Deep Images require Deep Learning: A Pixel-Based Convolutional Neural Network Classifier can Accurately Identify Tree Species Using Imaging Spectroscopy

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Abstract

Our study uses field training data, airborne LiDAR (Light Detection and Ranging), imaging spectroscopy, and a Convolutional Neural Network (CNN) classifier to identify individual tree species in a mixed conifer forest in the Southern Sierra Nevada Mountains. The remote sensing data was collected on the National Ecological Observatory Network (NEON) Airborne Observation Platform in 2017. We trained the classifier using existing field plot data, and an independently collected validation dataset which identifies trees location of the 7 dominant species (Pine, Fir, Cedar and Oak), including condition and 'live' or 'dead' status. The LiDAR canopy height model was used to identify tree crowns and imaging spectroscopy data around these crowns were created as image 'labels'. These species level 'labels' were used to train, test and validate a CNN tree species classifier. Our method achieved greater than 63-90% accuracy for all field validated stems and worked best for large diameter trees. On an independent tree stem dataset, we performed a species-level logistic regression to study which cases the classifier works most and least effectively. Spatially, in the southern areas scattered Black Oak were present and tree species often were confused with shrub species or covered by adjacent conifer species. In the north where the upper elevation forest is dominated by red and white fir the classifier achieved greater than 96% accuracy for larger canopy trees, with accuracy degrading to about 59-70% when smaller trees are included in the model. There is also genus level mis-classification, particularly between Red and White Fir species. There was high tree mortality in this forest and the classifier was effective in detecting large tree mortality, which also varies as a function of species and size of trees. This work leverages newly developed 'deep learning' tools which have yet to be extensively applied to the remote detection of large trees or in plant biogeography generally. This research is a proof-of-concept for forest community ecologists who want accurate 'tree species maps' to study how plants are distributed across space. Generally, this method will be of interest to biogeographers or remote sensing scientists looking to apply novel classification methods to problems beyond remote tree species identification.

Deep images require Deep Learning: A convolutional neural network classifier identifies tree species in a mixed conifer forest from hyperspectral imagery

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Abstract

In this study we automate tree species classification using field-based training data, high spatial resolution airborne hyperspectral imagery, and a convolutional neural network classifier (CNN). We test our methods by identifying seven dominant trees species as well as dead trees in a mixed conifer forest in the Southern Sierra Nevada Mountains, CA (USA) using training, testing and validation datasets composed of spatially explicit transects and plots sampled across a single strip of hyperspectral imagery (approximately 1 x 16 km). By training a convolutional neural network (CNN) classifier using field data and hyperspectral imagery, we were able to accurately predict tree species distribution across the landscape. Using a window size of 15 m and 2 hidden convolutional layers, a CNN model accurately classified >95% of all trees in the training datasets and 67.49-82.3% of all trees in an independently collected validation dataset, with classification accuracy higher for larger trees. Our methods are pixel-based rather than object based, although we use three-dimensional structural information from airborne Light Detection and Ranging (LiDAR) to identify trees (points >5 m above the ground) and the classifier was applied to hyperspectral image pixels that were thus identified as tree crown. This model captures the species composition changes across ~700 meters (from 1935 m to 2630 m) of elevation from a lower-elevation mixed oak conifer forest to a higher-elevation fir dominated coniferous forest. Nearly all tree mortality was found in the transitional forest zone at lower elevations (< 2200 m). High resolution tree species maps can support forest ecosystem monitoring and management and identifying dead trees aids landscape assessment of e.g. forest mortality resulting from drought, insects and pathogens.

Research Objectives

We implemented and evaluated a CNN supervised classifier applied to airborne hyperspectral high-resolution imagery to discriminate seven tree species, as well as dead trees, in temperate mixed conifer forest in North America. Imagery was acquired by the NEON AOP in a region of the Southern Sierra Nevada, California, USA at 1m spatial resolution. Field data collected for this study were used to train the classifier, while independently collected data were used for testing. We had the following objectives:

1. Evaluate parameter settings for applying CNNs to identify tree species in our geospatial imagery. How do hyperparameters influence model performance? Do variants of model architecture perform differently?
2. Assess the accuracy of the tree species classification using both cross-validation and independently-collected data.
3. Demonstrate potential uses of high-resolution tree species maps, i.e., show the distribution of trees across and elevation gradient.

Study Site

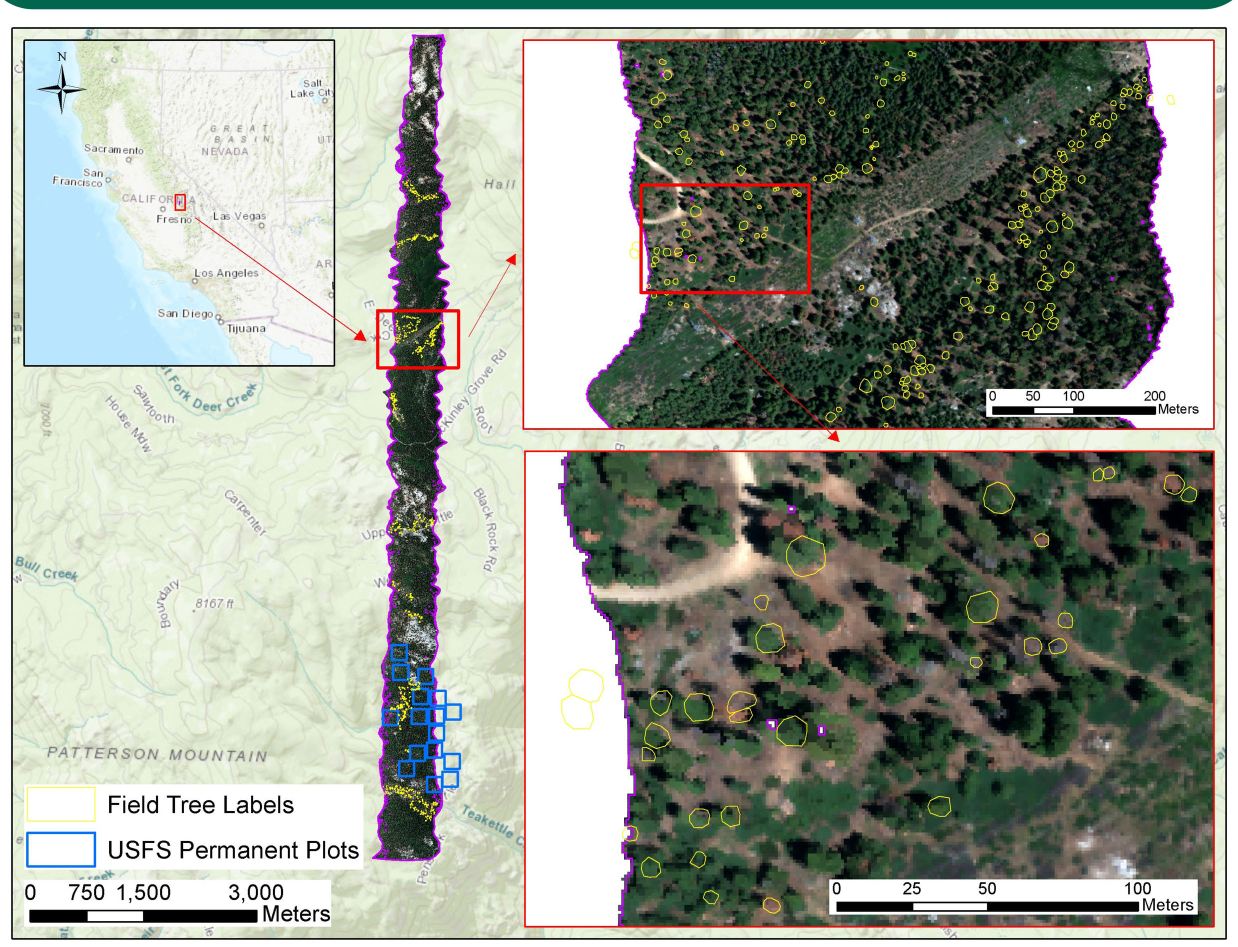

Figure 1: A single strip of hyperspectral imagery (left) in the Teakettle Experimental Forest Watershed north-east of Fresno, CA (upper left). US Forest Service permanent plots are in the southern region of the strip (blue squares). Zoomed views of the transect (upper right) and individual tree canopy label polygon (lower right). Model training data are shown in yellow and can be seem as 'transects' crossing the flightline (left).

Methods: Field Work

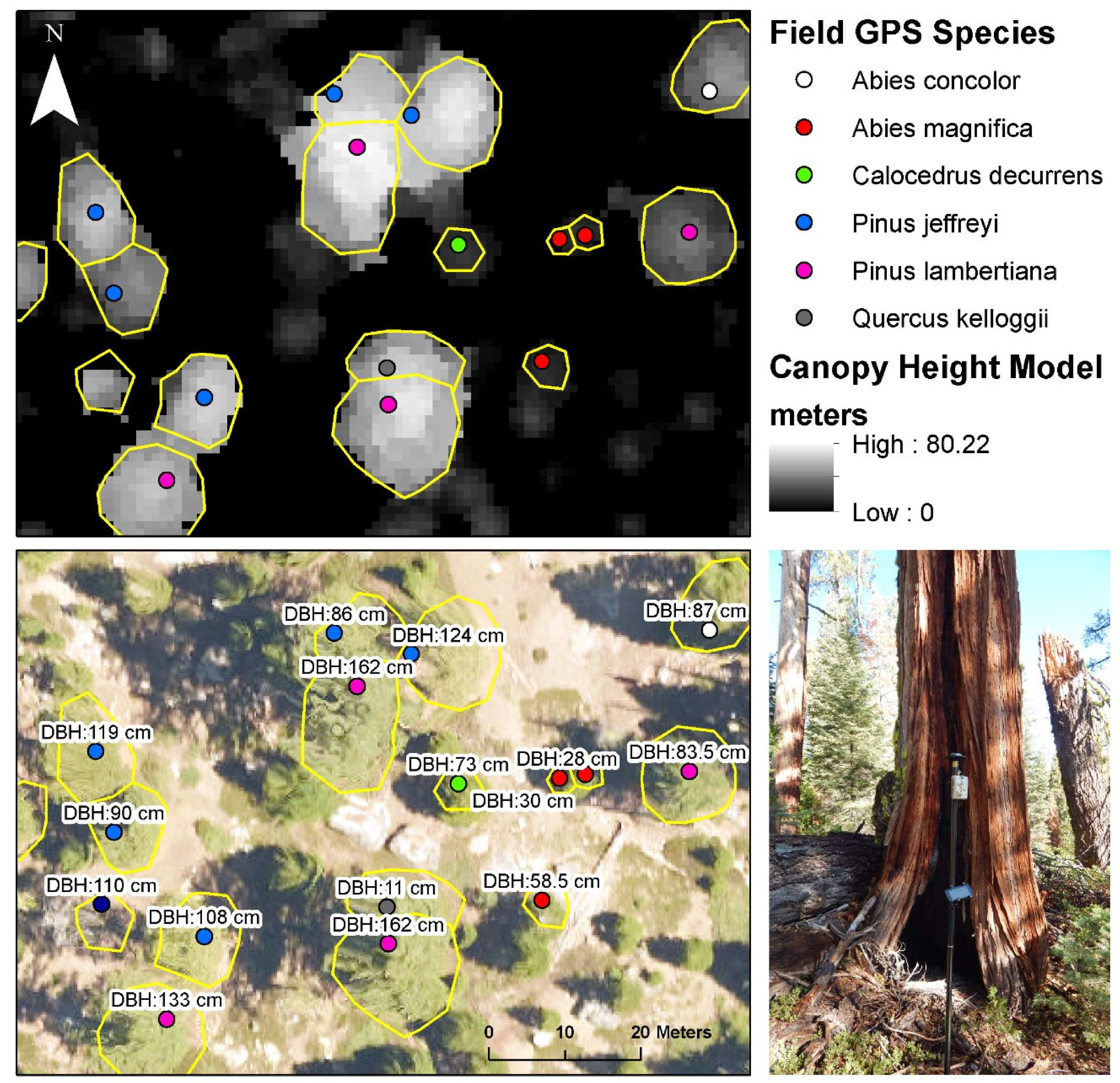

Figure 2: High precision GPS points, colored by species on the LiDAR derived Canopy Height Model (upper-left), the high resolution ortho photos with points labelled using the field measured diameter at breast height (DBH) in centimeters (lower-left). Digitized canopy label outlines are shown as yellow polygons. The GPS antenna taking a static position next to an Incense Cedar (*Calocedrus decurrens*) tree in the field (lower right).

Model Architecture

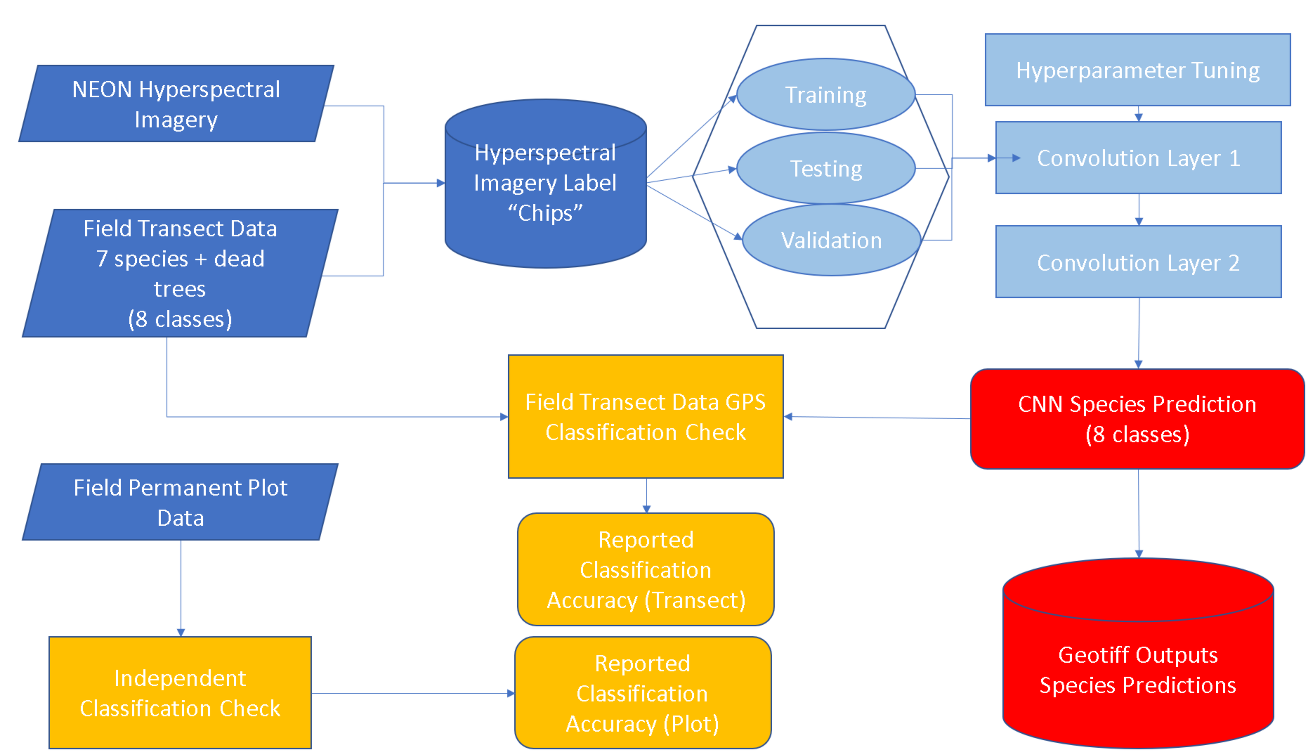

Figure 3: Generalized schematic of the data processing flow and architecture. Datasets (dark blue), CNN model (light blue), CNN Model Architecture (light blue) cross-validations (orange) and final tree species predictions (red).

We evaluated a variety of convolutional neural network architectures. All models took as input a tensor of size $L \times L \times D$. D was a constant value of 426 for the hyperspectral image, while L was a hyperparameter. We considered CNN's with different numbers of convolutional layers. We implemented the models using a Linux environment, using Python 3,GDAL and Keras using the TensorFlow backend.

Results

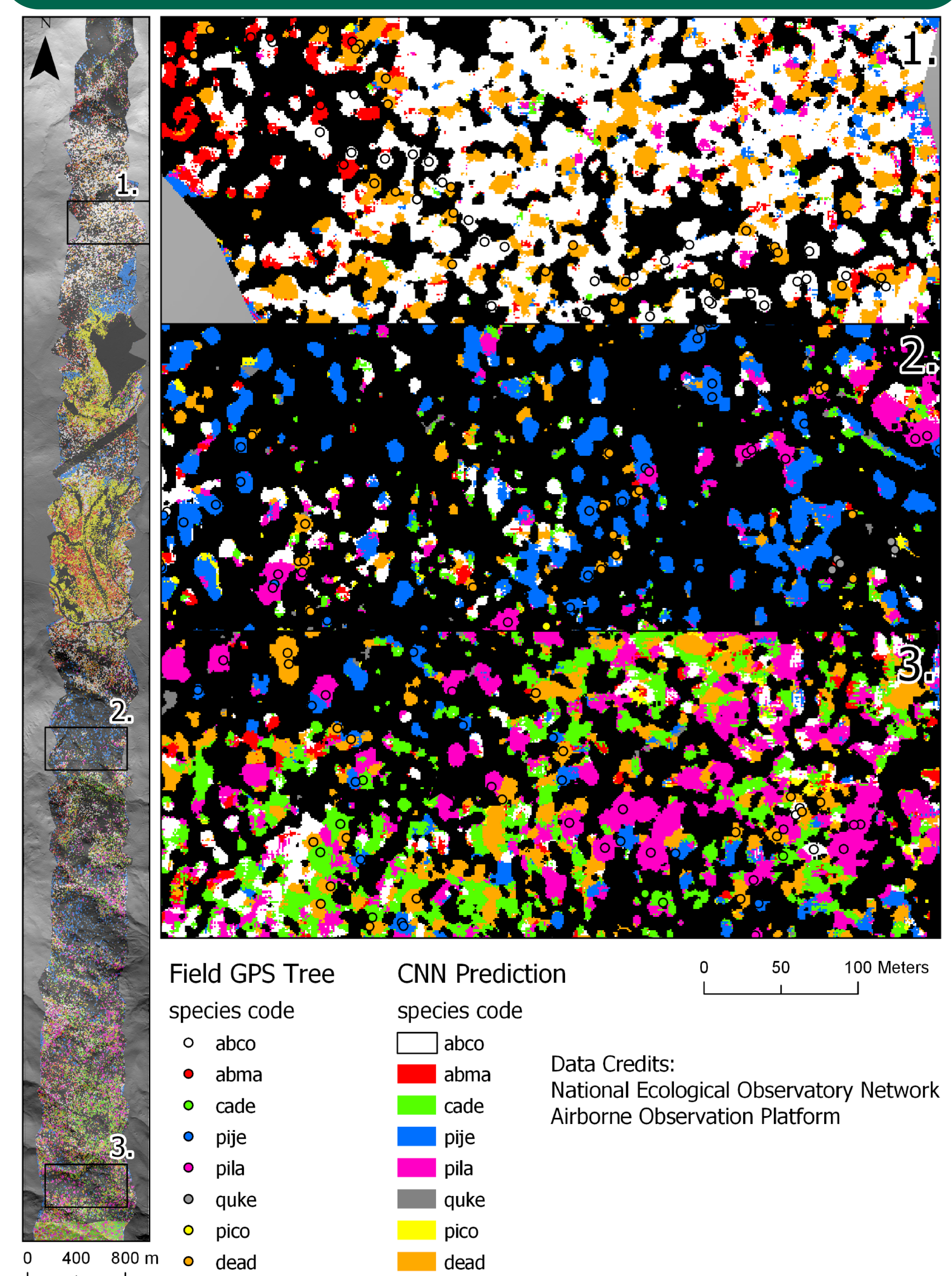

Figure. 4. Full flight line strip showing species as colors on a hill shade digital elevation model (left), Field GPS points are represented with points and CNN model prediction results are represented as the colorized raster image for three sections at high (1.), mid (2.) and lower (3.) elevation sites.

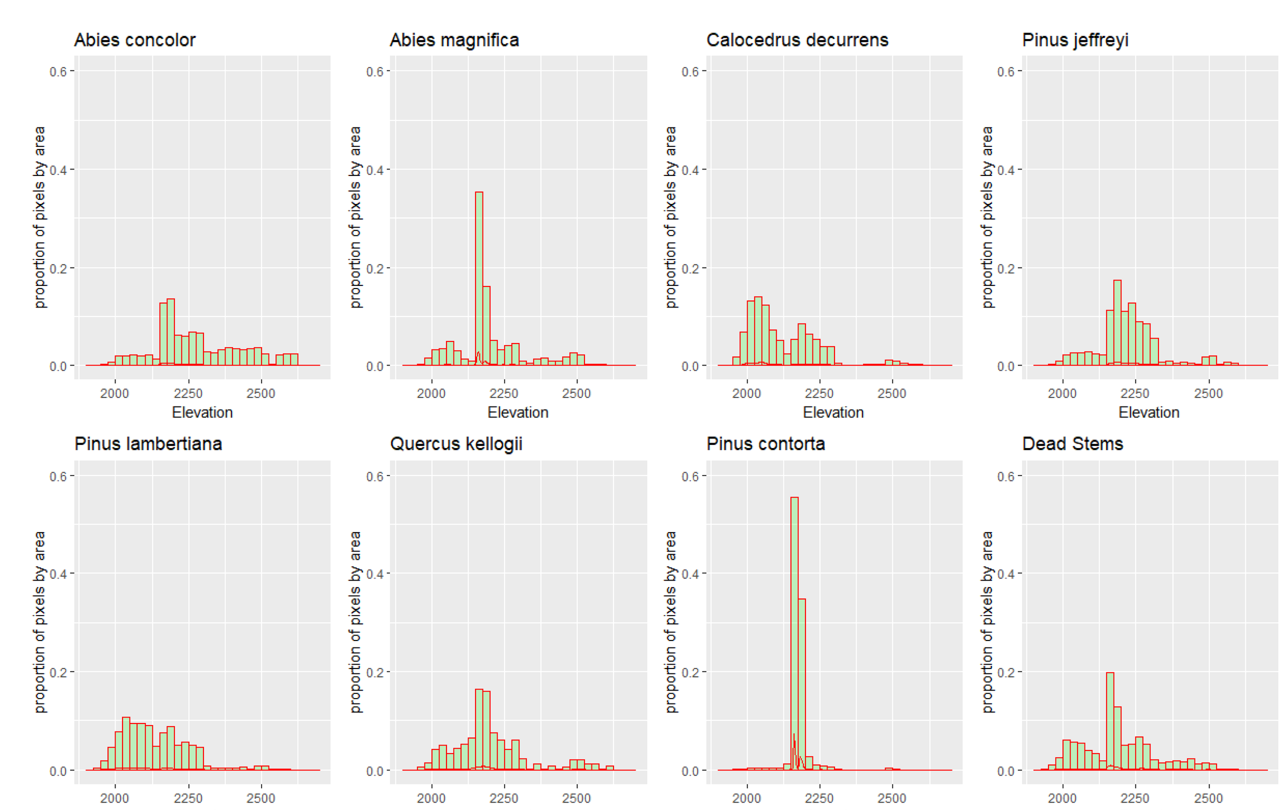

Figure 5. The frequency of pixels classified as each species as a function of elevation along the elevation gradient for the 7 mapped species and dead canopies.

Results

		Species from Field GPS							
	Species	abco	abma	cade	pije	pila	quke	pico	dead
CNN Predicted Species	*Abies concolor* (abco)	**130**	2	0	0	0	0	0	3
	Abies magnificia (abma)	1	**57**	0	0	0	0	0	5
	Calocedrus decurrens (cade)	1	0	**55**	2	0	0	0	6
	Pinus jeffreyi (pije)	1	1	1	**190**	0	1	1	6
	Pinus lambertiana (pila)	0	0	0	2	**79**	0	0	3
	Quercus kelloggii (quke)	0	0	0	0	0	**59**	1	3
	Pinus concolor (pico)	0	0	0	0	0	0	**90**	4
	Dead	0	0	0	0	0	0	0	**216**
	Number of Samples (n)	133	60	56	194	79	60	92	246
	Classification Accuracy (%)	97.74%	95.00%	98.21%	97.94%	100.00%	98.33%	97.83%	87.80%

Table 1: The classification confusion matrix for tree species identified using high-precision field GPS (columns) compared to the CNN model species prediction (rows). The number of samples is visualized by the width of the blue bars and accurate classification is highlighted as light gray cells forming the diagonal across the table.

Stems greater than 150 cm DBH

			Permanent Plot Species								
			abco	abma	cade	pije	pila	quke	pico	Dead	
	Code	Species	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Sum**
CNN Predicted Species	0	*Abies concolor* (abco)	2	0	3	0	0	0	0	0	5
	1	*Abies magnificia* (abma)	0	0	0	0	0	0	0	0	0
	2	*Calocedrus decurrens* (cade)	2	0	34	0	0	0	0	0	36
	3	*Pinus jeffreyi* (pije)	1	0	0	5	0	0	0	0	6
	4	*Pinus lambertiana* (pila)	1	0	1	2	10	0	0	0	14
	5	Quercus kelloggii (quke)	0	0	0	0	0	0	0	0	0
	6	*Pinus concolor* (pico)	0	0	1	0	0	0	0	0	1
	7	Dead	3	0	1	2	6	0	0	0	12
		%accurate (live)	33.3%	0.0%	87.2%	71.4%	62.5%	0.0%	0.0%	0.0%	
		%Accuracy All	82.3%								

No DBH Restriction

			Permanent Plot Species								
			abco	abma	cade	pije	pila	quke	pico	Dead	
	Code	Species	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Sum**
CNN Predicted Species	0	*Abies concolor* (abco)	75	0	13	1	1	0	0	0	90
	1	*Abies magnificia* (abma)	11	0	1	0	0	1	0	0	13
	2	*Calocedrus decurrens* (cade)	20	0	74	6	1	0	0	0	101
	3	*Pinus jeffreyi* (pije)	4	0	2	41	2	1	0	0	50
	4	*Pinus lambertiana* (pila)	10	0	8	12	27	0	0	0	57
	5	Quercus kelloggii (quke)	0	0	0	0	0	1	0	0	1
	6	*Pinus concolor* (pico)	3	0	3	5	0	0	0	0	11
	7	Dead	76	4	9	5	15	1	0	0	110
		%accurate (live)	60.98%	0.00%	73.27%	63.08%	58.70%	0.00%	0.00%	0.00%	
		%Accuracy All	67.49%								

Table 2: Confusion Matrices for all stems by species in the permanent plots with no DBH restriction (top) and only trees > 150 cm DBH (bottom). Actual occurrence species data (columns) from the permanent plots are plotted against the predicted species data from the CNN models (rows).

Conclusions

Our study evaluates Deep Learning CNN models applied to high-resolution hyperspectral imagery labeled using field training data to predict individual tree species at a pixel level along an elevational and species composition gradient. We present a framework for applying the methods necessary to repeat our analysis in different ecosystems with similar remote sensing and field datasets. Overall the classified was highly accurate (>95%) and ranged in accuracy when compared to an independent validation dataset (67.5-82.3%). There were misclassifications present, particularly at lower elevation among the *Quercus kellogii* (Black Oak), which were smaller and less numerous than the larger conifer trees in our study area. *Abies concolor* and *Abies magnifica* (White and Red Fir) which dominate at higher elevations were also occasionally confused by the CNN classifier. Our study shows the CNN classifier to be a robust approach to species level classification, and points to specific limitations which impact results, such as inaccuracies in canopy segmentation, crown overlap and similar spectral characteristics of species in the same genus. This methods shows promise for species level identification at the crown level.

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*References available upon request