A solution to this problem is a discriminative approach, similar to that taken in classifiers such as logistic regression. The conditional distribution $P(y|x)$ is modeled directly, which is all that is required for classification. Dependencies that involve only variables in x play no role in $P(y|x)$, so an accurate conditional model can have much simpler structure than a joint model, $P(x,y)$. The posterior probabilities of each label are modeled directly, so no attempt is made to capture the distributions over x, and there is no need to model the correlations between them. Therefore, there is no need to specify an underlying prior statistical model, and the conditional independence assumption of a pixel value given a label, commonly used by generative models, can be relaxed.

This is the approach taken by conditional random fields (CRFs), which are a combination of classification and graphical modeling known as structured prediction [51,50]. They combine the ability of graphical models to compactly model multivariate data (the continuum of land cover and land use labels) with the ability of classification methods to leverage large sets of input features, derived from imagery, to perform prediction. In CRFs based on 'local' connectivity, nodes connect adjacent pixels in x [51,52], whereas in the fully connected definition, each node is linked to every other [53,54]. CRFs have recently been used extensively for task-specific predictions such as in photographic image segmentation [55,56,42] where, typically, an algorithm estimates labels for sparse (i.e. non-contiguous) regions (i.e. supra-pixel) of the image. The CRF uses these labels in conjunction with the underlying features (derived from a photograph), to draw decision boundaries for each label, resulting in a highly accurate pixel-level labeled image [54,42].

1.4. Paper purpose, scope, and outline

In summary, this paper evaluates the utility of DCNNs for both image recognition and semantic segmentation of images of natural landscapes. Whereas previous studies have demonstrated the effectiveness of DCNNs for classification of features in satellite imagery, we specifically use examples of high-vantage and nadir imagery that are commonly collected during geomorphic studies and in response to disasters/natural hazards. In addition, whereas many previous studies have utilized DCNNs either specifically designed to recognize landforms, land cover or land use, or trained existing DCNN architectures from scratch using a specific dataset, the comparatively simple approach taken here is to repurpose an existing DCNN to a specific task. Previous studies have tended to use relatively large DCNN architectures, whereas here we use the comparatively small, very fast MobileNetV2 framework. Further, we demonstrate how structured prediction using a fully connected CRF can be used in a semi-supervised manner to efficiently generate ground truth label imagery and DCNN training libraries. Finally, we propose a hybrid method for accurate semantic segmentation based on combining 1) the recognition capacity of DCNNs to classify small regions in imagery, and 2) the fine grained localization of fully connected CRFs for pixel-level classification.

The rest of the paper is organized as follows. First, we outline the CRF method, and its use in the generation of ground truth label images and DCNN training libraries. Then we detail the transfer learning approach taken to DCNN model repurposing, and how DCNN model predictions on small regions of an image may be used in conjunction with a CRF for semantic classification. Four datasets for image classification are introduced. The first is a large satellite dataset consisting of various natural land covers and landforms, and the final three are from high-vantage or aerial imagery. Those three are also used for semantic classification. In either case, some data is used for training the DCNN, and some for testing classification skill (out-of-calibration validation). For each of the datasets, we evaluate the ability of the DCNN to classify regions of images or whole images correctly. The skill of the semantic segmentation is assessed. Finally, we discuss the utility of these findings and broader application of these methods for geomorphic research, before conclusions are drawn.

2. Materials and Methods

2.1. Fully connected Conditional Random Field

A conditional random field (CRF) is an undirected graphical model that we use here to probabilistically predict pixel labels based on weak supervision, which could be manual label annotations or classification outputs from discrete regions of an image based on outputs from a trained DCNN. Image features x and labels y are mapped to graphs, whereby each node is connected to an edge to its neighbors according to a connectivity rule. Linking each node of the graph created from x to every other node enables modeling of the long-range spatial connections within the data by considering both proximal and distal pairs of grid nodes, resulting in refined labeling at boundaries and transitions between different label classes. We use the fully connected CRF approach detailed in [54], which is summarized briefly below. The probability of a labeling $\boldsymbol{y}$ given an image-derived feature, $\boldsymbol{x}$, is

$$P(y|x,\theta) = \frac{1}{Z(x,\theta)}\exp(-E(y|x,\theta)) \tag{1}$$

where θ is a set of hyperparameters, Z is a normalization constant, and E is an energy function that is minimized, obtained by

$$\mathrm{E}(y|x,\theta) = \sum_i \psi_i(y_i, x_i|\theta) + \sum_{i<j} \psi_{ij}(y_i, y_j, f_i, f_j|\theta) \tag{2}$$

where i and j are pixel locations in the horizontal (row) and vertical (column) dimensions. The vectors f_i and f_j are features created from x_i and x_j and are functions of both relative position and intensity of the image pixels. The term ψ_i indicate so-called 'unary potentials', which depend on the label at a single pixel location (*i*) of the image, whereas 'pairwise potentials', ψ_{ij}, depend on the labels at a pair of separated pixel locations (*i* and *j*) on the image. The unary potentials represent the cost of assigning label y_i to grid node i. In this paper, unary potentials are defined either through sparse manual annotation or automated classification using DCNN outputs. The pairwise potentials are the cost of simultaneously assigning label y_i to grid node i and y_j to grid node j, and are computed using image feature extraction, defined by:

$$\psi_{ij}(y_i, y_j, f_i, f_j|\theta) = \Lambda(y_i, y_j|\theta) \sum_{l=1}^{L} k^l\left(f_i^l, f_j^l\right) \tag{3}$$

where $l = 1{:}L$ are the number of features derived from x, and where the function Λ quantifies label 'compatibility', by imposing a penalty for nearby similar grid nodes that are assigned different labels. Each k^l is the sum of two Gaussian kernel functions that determines the similarity between connected grid nodes by means of a given feature f^l:

$$k^l(f_i^l, f_j^l) = \exp\left(-\frac{|p_j - p_j|^2}{2\theta_\alpha^2} - \frac{|x_j - x_j|^2}{2\theta_\beta^2}\right) + \exp\left(-\frac{|p_j - p_j|^2}{2\theta_\gamma^2}\right) \tag{4}$$

The first Gaussian quantifies the observation that nearby pixels, with a distance controlled by θ_α (standard deviation for the location component of the color-dependent term), with similar color, with similarity controlled by θ_β (standard deviation for the color component of the color-dependent term), are likely to be in the same class. The second Gaussian is a 'smoothness' kernel that removes small isolated label regions, according to θ_γ, the standard deviation for the location component. This penalizes small pieces of segmentation that are spatially isolated, enforcing more spatially consistent classification. Hyperparameter θ_β controls the degree of allowable similarity in image features between CRF graph nodes. Relatively large θ_β means image features with relatively large differences in intensity may be assigned the same class label. Similarly, a relatively large θ_α means image pixels separated by a relatively large distance may be assigned the same class label.

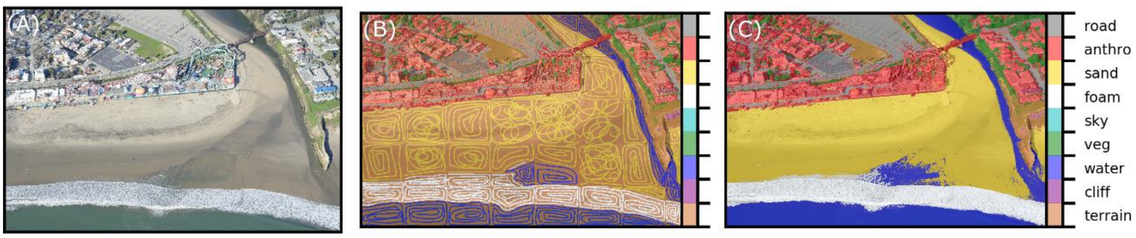

Figure 1. Application of the semi-supervised CRF at Seabright beach for generation of DCNN training tiles and ground-truth labeled images. From left to right, (A) the input image, (B) the hand-annotated sparse labels, and (C) the resulting CRF-predicted pixelwise labeled image.

2.2. Generating DCNN training libraries

We developed a user-interactive program that segments an image into smaller chunks, the size of which is defined by the user. On each chunk, cycling through a pre-defined set of classes, the user is prompted to draw (using the cursor) example regions of the image that correspond to each label. Unary potentials are derived from these manual on-screen image annotations. Using this information, the CRF algorithm estimates the class of each pixel in the image (Figure 1). Finally, the image is divided up into tiles of a specified size, *T*. If the proportion of pixels within the tile is greater than a specified amount, P_{class}, then the tile is written to a file in a folder denoting its class. This simultaneously and efficiently generates both ground-truth label imagery (to evaluate classification performance) and sets of data suitable for training a DCNN. A single photograph typically takes 5-30 minutes to process with this method, so all the data required to retrain a DCNN (see section below) may take only up to a few hours to generate. CRF inference time depends primarily on image complexity and size, but also secondarily affected by the number and spatial heterogeneity of class labels.

2.3. Retraining a deep neural network (transfer learning)

Among many suitable popular and open-source frameworks for image classification using deep convolutional neural networks, we chose MobileNetV2 [57] because it is relatively small and efficient (computationally faster to train and execute) compared to many competing architectures designed to be transferable for generic image recognition tasks, such as Inception [58], Resnet [59], and NASnet [60], and it is smaller and more accurate than MobileNetV1 [61]. It also is pretrained for various tile sizes (image windows with horizontal and vertical dimensions of 96, 128, 192, and 224 pixels) which allows us to evaluate that effect on classifications. However, all of the aforementioned models are implemented within TensorFlow-Hub [62], which is a library specifically designed for reusing pre-trained TensorFlow [63] models on new tasks.

For all datasets, we only used tiles (in the training and evaluation) where 90% of the tile pixels were classified as a single class (that is, $P_{class} > 0.9$). This avoided including tiles depicting mixed land cover/use classes. We chose tile sizes of T = 96x96 pixels and T = 224x224 pixels, which is the full range available for MobileNets, in order to compare the effect of tile size. All model training was carried out in Python using TensorFlow library version 1.7.0 and TensorFlow-hub version 0.1.0. For each dataset, model training parameters (1000 training steps, and a learning rate of 0.01) were kept constant, but not necessarily optimal. For most datasets, there are relatively small numbers of very general classes (water, vegetation, etc.), which in some ways is a more difficult classification task than much more specific classes, owing to the greater within-class variability to be expected from having broadly defined categories.

Each training and testing image tile is normalized against varying illumination and contrast, which greatly aids transferability of the trained DCNN model. A normalized image (X′) is calculated from a non-normalized image (X) using

$$X' = \frac{X - \mu}{\sigma} \tag{5}$$

where μ and σ are mean and standard deviation, respectively [47]. We chose to scale every tile by a maximum possible standard deviation (for an 8-bit image) by using σ=255. For each tile, μ was chosen as the mean across all three bands for that tile. This procedure could be optimized for a given dataset but in our study the effects of varying values of σ were minimal.

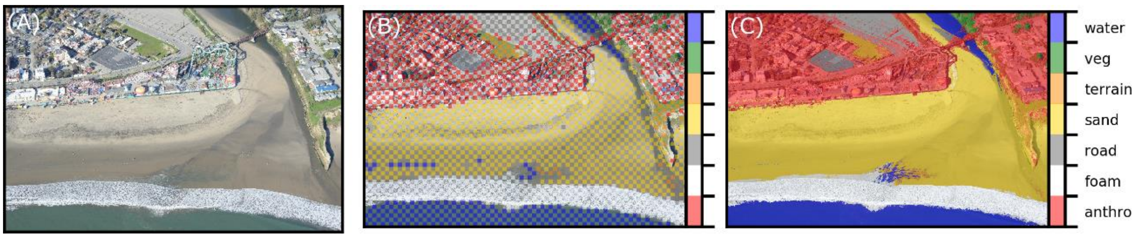

Figure 2. Application of the unsupervised CRF for pixelwise classification, based on unary potentials of regions of the image classified using a DCNN. Example comes from Seabright beach. From left to right, (A) the input image, (B) the DCNN-estimated sparse labels, and (C) the resulting CRF-predicted pixelwise labeled image.

2.4. CRF-based semantic segmentation

We developed a method that harnesses the classification power of the DCNN, with the discriminative capabilities of the CRF, for pixel-scale semantic segmentation of imagery. An input image is windowed into small regions of pixels, the size of which is dictated by the size of the tile used in the DCNN training (here, T=96x96 or T=224x224 pixels). Some windows, ideally with an even spatial distribution across the image, are classified with a trained DCNN. Collectively, these predictions serve as unary potentials (known labels) for a CRF to build a probabilistic model for pixelwise classification given the known labels and the underlying image (Figure 2).

Adjustable parameters are: 1) the proportion of the image to estimate unary potentials for (controlled by both T and the number/spacing of tiles), and 2) a threshold probability, P_{thres}, larger than which a DCNN classification was used in the CRF. Across each dataset, we found that using

50% of the image as unary potentials, and P_{thres} = 0.5, resulted in good performance. CRF hyperparameters were also held constant across all datasets. We found that good performance across all datasets was achieved using θ_α= 60, θ_β = 5, and θ_γ = 60. Holding all of these parameters constant facilitates comparison of the general success of the proposed method. However, it should be noted that accuracy could be further improved for individual datasets by optimizing the parameters for those specific data. This could be achieved by minimizing the discrepancy between ground truth label images and model-generated estimates using a validation dataset.

2.5. Metrics to assess classification skill

Standard metrics of precision, P, recall, R, accuracy, A, and F1 score, F, are used to assess classification of image regions and pixels. Where TP, TN, FP, and FN are, respectively, the frequencies of true positives, true negatives, false positives, and false negatives:

$$P = \frac{TP}{TP + FP} \tag{6}$$

$$R = \frac{TP}{TP + FN} \tag{7}$$

$$A = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$F = 2 \cdot \frac{P \cdot R}{P + R} \tag{9}$$

True positives are image regions/pixels correctly classified as belonging to a certain class by the model, while true negatives are correctly classified as not belonging to a certain class. False negatives are regions/pixels incorrectly classified as not belonging to a certain class, and false positives are those regions/pixels incorrectly classified as belonging to a certain class. Precision and recall are useful where the number of observations belonging to one class is significantly lower than those belonging to the other classes. These metrics are therefore used in evaluation of pixelwise segmentations, where the number of pixels corresponding to each class vary considerably. The F1 score is an equal weighting of the recall and precision and quantifies how well the model performs in general. Recall is a measure of the ability to detect the occurrence of a class, which is a given landform, land use or land cover.

A 'confusion matrix', which is the matrix of normalized correspondences between true and estimated labels, is a convenient way to visualize model skill. A perfect correspondence between true and estimated labels is scored 1.0 along the diagonal elements of the matrix. Misclassifications are readily identified as off-diagonal elements. Systematic misclassifications are recognized as off-diagonal elements with large magnitudes. Full confusion matrices for each test and dataset are provided as Supplemental Data 2.

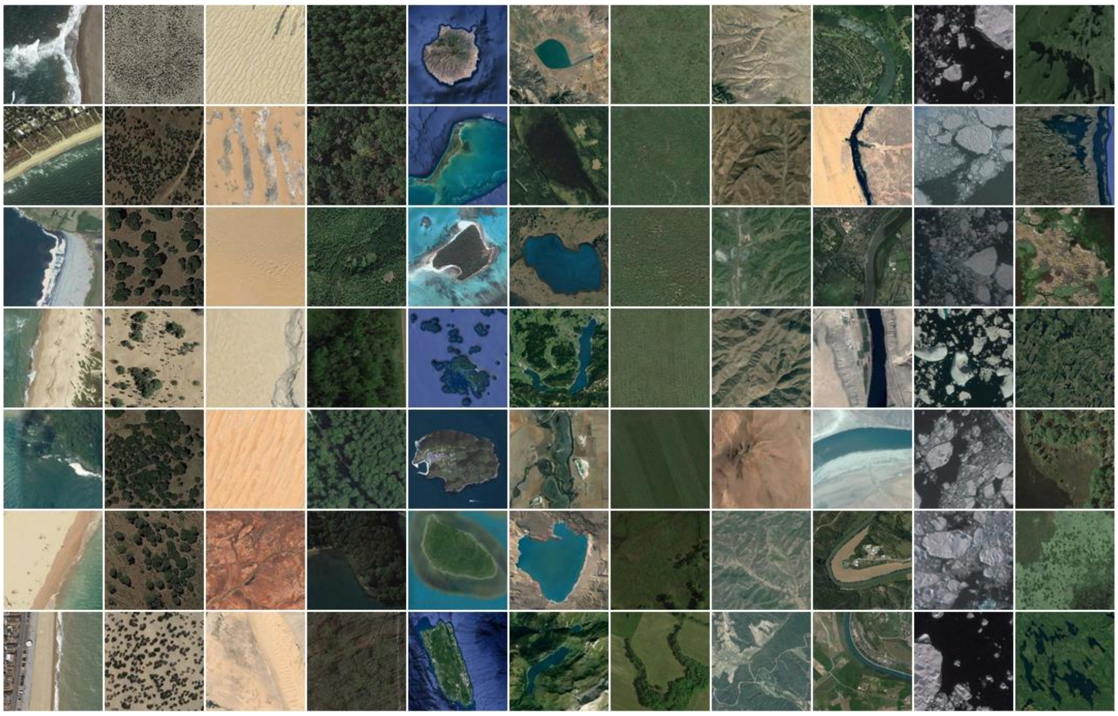

Figure 3. Example tiles from NWPU dataset. Classes, from left to right, are beach, chaparral, desert, forest, island, lake, meadow, mountain, river, sea ice, and wetland.

2.6. Data

The chosen datasets encompass a variety of shoreline environments (coastal, fluvial and lacustrine) and collection platforms (oblique stationary cameras, oblique aircraft, nadir UAV, and nadir satellite).

2.6.1. NWPU-RESISC45

To evaluate the MobileNetV2 DCNN with a conventional satellite-derived land use/land cover dataset, we chose the NWPU-RESISC45, which is a publicly available benchmark for REmote Sensing Image Scene Classification (RESISC), created by Northwestern Polytechnical University (NWPU). The entire dataset, described by [6], contains 31,500 high-resolution images from Google Earth imagery, in 45 scene classes with 700 images in each class. The majority of those classes are urban/anthropogenic. We chose to use a subset of 11 classes corresponding to natural landforms and land cover (Figure 3), namely: beach, chaparral, desert, forest, island, lake, meadow, mountain, river, sea ice, and wetland. All images are 256x256 pixels. We randomly chose 350 images from each class for DCNN training, and 350 for testing.

Figure 4. Example tiles from Seabright beach. Classes, from left to right, are anthropogenic/buildings, foam, road/pavement, sand, other natural terrain, vegetation, and water.

2.6.2. Seabright beach, CA.

The dataset consists of 13 images of the shorefront at Seabright, Santa Cruz, CA. Images were collected from a fixed-wing aircraft in February 2016, of which a random subset of seven were used for training, and six for testing (Supplemental data S1A and S1B). Training and testing tiles were generated for seven classes (Table A1 and Figures 2, 3, and 4).

317 **Figure 5.** Example tiles from Lake Ontario shoreline. Classes, from left to right, are
318 anthropogenic/buildings, sediment, other natural terrain, vegetation, and water.

319 2.6.3. Lake Ontario, NY.

320 The dataset consists of 48 images obtained in July 2017 from a Ricoh GRII camera mounted to a
321 3DR Solo quadcopter, a small unmanned aerial system (UAS), flying 80-100 meters above ground
322 level in the vicinity of Braddock Bay, New York, on the shores of southern Lake Ontario [64]. A
323 random subset of 24 were used for training, and 24 for testing (Supplemental data S1C and S1D).
324 Training and testing tiles were generated for five classes (Table A2 and Figure 5).

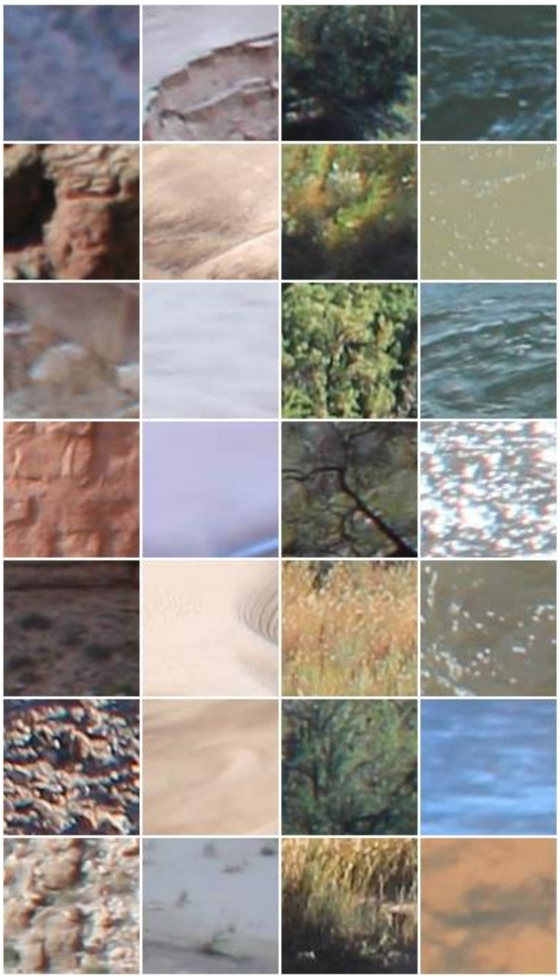

Figure 6. Example tiles from Grand Canyon. Classes, from left to right, are rock/scree, sand, vegetation, and water.

2.6.4. Grand Canyon, AZ.

The dataset consists of 14 images collected from a stationary autonomous camera systems monitoring eddy sandbars along the Colorado River in Grand Canyon. The camera system, sites and imagery is described in [16]. Imagery came from various seasons and river flow levels, and sites differ considerably in terms of bedrock geology, riparian vegetation, sunlight/shade, and water turbidity. One image from each of seven sites were used for training, and one from each those of same seven sites were used for testing (Supplemental data S1E and S1F). Training and testing tiles were generated for four classes (Table A3 and Figure 6).

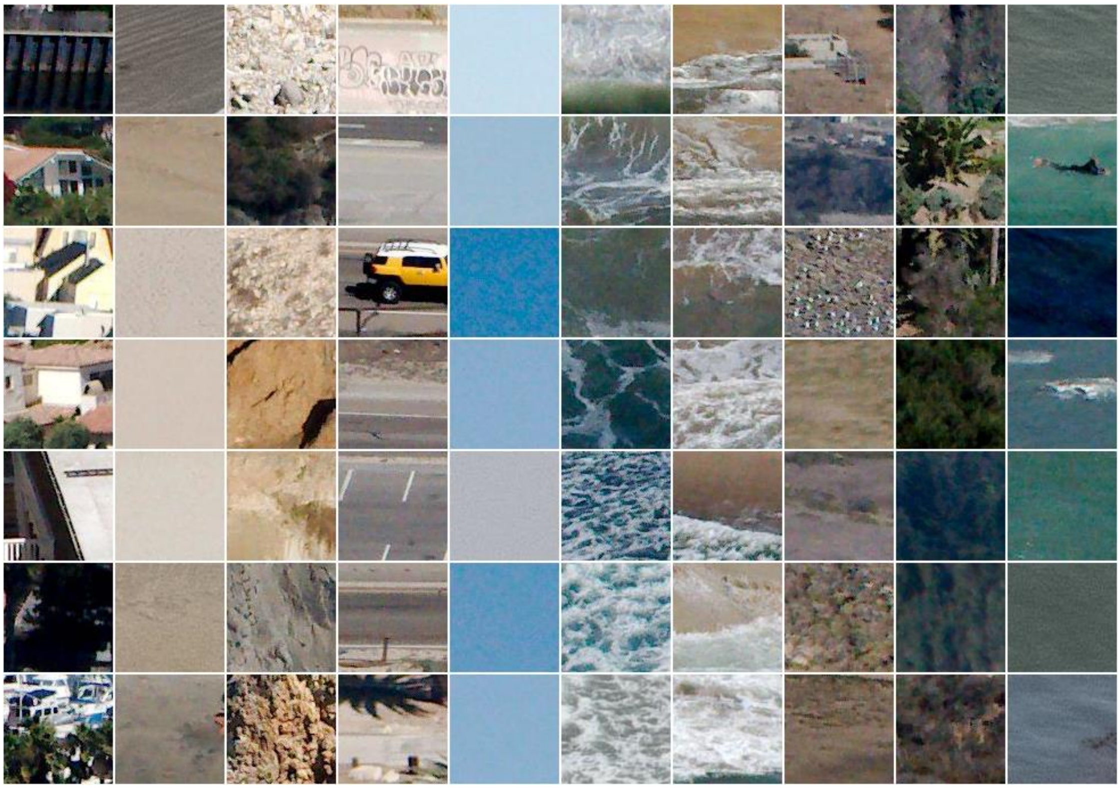

Figure 7. Example tiles from CCRP dataset. Classes, from left to right, are buildings/anthropogenic, beach, cliff, road, sky, surf/foam, swash, other natural terrain, vegetation, and water.

2.6.5. California Coastal Records (CCRP).

The dataset consists of a sample of 75 images from the California Coastal Records Project (CCRP) [65], of which 45 were used for training, and 30 for testing (Supplemental data S1G and S1H). The photographs were taken over several years and times of the year, from sites all along the California coast, with a handheld digital single-lens reflex camera from a helicopter flying at approximately 50–600 m elevation [20]. The set includes a very wide range of coastal environments, at very oblique angles, with a corresponding very large horizontal footprint. Training and testing tiles were generated for ten classes (Table A4 and Figure 7).

Table 1. Out-of-calibration whole tile classification accuracies and F1 scores for each dataset and tile size.

	T **= 96**		***T*** **= 224**	
Dataset	**Mean accuracy**	**Mean F1 score**	**Mean accuracy**	**Mean F1 score**
1. NWPU	87%	93%	89%	94%
2. Seabright	94%	97%	96%	97%
3. Ontario	83%	91%	96%	98%
4. Grand Canyon	92%	96%	94%	97%
5. CCRP	79%	88%	84%	91%

3. Results

Table 2. Mean out-of-calibration whole tile classification accuracies (%), per class, for each of the non-satellite datasets (T=96 / T=224).

	Seabright	Ontario	Grand Canyon	CCRP
Sediment/sand	93 / 98	76 / 93	94 / 89	91 / 89
Terrain/rock	91 / 91	78 / 91	89 / 95	84 / 78
Cliff				69 / 86
Vegetation	89 / 95	96 / 98	94 / 90	49 / 74
Water	99 / 98	94 / 97	92 / 99	92 / 91
Anthropogenic	95 / 98	72 / 94		79 / 85
Foam/Surf	97 / 96			72 / 81
Swash				79 / 79
Road	96 / 98			85 / 83
Sky				90 / 97

3.1. Whole image tile classification accuracy

With no fine tuning of model parameters, we achieved average classification accuracies of between 91 and 98% (F1 scores) across five datasets with *T*=224 tiles, and between 88% and 97% with *T*=96 tiles (Table 1). Over 26 individual land cover/use classes (Table 2) in four datasets, average classification accuracies ranged between 49 and 99%. Confusion matrices (Supplemental 2, Figures S2A through S2E) for all classes reveal that most mis-classifications occur between similar groupings, for example swash and surf, and roads and buildings/anthropogenic. Confusion matrices therefore provide the means with which to identify which classes to group, if necessary, to achieve even greater overall classification accuracies. Only for certain data and classes did the distinction between *T*=96 and *T*=224 tiles make a significant difference, particularly for the Lake Ontario data where classifications were systematically better using *T*=224.

3.2. Pixel classification accuracy

With no fine tuning of model parameters, we achieved average pixelwise classification accuracies of between 70 and 78% (F1 scores, Table 3) across four datasets, based on CRF modeling of sparse DCNN predictions with *T*=96 tiles (Figure 8). Classification accuracy for a given feature was found to be strongly related to size of that feature (Figure 9). For those land cover/uses that are much greater in size than a 96x96 pixel tile, average pixelwise F scores were much higher, ranging from 86 to 90 %. Confusion matrices (Supplemental A, Figures S2F through S2I) again show how mis-classifications only systematically tend to occur between pairs of the most similar classes.

Table 3. Mean out-of-calibration P/R/F/A (all %) per class for pixelwise classifications using each of the non-satellite datasets (*T*=96).

	Seabright	Ontario	Grand Canyon	CCRP
Sediment/sand	98/92/95/92	72/72/74/67	76/79/80/78	84/90/86/78
Terrain/rock	44/51/46/50	32/32/30/41	80/97/87/96	47/86/54/75
Cliff				72/91/66/74
Vegetation	63/41/48/42	90/93/89/91	92/31/46/43	94/40/48/26
Water	95/92/93/91	95/95/95/89	94/92/93/94	93/88/86/79
Anthropogenic	87/95/90/94	78/59/64/55		85/70/76/71
Foam/Surf	87/93/90/94			93/74/73/70
Swash				42/40/48/27

Road	86/81/83/79			35/70/35/64
Sky				95/97/94/82
Average:	80/78/78/77	73/70/70/69	86/75/77/78	74/75/67/65

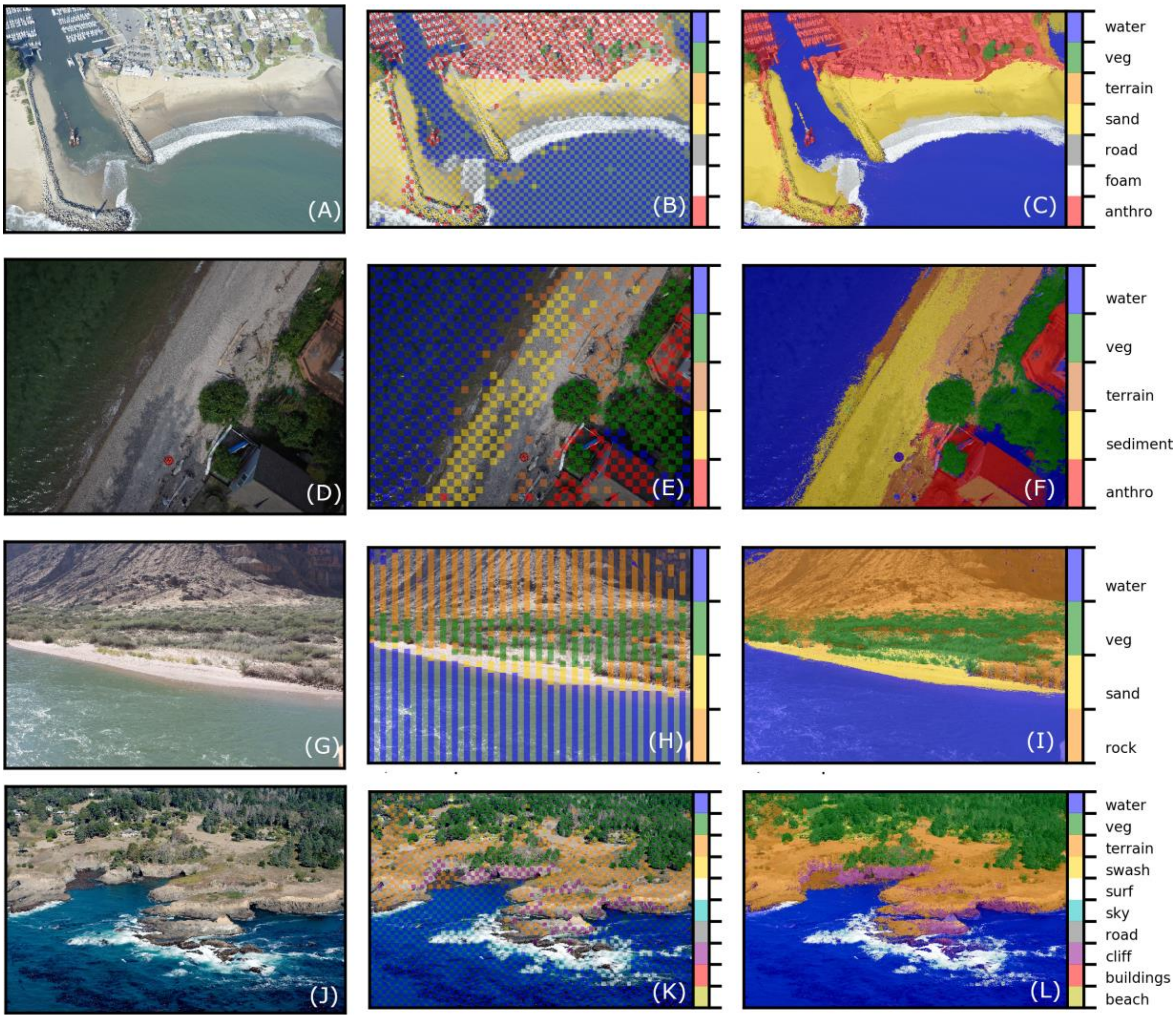

Figure 8. Example images (left column), DCNN-derived unary potentials (middle column), and CRF-derived pixelwise semantic segmentation (right column) for each of the four datasets, from top to bottom, Seabright, Lake Ontario, Grand Canyon, and CCRP.

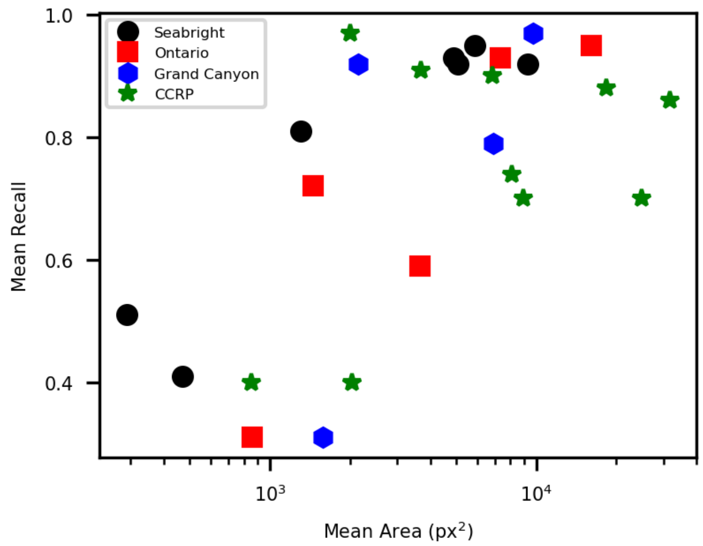

Figure 9. Average recall versus average area (in square pixels) of classes.

4. Discussion

Deep learning has revolutionized the field of image classification in recent years [36-39,42-49]. However, the general usefulness of deep learning applied to conventional photographic imagery at a landscape scale is, at yet, largely unproven. Here, similar to previous workers who have demonstrated the ability of DCNNs for classification of land use/cover in long-range remotely sensed imagery from satellites [6,9,45-49], we show that DCNNs are powerful tools for classifying landforms and land cover in medium-range imagery acquired from UAS, aerial, and ground-based platforms. Further, we show that the smallest and most computationally efficient widely available DCNN architecture, MobilenetsV2, classifies land use/cover with comparable accuracies to larger, slower, DCNN models such as AlexNet [66,45,6], VGGNet [67,45,6], GoogLeNet [6,68,69], or custom-designed DCNNs [9,46,47]. Here, we deliberately chose a standard set of model parameters, and achieved reasonable pixel-scale classifications across all classes, but even greater accuracy is likely attainable with a model fine-tuned to a particular dataset [6].

In remote sensing, the acquisition of pixel-level reference/label data is time-consuming and limiting [46], so acquiring a suitably large dataset for training DCNN is often a significant challenge. Therefore most studies that use pixel-level classifications only use a few hundred reference points [70,71]. We have suggested a new method for generating pixel-level labeled imagery for use in developing and evaluating classifications (DCNN-based and others), based on manual on-screen annotations in combination with a fully connected conditional random field (CRF, Figure 1). This, in conjunction with transfer learning and small, efficient DCNNs, provides the means to rapidly train a DCNN with a small dataset. In turn, this facilitates the rapid assessment of the general utility of DCNN architectures for a given classification problem, as well as the means to fine-tune a feature class or classes iteratively based on classification mismatches. The workflow presented here can be used to quickly assess the potential of a small DCNN like MobilenetV2 for a specific classification task. This 'prototyping' stage can also be used to assess classes that should be grouped, or split, depending on analysis of confusion matrices such as presented in Supplemental 2, Figures S2A through S2E. If promising, larger models such as Resnet [59] or NASnet [60] could be used, within the same framework provided by Tensorflow Hub, for even greater classification accuracy.

Recognizing the capabilities of the CRF as a discriminative classification algorithm given a set of sparse labels, we propose a pixel-wise semantic segmentation algorithm based upon DCNN-estimated regions of images in combination with the fully-connected CRF. This hybrid DCNN-CRF approach to semantic segmentation is offered as a simpler alternative to so-called `fully convolutional' DCNNs [8,39,72] which, in order to achieve accurate pixel level classifications, require much larger, more sophisticated DCNN architectures [37], which are often computationally more demanding to train. Since pooling within the DCNN results in a significant loss of spatial resolution, these architectures require an additional set of convolutional layers that learn the 'upscaling' between the last pooling layer, which will be significantly smaller than the input image, and the pixelwise labelling at the required finer resolution. This process is imperfect, therefore label images appear coarse at object/label boundaries [72] and some post-processing algorithm, such as a CRF or similar approach, is required to refine predictions. Because of this, we suggest that our hybrid approach might be a simpler approach to semantic segmentation, especially for rapid prototyping (as discussed above) and in the cases where the scales of spatially continuous features are larger than the tile size used in the DCNN (Figure 9). However, for spatially isolated features, especially those that exist over small spatially contiguous areas, the more complicated fully convolutional approach to pixelwise classification might be necessary.

The CRF is designed to classify (or in some instances, where some unary potentials are considered improbable by the CRF model, reclassify) pixels based on both the color/brightness and the proximity of nearby pixels with the same label. We found that, typically, the CRF algorithm requires DCNN-derived unary potentials, regularly spaced, for at least one quarter of pixels in relatively simple scenes and about one half in relatively complicated scenes (e.g. Figure 10B) for satisfactory pixelwise classifications (e.g. Figure 10C). With standardized parameter values not fine-tuned to individual images or datasets, CRF performance was mixed, especially for relatively small objects/features (Table 3). This is exemplified by Figure 10, in which several small outcropping rocks whose pixel labels were not included as CRF unary potentials, were either correctly or incorrectly labeled by the CRF, despite the similarity in their location, size, color, and their relative proximity to correctly labeled unary potentials. We found that optimizing CRF parameters to reduce such misclassifications could be done for an individual image, but not in a systematic way that would improve similar misclassifications in other images. Whereas here we have used RGB imagery, the CRF would work in much the same way with larger multivariate datasets such as multispectral or hyperspectral imagery, or other raster stacks consisting of information on coincident spatial grids.

If DCNN-based image classification is to gain wider application and acceptance within the geoscience community, demonstrable successes such as presented in this paper, need to be coupled with accessible tools and datasets in order to develop deep neural network architectures to better discriminate landforms and land uses in landscape imagery. To that end, we invite interested readers to use our data and code (see Acknowledgements) to explore variation in classifications among multiple DCNN architectures, and to use our extensive pixel-level label dataset to evaluate and facilitate in the development of custom DCNN models for specific classification tasks in the geosciences.

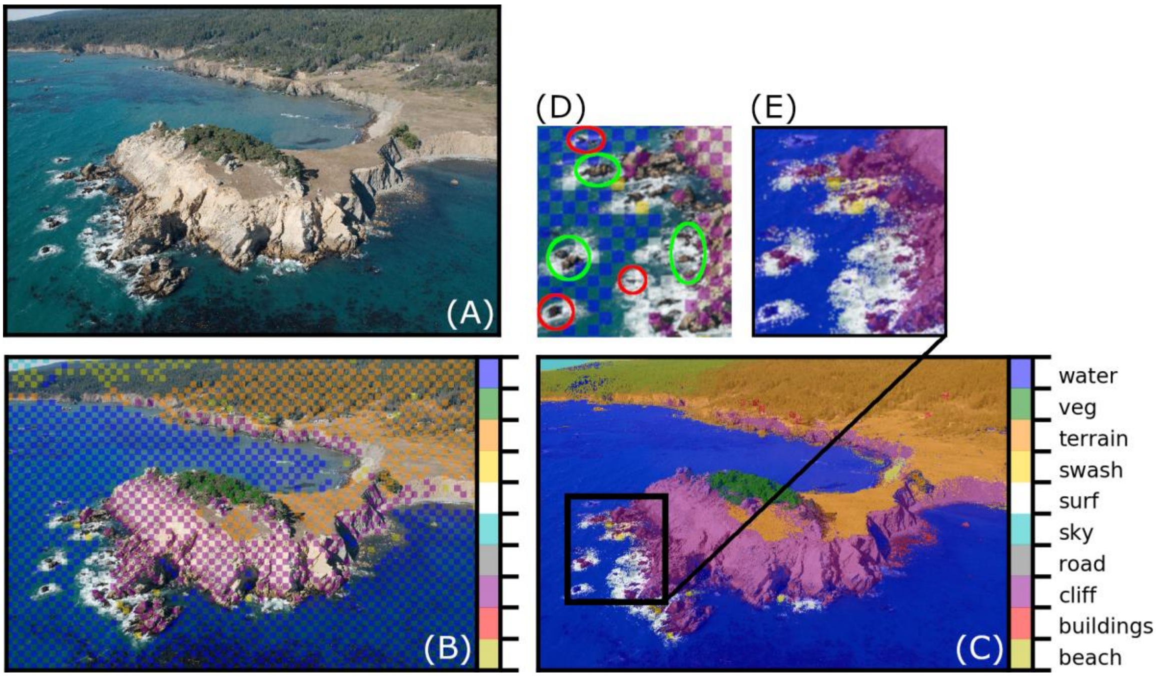

Figure 10. Classification of a typical CCR image: (A) Original image; (B) DCNN predictions; (C) CRF predictions; (D) and (E) show the same region (magnification x2) from the DCNN and CRF labels, respectively. The colored ellipses in (D) indicate small rocky areas either misclassified (red ellipses) or correctly classified (green ellipses).

5. Conclusions

Our work demonstrates the general effectiveness of a repurposed, small, very fast, existing DCNN framework called MobileNetV2 for classification of landforms, land use, and land cover features in both satellite and high-vantage, oblique and nadir imagery collected using planes, UAVs and static monitoring cameras. With no fine tuning of model parameters, we achieve average classification accuracies of between 91 and 98% (F1 scores) across five disparate datasets, ranging between 71 and 99% accuracies over 26 individual land cover/use classes across four datasets. Further, we demonstrate how structured prediction using a fully connected CRF can be used in a semi-supervised manner to very efficiently generate ground truth label imagery and DCNN training libraries. Finally, we propose a hybrid method for accurate semantic segmentation of imagery of natural landscapes based on combining 1) the recognition capacity of DCNNs to classify small regions in imagery, and 2) the fine grained localization of fully connected CRFs for pixel-level classification. Where land cover/uses that are typically much greater in size than a 96x96 pixel tile, average pixelwise F1 scores range from 86 to 90%. Smaller, and more isolated features have greater pixelwise accuracies. This is in part due to our usage of a common set of model parameters for all data sets, however further refinement of this technique may be required to classify features that are much smaller than a 96x96 pixel tile with similar accuracies as larger features and land covers.

These techniques should find numerous application in the classification of remotely sensed imagery for geomorphic and natural hazards studies, especially for rapidly evaluating the general utility of DCNNs for a specific classification task, and especially for relatively large and spatially extensive land cover types. All of our data, trained models, and processing scripts are available at https://github.com/dbuscombe-usgs/dl_landscapes_paper.

Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Figure S1: Datasets, Figure S2: Confusion matrices.

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Appendix A

Table A1. Classes and number of tiles used for the Seabright dataset.

Class	Number of training tiles (*T*=96/224)	Number of evaluation tiles (*T*=96/224)
Anthropogenic	23,566 / 4,548	15,575 / 3,031
Road and pavement	314 / 60	525 / 103
Sand	38,250 / 6,887	25,318 / 5,802
Vegetation	386 / 76	240 / 38
Other terrain	77 / 24	117 / 22
Water	11,394 / 1,723	14,360 / 2,251
Foam	5,076 / 735	5,139 / 843
Total:	76,063 / 14,053	61,274 / 12,090

Table A2. Classes and number of tiles used for the Lake Ontario dataset.

Class	Number of training tiles (*T*=96/224)	Number of evaluation tiles (*T*=96/224)
Anthropogenic/buildings	467 / 219	3,216 / 333
Sediment	2,856 / 289	3,758 / 407
Vegetation	33,871 / 5,139	33,421 / 5,001
Other terrain	1,596 / 157	1,094 / 92
Water	80,304 / 13,332	77,571 / 12,950
Total:	119,094 / 19,136	119,060 / 18,783

Table A3. Classes and number of tiles used for the Grand Canyon dataset.

Class	Number of training tiles (*T*=96/224)	Number of evaluation tiles (*T*=96/224)
Rock/scree/terrain	15,059 / 2,405	12,151 / 1,999
Sand	751 / 39	1,069 / 91
Riparian vegetation	2,971 / 408	2,158 / 305
Water	8,568 / 1,462	5,277 / 1,130
Total:	27,349 / 4,314	20,655 / 3,525

Table A4. Classes and number of tiles used for the California Coastal Records dataset.

Class	**Number of training tiles (*T*=96/224)**	**Number of evaluation tiles (*T*=96/224)**
Beach	39,206 / 6,460	42,616 / 7,438
Anthropogenic/buildings	34,585 / 6,904	45,831 / 8,452
Cliff	29,844 / 4,666	17,488 / 3,108
Road	6,000 / 705	3,782 / 440
Sky	41,139 / 6,694	26,240 / 4,267
Surf/foam	18,775 / 2,745	25,025 / 3,549
Swash	5,825 / 1,280	4,535 / 552
Other terrain	87,632 / 18,517	50,254 / 8,647
Vegetation	81,896 / 19,346	46,097 / 7,639
Water	121,684 / 17,123	49,427 / 11,019
Total:	466,586 / 84,440	311,295 / 55,111

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