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Semantic Segmentation and Classification of Active and Abandoned Agricultural Fields through Deep Learning in the Southern Peruvian Andes

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Abstract: The monumental scale agricultural infrastructure systems built by Andean peoples during pre-Hispanic times have enabled intensive agriculture in the high-relief, arid/semi-arid landscape of the Southern Peruvian Andes. Large tracts of these labor-intensive systems have been abandoned, however, owing in large measure to a range of demographic, economic, and political crises precipitated by the Spanish invasion of the 16th century CE. This research seeks to better understand the dynamics of agricultural intensification and deintensification in the Andes by inventorying through the semantic segmentation of active and abandoned agricultural fields in satellite imagery across approximately 77,000 km² of the Southern Peruvian Highlands. While manual digitization of agricultural fields in satellite imagery is time-consuming and labor-intensive, deep learning-based semantic segmentation makes it possible to map and classify en masse Andean agricultural infrastructure. Using high resolution satellite imagery, training and validation data were manually produced in distributed sample areas and were used to transfer-train a convolutional neural network for semantic segmentation. The resulting dataset was compared to manual surveys of the region and results suggest that deep learning can generate larger and more accurate datasets than those generated by hand.

Keywords: landscape archaeology; AI; remote sensing; convolutional neural networks; Andean agriculture; agricultural terracing; agricultural deintensification



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1. Introduction

Over millennia, the peoples of the south-central Andes developed elaborate, monumental-scale infrastructural systems to expand and intensify agricultural production, converting the potential environmental liabilities of high elevation, cold and dry conditions, and high topographic relief of this landscape into assets for sustaining large populations. As in other world areas [1–3], terraces cover large expanses of Andean valleys and are among the most visible anthropogenic features on the landscape. In the irrigated agricultural systems found throughout the western drainages of the central and south-central Andean highlands, terracing primarily facilitates the control of scarce water by creating gently sloping surfaces and entraining water across them [4–9]. However, Andean peoples devised a range of agricultural field systems with a range of ecological and agronomic benefits, including erosion control, runoff control, topsoil depth, quality, tilth [10–13], enhanced insolation [14], mitigation of frost risk, and the creation of level planting surfaces [3,5,8,9]. Large-scale agricultural complexes and their supporting irrigation systems shaped the social landscape through the communal labor required for their construction, maintenance, and management [15–21]. In many areas of the central and south-central Andes, terracing and irrigation systems reached their apogee under Inka imperialism, when they were renovated and further rationalized, and terracing expanded into areas that were previously marginal to agricultural production [18,22,23]. In the wake of the Spanish invasion of Tawantinsuyu (the Inka Empire), colonial populations remained dependent on the continued productivity of Andean agricultural systems, and the colonial economy functioned largely by siphoning

agricultural surplus indirectly through the vestiges of mid-level imperial institutions and local elites [24,25]. The dislocation and exploitation of colonial rule, however, generated myriad demographic, political, and economic crises, and many agricultural systems lapsed into dereliction or outright abandonment. These political and economic crises interacted with ecological dynamics at local and regional scales in varied and complex ways [26–30]. The distribution of abandoned terrace systems and their relationships to those still in use can therefore shed light on such political and ecological processes in the past, while also offering potential lessons for how abandoned terrace systems might be brought online again.

A holistic perspective on the extent of agricultural terracing and the distribution of abandoned terracing is needed to understand the quantity and distribution of both active and abandoned agricultural field systems in the Andes. But given the scale of agricultural terraforming in the Andean highlands, and the challenge of accurately detecting these field systems, such a perspective has been exceedingly difficult to achieve. Rough estimates and relatively small-scale inventories have been possible because of imagery and analytic limitations. Accurate detection of both active and abandoned Andean field systems requires high resolution imagery and a means to detect field systems as distinct from other landforms. Actively cultivated fields and terraces are visually and spectrally distinctive, but inactive/abandoned ones pose challenges because the features of interest lack crisp edges, and there is often little or no spectral difference between, for instance, land cover (plant communities, rocks, soil, etc.) among abandoned terraces and the surrounding landscape matrix. Traditional supervised or unsupervised classifications are thus prone to either miss large areas of abandoned fields or produce large areas of false positive classification. For this reason, much of the research in the Andes on the topic of agricultural abandonment has relied on the manual digitization of active and abandoned fields in satellite imagery [31–33]. Manual digitization, while generally accurate, is labor intensive, limiting the scale of analysis, and thus, again, our capability to characterize the scale and proportion of abandonment at regional and inter-regional scales.

Here we present a methodology using a convolutional neural network (CNN)-based automated detection of abandoned and active field systems over a large area of the south-central Andean highlands, producing a new estimate of total terraced area, as well as the proportions of these systems that are active and abandoned. We used high-precision manual imagery survey data to train a CNN and then conducted a semantic segmentation of high-resolution satellite imagery to register the presence and maintenance status of agricultural infrastructure across approximately 77,000 km² of the south-central Andes. These new estimates provide an important inter-regional scale baseline that locality- and region-based studies can use to contextualize variation in the total cultivated area and abandonment rates.

2. Investigating Agricultural Systems in the South-Central Andean Highlands

The south-central Andean highlands encompass diverse regions including the Titicaca Basin and several Pacific drainages such as the Moquegua, Tambo, Sigüas, Vitor, Colca, and Cotahuasi Valleys, as shown in Figure 1. The agricultural terrace systems of this area constitute monumental scale anthropogenic transformations of landscapes through centuries of coordinated collective labor and knowledge. The arid and semi-arid highland valleys stand out as some of the most intensively terraced landscapes in the Andes [4,5]. Irrigation is required for reliable yields of maize, quinoa, potatoes, and other Andean crops (and, since colonial times, wheat, barley, oats, and other Old-World cultigens) [16,34]. Extensive irrigation systems draw their waters from glacial meltwater, springs, and small streams above the agricultural zone, sometimes traversing dozens of kilometers to terrace systems below [4,8,15–17,35]. In the Western Titicaca Basin, the thermoregulatory effects of the lake make agriculture possible at altitudes above 3800 by reducing frost and increasing the rate of rainfall [36–38].

The longue durée of agricultural field construction, reuse, remodeling, and abandonment has produced a complex palimpsest of field systems visible on the landscape today. It

should not be assumed that there was ever a time when all the agricultural field systems visible today were in use simultaneously, or that patterns of field abandonment are the outcome of discrete historical processes. This landscape history is especially difficult to unravel as agricultural features are continually remodeled through routine maintenance. Fields continue to be constructed, renovated, reclaimed, and abandoned up to the present. This complicates temporal control of construction date, use life, and abandonment processes. Nonetheless, the large-scale perspective offered by remotely sensed, AI-assisted feature detection can provide a trans-regional perspective on the overall distribution of terraforming in the Andes and contextualize complementary field-based regional- and locality-scale studies.

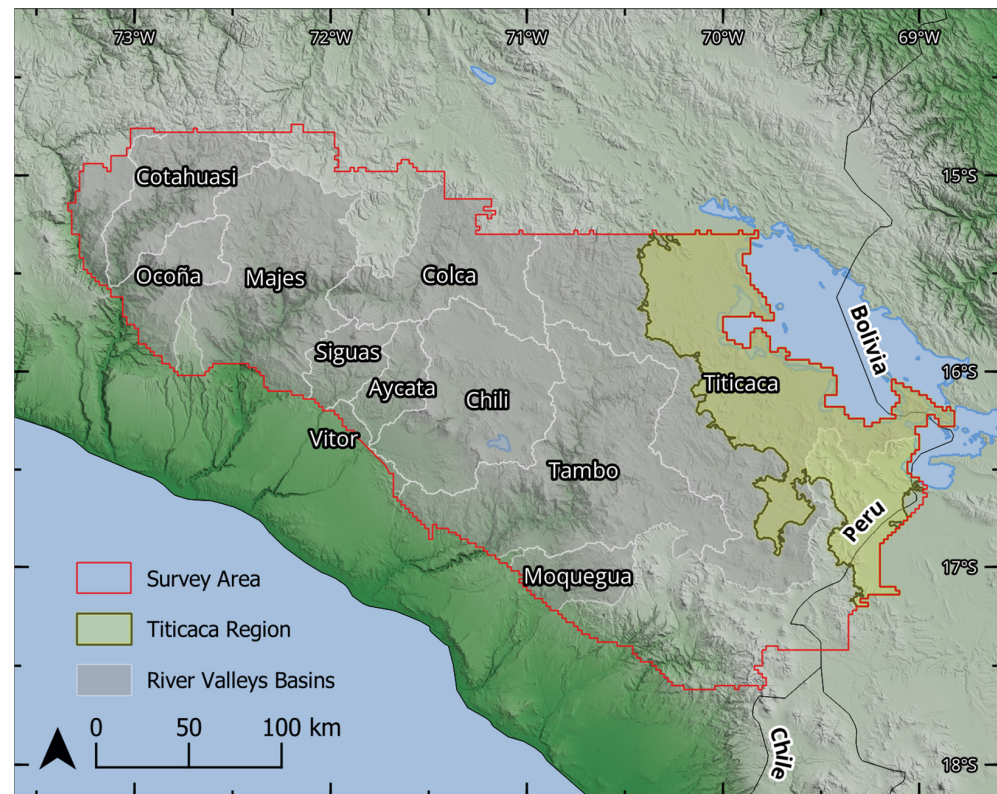


Figure 1. Map of the survey region, including a boundary outlining the Titicaca region as defined for this study.

Estimates of the proportion of terracing that has fallen into disuse vary widely, both regionally and across localities. For instance, in the Colca Valley of southern Peru (Arequipa Department), Denevan measured 61% of bench terraces as abandoned, based on an analog photogrammetric study of air photos [39]. In northern Chile, Wright [40] estimated 80% of terracing was abandoned. Masson has estimated between 50 and 75% of terracing in Peru has been abandoned [4,41]. These widely varying estimates beg questions about variation in rates of abandonment among localities versus trans-regional processes that might account for the overall high rates of abandonment. They may reflect real differences across localities, yet it is hard to square the high variance in estimates produced by these prior studies, based on limited data, imagery, and scant sampling across regions, with recent government-sponsored transregional agronomic studies that estimate rates of abandonment between 15% and 25% [32]. It may be that the ubiquity of abandoned terracing in certain locales is what attracted the researchers to begin with, so that studies focused on agricultural deintensification, and attendant terrace abandonment are concentrated in areas with especially high abandonment rates. Our project seeks to document at a trans-

regional scale the total extent of agricultural terracing and how much of it is abandoned via deep-learning-based satellite image segmentation methodology.

3. Materials and Methods

3.1. Data Collection

3.1.1. Satellite Imagery

Our survey was conducted with WorldView-2 (WV2) and WorldView-3 (WV3) satellite imagery. All images were delivered as OrthoReady Standard 2A data, which include atmospheric corrections and geographic projection. Images with less than 10% cloud cover per image were selected for inclusion. Thirty images were from the WV3 satellite with 8 spectral bands and a 0.31-m spatial resolution, and 96 images were from the WV2 satellite with the same 8 spectral bands and a 0.46-m spatial resolution. Each image was pre-processed through a pipeline for orthorectification, pansharpening, and resampling to 8-bit depth (to reduce computational load) using the Python API for Orfeo Toolbox (OTB) [42].

3.1.2. Terracing Polygons

This project builds on the inter-regional scale imagery survey conducted through the Geospatial Platform for Andean Culture, History, and Archaeology (GeoPACHA) [33]. GeoPACHA is a geospatial web app for documenting archaeological sites in the Andes through the systematic visual survey of satellite imagery and air photos by a network of trained teams [43]. GeoPACHA was also designed to provide training data for an AI-assisted imagery survey [44]. In outline, we edited and augmented the manually digitized boundaries of areas with agricultural terracing (as visible in Worldview-2 and Worldview-3 imagery) that were registered during the previous survey round of GeoPACHA [33]. We used these precise digitizations of active and abandoned agricultural fields within 51 sampling areas (each 0.05° latitude $\times$ 0.05° longitude) as examples of known active and abandoned agricultural fields. These labeled data provide the CNN model with examples of the features of interest. The labels were composed of three categories, “Abandoned Field” (class id = 2), which comprised 74 km² of the collected data, “Active Field” (class id = 1) comprising 175 km² of the collected data, and “Background” (class id = 0) comprising 1258 km². A sample image and label are shown in Figure 2. Finally, the digitized regions were split into training ($n = 41$) and validation ($n = 10$) datasets, with care taken to ensure that adjoining regions were not split between training and validation, thereby limiting the effects of spatial autocorrelation on the evaluation of the model [45]. These data are referred to as the “high-precision agricultural dataset” below.

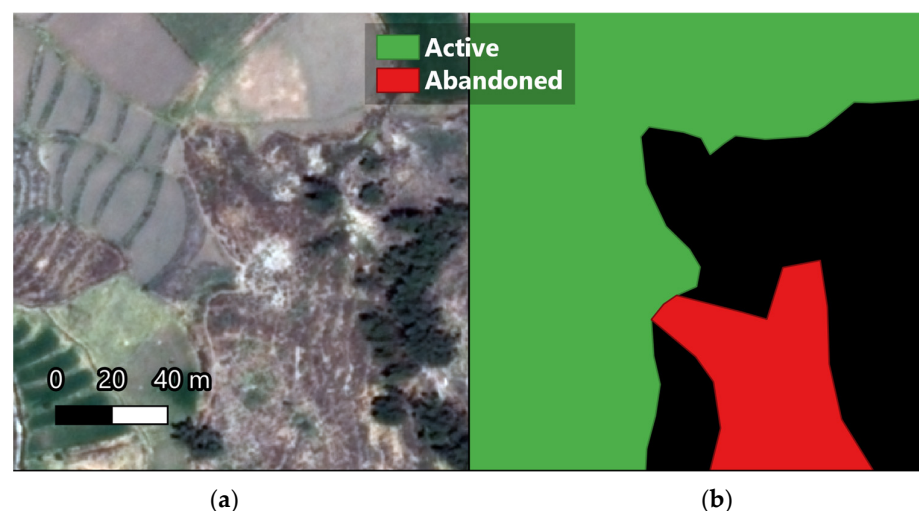


Figure 2. (a) Satellite image containing active and abandoned agricultural terracing; (b) manually digitized label segmenting the image into three classes: active field, abandoned field, and untterraced background.

3.2. Methods

3.2.1. CNN Model Training and Automated Survey

The processed imagery and high-precision agricultural data were used for model training and deployment in RasterVision [46], a free and open-source deep-learning framework for geospatial imagery. Using RasterVision, 1000 image chips of 300-pixel $\times$ 300-pixel dimensions, along with corresponding label chips, were randomly extracted from within each sample area, for a total of 51,000 chips. The training data were augmented using random 90° rotations and horizontal and vertical flips (a common computer vision procedure to increase training data size and reduce overfitting), and used to transfer-train DeepLabv3 [47], a Deep Learning semantic segmentation architecture with a pre-trained ResNet-50 [48] backbone for feature extraction. Data from the validation regions were reserved for evaluating model performance and not used for training. The model was fine-tuned using the Adam optimization algorithm for 30 epochs with a learning rate of 0.0001 and a batch size of 10. Configuration and log files are included in the GitHub repository. After each epoch, the model predictions were compared to the data in the validation dataset to track training progress and monitor for overfitting. Once the model was trained, Raster Vision was used to create a “model bundle” that contained all necessary model parameters and protocols for deploying the model on new imagery. The model was then deployed on images in the study region, thereby producing pixel-segmented raster maps of the presence of active and abandoned fields for each image.

3.2.2. Compiling and Evaluating the Results

In many regions, several satellite images overlap with each other. This can be advantageous because it provides multiple opportunities for the deep learning model to identify features, thereby reducing false negatives. Simultaneously, it increases the potential for false positives and conflicting predictions between images. The *r.series* function in GRASS GIS [49] was used to merge the predictions into a single and cohesive dataset, generating a raster dataset with a 1-m pixel resolution. For each pixel, it was evaluated whether any image predicted active or abandoned agricultural fields at that location. If there were multiple predictions, the modal result was selected. In the limited cases of conflict where the mode was equally split between active and abandoned terracing, the result defaulted to active terracing, as these predictions were much more accurate in the validation data. This suggests that the model results may overestimate the amount of active terracing for locations of conflicting information. However, the accuracy of the active terracing results and visual inspection suggests that the effects of this bias are marginal and are also likely countered in overall estimations of abandonment rates by the higher prevalence of false positives in the abandoned fields dataset (discussed below). Finally, the predictions for the study region were converted from raster to vector format using the GRASS GIS *r.to.vect* function for data cleaning and analysis.

Of the 51 areas that were manually surveyed in detail, 10 were reserved to evaluate model quality, including a mixture of active and abandoned agricultural features, and background non-agricultural land. For semantic segmentation, a common and easy-to-interpret metric for measuring data quality is the Intersection over Union (IOU), also known as the Jaccard Index. This calculates the area of the intersection between the predicted label and true label, and divides it by the total area covered by both the predicted and the true label, resulting in a value between 0 and 1, where 0 represents no overlap between the predicted and true labels, and 1 represents a perfect alignment between the two. Therefore, we used IOU to evaluate the model’s performance, comparing the model output to the validation dataset. This provides a conservative description of model performance, with post-hoc manual data cleaning ensuring the results of the AI-assisted survey are better than those reported for the automated survey alone.

3.2.3. Manual Survey Comparison

To better understand the quality of the data produced by the AI model, we compared the model results to manually coded agricultural data collected as a part of the GeoPACHA survey project. In the GeoPACHA schema, a survey grid of 0.005 degrees (~500 m) covered the survey area, and grid cells containing any amount of abandoned agricultural infrastructure were marked. This method allows for the rapid mapping of very large areas, but also produces relatively low-granularity data that tend to overestimate the total area of abandoned agricultural fields. Extracting the GeoPACHA grid cells that fall within our validation regions allows us to directly compare the results of the GeoPACHA abandoned fields survey to the high-precision and CNN model datasets.

As an adjunct to the GeoPACHA imagery survey, Grecia Roque and Steven Wernke also digitized polygons of active agricultural areas in the GeoPACHA southern highlands survey area. These data may be described as “regionally accurate”, which is to say that they approximate the boundaries of agricultural feature complexes, but they also include other features of the landscape such as paths, walls, settlements, rivers, and hills which are not terraced but are surrounded by terracing. This is necessary for such large-scale manual surveys, as a finer-grained approach which would exclude these features would be impractical to complete over many thousands of square kilometers. Manual methods necessitate compromise between scale and granularity. Our research seeks to generate data at a higher level of precision than is practical by hand at the trans-regional scale, and so the GeoPACHA data provide a vital benchmark against which to compare our results.

3.2.4. Characterizing Agricultural Distributions

Once we mapped the extent of agricultural infrastructure at a trans-regional scale and validated the results, we sought to understand its geographic distribution. The agricultural infrastructure adjacent to Lake Titicaca is substantially different from that of the other river valleys of the study region. In part, this is owing to the distinctive climatological and environmental conditions driven by the lake itself, which moderate temperatures relative to the altiplano context beyond the circum-lacustrine area. The extent of agricultural features in the western Titicaca Basin far surpasses that of the neighboring valleys of the western cordillera—a basic fact that was perhaps intuitively understood by researchers but not well documented. Analyzing data from the western Titicaca Basin and the river valleys simultaneously obscures regional variation in the distribution of fields outside of the vicinity of Lake Titicaca. For our environmental analyses, we therefore divided the data into two regional sets, one which includes the Western Cordillera river valleys, and the other which covers the extensive fields that extend several kilometers from the northern, western, and eastern shores of Lake Titicaca.

Taking the temperature-moderating effect of the lake as a primary driver of the agricultural landscape in the region, we modeled the boundary of its agricultural effect. Elevation and mean annual temperature for the study region are strongly negatively correlated (cov: −0.96), however, this relationship changes with proximity to the lake. Calculating the expected temperature contingent on elevation, we measured mean annual temperatures to map their deviation from expectation. The contour line representing 0.75 degrees C above the expected temperature aligns closely with the boundary of the increased density of agricultural activity near Lake Titicaca. Therefore, any agricultural fields within the 0.75-degree contour were labeled as Titicaca fields, while those outside it were labeled as “River Valley” fields for the purposes of analysis. The one deviation from this pattern was near the southern edge of Huiñaymarca where the temperature is slightly cooler, possibly due to air currents from the glaciated peaks to the east. Due to their proximity to the lake, these fields are clearly a part of the Titicaca agricultural system and were manually added to the Titicaca dataset.

3.2.5. Ecological Modeling of Agricultural Deintensification

We also explored the distribution of agricultural fields and their abandonment in relation to the distribution of elevation, slope, aspect, and geomorphology. These variables were selected a priori as characteristics of the environment that may have had an effect on the construction, maintenance, and abandonment of agricultural fields. Certainly, these ecological variables are not the only factors of relevance, as agriculturalists in the Andes have transformed their environments by working around, with, and through the ecological variety afforded to them. Nevertheless, as the below analysis will show, environmental factors do impact the process of deciding where to invest the time and energy to make these environmental transformations. This analysis establishes broad use patterns, against which such transformations can be understood.

The elevation data used in this analysis were a 30-m Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) [50]. The Slope (in degrees) and Aspect (in degrees clockwise from North) variables were calculated from the DEM using the `r.slope.aspect` function in GRASS GIS [49]. The geomorphon dataset was calculated using the `r.geomorphon` tool in GRASS which categorizes the landscape into 8 different morphological classes that correspond to commonly used terms in geographical and archaeological descriptions. This provides a clear way to examine geographically defined proposals such as: most active agricultural fields occur in the valley bottom (flat, valley, footslope), while terraces on the valley wall are more likely to be abandoned (slope, shoulder, spur).

4. Results

The AI-assisted survey area comprises a total area of 81,149 km² and encompasses the Western Titicaca Basin, surrounding uplands, and the Pacific drainages of a large portion of the south-central Andean highlands to the west. In this region, the CNN-based semantic segmentation identified 5121 km² of agricultural fields in the study region—about 6.3% of the total survey area (Figure 3). Of the area with agricultural fields, 76.4% (3911.6 km²) were under cultivation at the time the imagery was collected, while the remaining 23.6% (1209.40 km²) were identified as abandoned. The Titicaca Basin dominates the dataset with 3996 km² of agricultural land or 78% of all agricultural fields in the study area, with the remaining 22% (1125 km²) concentrated in the valleys that incise through the high plateau to the west and south.

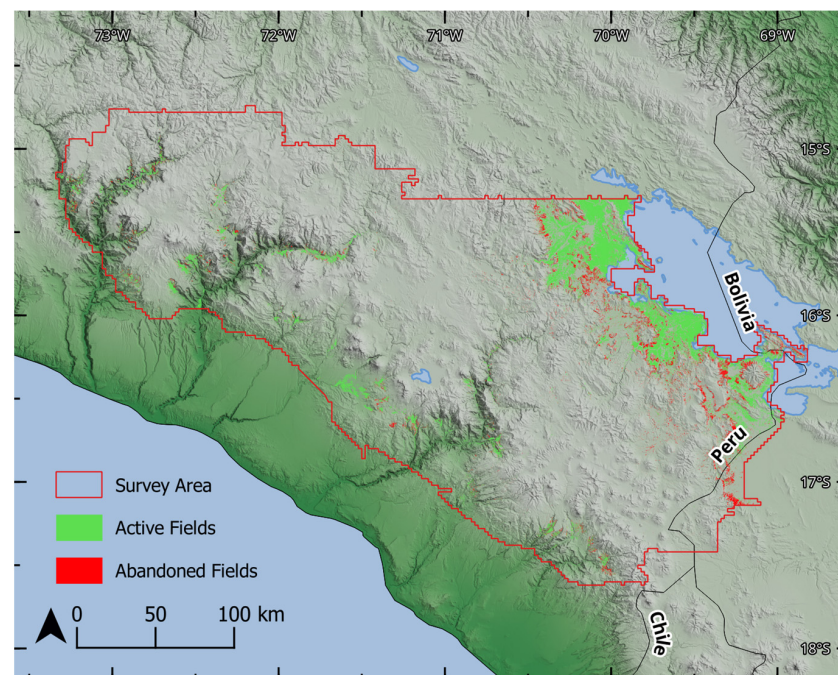


Figure 3. Map of AI-assisted inventory of active and abandoned agricultural fields in the study area.

4.1. Data Quality Evaluation

The IOU for active and abandoned fields were calculated separately, and an overall IOU score was obtained by averaging the two metrics together. For active agricultural fields, the model achieved an IOU of 0.66 when compared to the high-precision validation data, while its performance on abandoned agricultural fields was lower, with an IOU of 0.44 for a mean IOU of 0.55. As can be seen from the confusion matrix (Figure 4), approximately 75% of the validation survey region was not agricultural, while approximately 18% was under cultivation at the time the imagery was collected. The model performed well, excluding background and identifying active fields. However, due to the transformations in form, color, and texture of abandoned fields as they decay, their identification and extent are inherently more difficult to evaluate in both human and automated surveys. As such, the model tended to overestimate the extent of abandoned agriculture, or identify features such as modern erosion control, water drainages, power lines, or other linear features with limited amounts of vegetation as abandoned terracing.

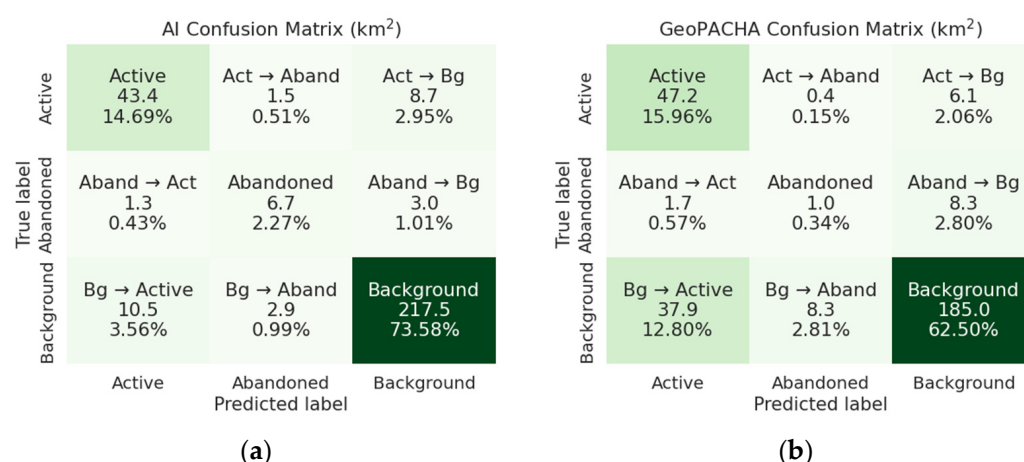


Figure 4. Confusion matrices comparing (a) AI and (b) “brute force” inventories to precise manual survey data collected for model validation.

We then calculated the IOU of the manual surveys conducted for the GeoPACHA project, in relation to the high-precision data collected in preparation for AI training and validation. This creates comparative metrics to understand the CNN’s performance in relation to that of human survey alone when working at very large scales. For active agricultural fields, GeoPACHA surveyors achieved an IOU of 0.51 while the lower resolution of abandoned fields data led to a much lower performance of ~0.05 for a mean IOU of 0.28. As can be seen from confusion matrix b in Figure 4, the lower IOU for active fields comes mostly from the lack of specificity of the data, with large areas of uncultivated land included in the active field dataset. The very low IOU for abandoned fields comes from both a lack of sensitivity and specificity. We can therefore confidently claim that the raw data produced by the AI model are of a quality as high or higher than that produced by the GeoPACHA survey. Quality metrics are summarized in Table 1. Following data evaluation, every effort was made to remove these errors where they were observed. The above evaluation is therefore a conservative estimate of the true accuracy of the AI-assisted survey performance.

Table 1. Intersection over union (IOU) metrics for active and abandoned fields, comparing the automated survey to the large-scale manual survey performed by the GeoPACHA project. Higher numbers are better.

	Automated Survey	GeoPACHA Survey
Active	0.66	0.51
Abandoned	0.44	0.05
Mean	0.5	0.28

4.2. Agricultural Abandonment Rates and Environmental Distributions

Of the Lake Titicaca region fields, only 21% (85,488 ha) are abandoned, while 31.5% (35,451 ha) are abandoned in the western valleys. Environmental factors also had marked effects on the distribution of agricultural features and the rates of their abandonment, with elevation and slope particularly affecting the likelihood of field creation and abandonment. Overlaying a 0.1-degree grid over the survey region, we can map the changes in abandonment rate across the entire survey region (Figure 5).

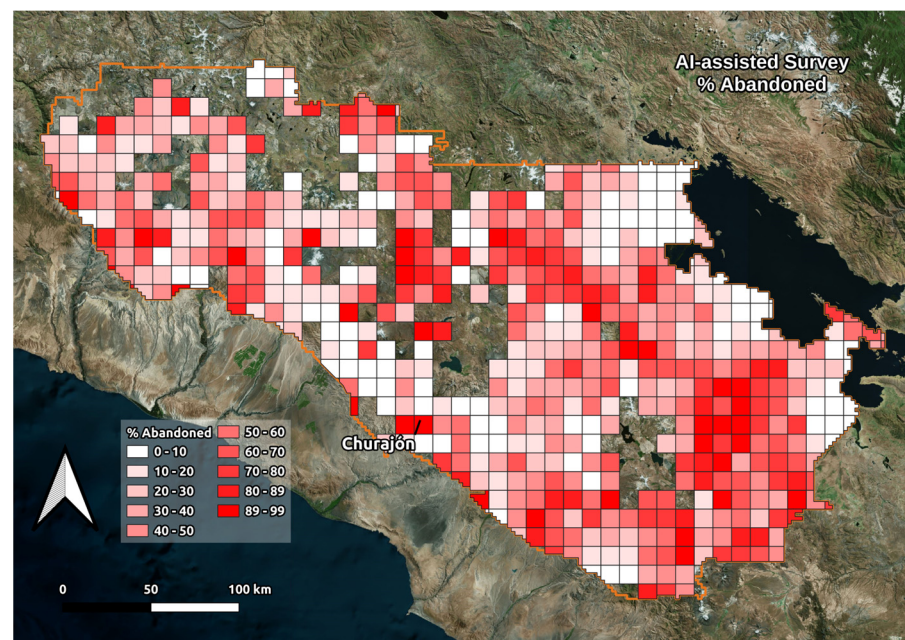


Figure 5. Map of local variation in percent of agricultural fields that have been abandoned. Missing squares indicate that no agricultural activity was recorded.

4.3. Elevation

One of the commonly cited environmental factors to limit agricultural production in the Andes is elevation. This is primarily due to elevation's strong correlation with temperature, and therefore the risk of frost. The average elevation of currently in-use agricultural fields is 3707 m, and the average elevation of abandoned fields is 3876 m, while the average elevation of non-agricultural land is 4101 m. Splitting the data into River Valley and Titicaca datasets, the pattern is even stronger in the River Valleys, with an average elevation of 3100 m for in-use fields, while abandoned fields have an average elevation of 3520 (Figure 6). Results are summarized in Table 2.

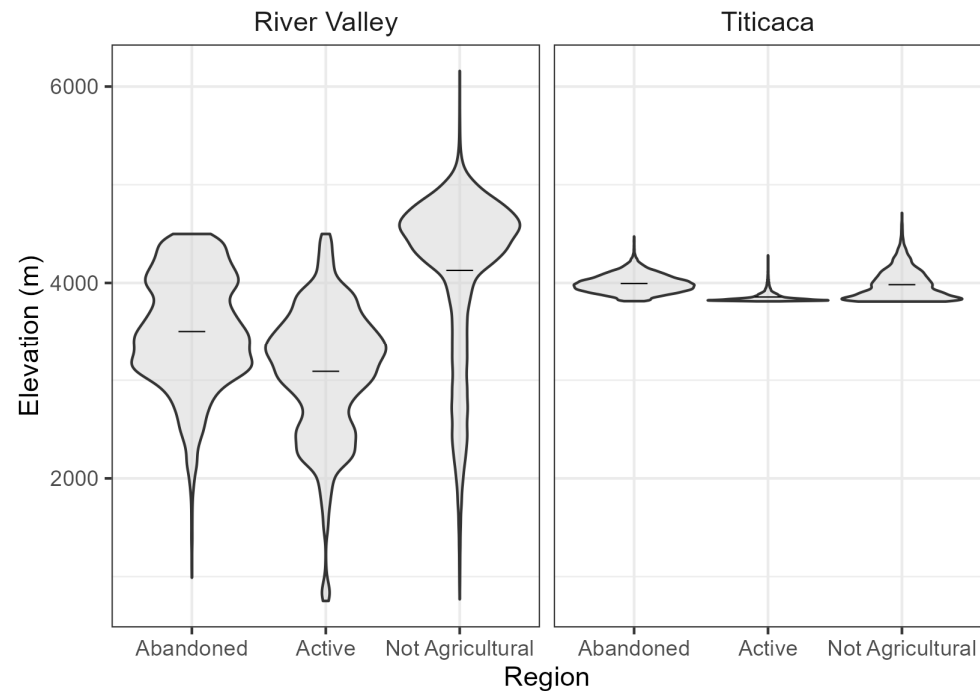


Figure 6. Distribution of active and abandoned agricultural fields by elevation and comparison to non-agricultural land, split by geographic region.

Table 2. Mean elevation of active and abandoned agricultural fields and non-agricultural land.

	River Valleys	Titicaca	Overall
Active	3091 m	3857 m	3709 m
Abandoned	3505 m	3994 m	3874 m
Not Agricultural	4128 m	3983 m	4108 m

4.4. Slope

Ground slope also had a significant effect on field creation and maintenance. Throughout the study region, active fields are located on terrain with lower-than-average slopes. This is especially true around Lake Titicaca, where the average slope is only around 4.24° because most of the active fields are located on the lake's floodplain. In the narrow River Valleys, active fields are primarily in the valley bottoms, with a smaller but significant portion on the valley walls, resulting in an average slope of 12.2° . The abandoned fields, in contrast, tend to occur on steeper slopes, with an average of 18.2° in the river valleys and 13.3° around Lake Titicaca (Table 3). These are both higher than the average slope for the regions due to the high-altitude puna (relatively flat grasslands), which are too high for agricultural production (Figure 7).

Table 3. Mean slope of active and abandoned agricultural fields and non-agricultural land.

	River Valleys	Titicaca	Overall
Active	12.5°	4.13°	5.8°
Abandoned	18.4°	13.4°	14.6°
Not Agricultural	14.9°	13.0°	14.7°

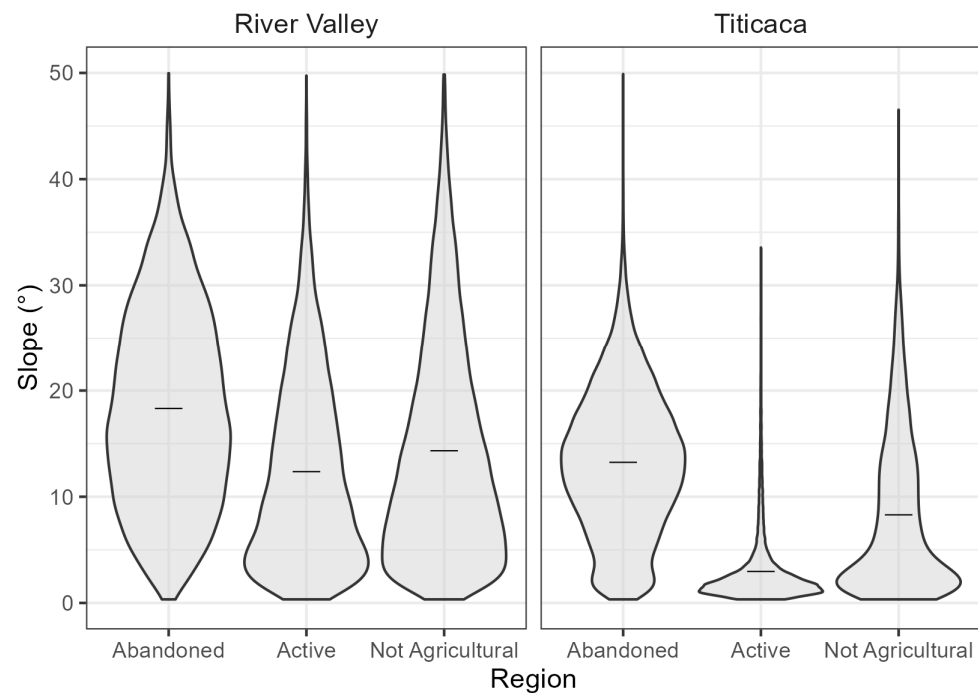


Figure 7. Distribution of active and abandoned agricultural fields by ground slope in degrees and comparison to non-agricultural land, split by geographic region.

4.5. Aspect

Aspect (the direction the slope faces) is another environmental variable that is commonly expected to be associated with agricultural production. In the southern hemisphere, north-facing slopes should receive more sunlight, which can be beneficial for plants as it allows for more photosynthesis and warmth. However, it also requires higher water demands [51]. Removing flat areas (which, by definition, do not have an aspect) we calculated the circular means of the aspect angles (Table 4). These results show little difference between Active, Abandoned, or Non-Agricultural classes, suggesting that, across the region, aspect does not have a substantial effect on the construction or maintenance of agricultural fields. In the river valleys, the circular mean for active and abandoned fields is $\sim 220^\circ$ from north, that is, the slopes on average face southwest following the course of water as it flows from the mountain slopes to the Pacific Ocean. Similarly, the survey area only includes land on the southwestern side of Lake Titicaca, therefore, for fields near Lake Titicaca, the average slope faces northeast, directing water towards the lake.

Table 4. Circular means of the aspect show that active and abandoned fields, as well as non-agricultural land, tend towards the direction of the drainage basin, the Pacific Ocean for the river valleys, and Lake Titicaca for the land in its zone of influence.

	River Valleys	Titicaca
Active	218° (SW)	57° (NE)
Abandoned	220° (SW)	90° (E)
Not Agricultural	212° (SW)	46° (NE)

5. Discussion

5.1. Variations in Agricultural Abandonment

This research offers a broader contextual perspective on the rates and distribution of agricultural field abandonment in the western cordillera of the south-central Andean highlands. Our AI-assisted approach aligns well with the governmental surveys on average, with a trans-regional abandonment rate of 23%, but provides more nuance by highlighting

variation, with local and regional abandonment rates ranging between 21 and 31%. Remembering that local rates of abandonment may be much higher (or much lower) than the average, this research demonstrates the importance of developing regional or trans-regional data to contextualize these variations and understand broader patterns. For example, aspect has reportedly had an impact on the suitability of land for agricultural production [52] in the Colca Valley. However, from the trans-regional perspective, aspect does not seem to have had a substantial impact on either the creation or maintenance of agricultural fields. Indeed, much archaeological research on terracing and agriculture has been devoted to the Colca Valley ([4,5,11,29,30,39,52,53]), though see [21,54,55] for examples from Cuzco and the Titicaca Basin where abandonment rates have been measured at around 40%, which is significantly higher than average according to our survey.

Rather than a point of concern, when put in a trans-regional context, these discrepancies between local, regional, and transregional patterns offer fruitful opportunities for generating and testing hypotheses about local decision making, affordances, and their effects on persistence and resilience. For example, detailed knowledge of local and regional environment, as well as the functioning of Andean social and economic systems, would have become especially crucial during the Toledan Reforms. Population declined under Spanish colonialism, and the forced resettlement of the indigenous population into centralized towns would have required agriculturalists to select which fields could continue to be maintained, and which should be abandoned. As the location of new resettlement towns were selected, the accessibility and quality of agricultural land would have been a key component in the persistence or abandonment of the settlement itself. Variations in rates of field abandonment and their relationships to Spanish resettlement towns may, therefore, provide key insights into the dynamics of indigenous life, power, and control under Spanish colonialism. Future research will seek to examine these relationships in detail. Trans-regional satellite surveys and local terrestrial archaeological explorations therefore form important and complementary modes of conducting archaeological research.

5.2. Distribution of Agricultural Development and Abandonment

Nevertheless, even initial exploratory analyses of the data offer insights into how intensive agricultural infrastructure is distributed on the landscape in the southwestern highlands of Peru. As expected, environmental variables such as elevation and ground slope have significant impacts on the creation and maintenance of agricultural fields across the study region. Future work will seek to further refine these analyses and to tease apart the relationships between them, as well as how they articulate histories of Spanish colonialism. Elevation and precipitation, for example, likely interact to confine the zones in which agricultural production is practical. Crops at high elevations are likely to receive more water, but are also more susceptible to frost, while crops at lower elevations are safer from frost, but may have difficulty receiving enough water without extensive irrigation. Establishing the environmental dynamics that afford agriculturalists the potential for creating agricultural production and comparing them to the locations in which agriculturalists chose to construct fields, irrigation networks, and other agricultural infrastructure, and to the locations where fields were ultimately abandoned, will allow us to better understand agriculturalists' priorities.

5.3. The Value of AI-Assisted Remote Sensing

The results of this research suggest that AI-assisted imagery surveys are promising for large scale perspectives on the archaeological record. A "brute force" manual imagery survey of agricultural landscapes can be highly detailed at a local level, achieving very precise and highly accurate data. However, achieving such a level of detail at regional or trans-regional scales can be prohibitively time-consuming for manual surveyors. As a result, large-scale manual surveys are often forced to operate at lower spatial resolutions, resulting in the inclusion of non-agricultural features. Deep learning offers a way to achieve both high-precision and large-scale surveys simultaneously. While the current

deep-learning model may not surpass human capacity at the local scale, it far exceeds it at the trans-regional scale. The resulting extensive and high-resolution data will enable more accurate analyses of the capacity of agricultural production, and the extent, distribution, and causes of agricultural deintensification and field abandonment.

Over the entire study region, the AI-assisted survey identified 391,158 ha of land currently under cultivation, a 30% reduction from the manual survey conducted as part of the GeoPACHA project. Visual comparison between the two datasets, as well as the data quality metrics, suggest that these differences are primarily due to the elimination of features that were incorrectly identified in the manual survey, rather than features that were missed in the AI-assisted survey. For analyses such as estimations of agricultural production capacity, a 30% reduction in land area is substantial, fundamentally changing our understanding of the agricultural landscape. This speaks powerfully to the value of an AI-assisted approach for inventorying agricultural fields in satellite imagery.

Furthermore, once trained, a deep learning model can be rapidly deployed on new imagery. Previously unsurveyed regions can be covered in a matter of hours, rather than months, and areas that have been previously examined can be monitored as new satellite imagery becomes available, allowing us to track for the first time the expansion and contraction dynamics of agricultural infrastructure in the Andes at a regional scale. Such a dynamic perspective would shed light on the flexibility and stability of Andean agricultural infrastructure in light of ongoing political and climatological transformations, providing insight into how past processes may have shaped agricultural production, and how best policymakers may respond to them in the future.

5.4. Future Research

The reliable identification of abandoned terracing is a major challenge, even for human researchers. Improving the training data and taking advantage of “weak supervision” AI methods may allow us to further improve our mapping of abandoned terracing in the region. Currently, the inventory has mapped the location of agricultural fields at the level of agricultural complexes. However, there is great variation in the types of field that may occur within a complex. Denevan [52] discussed six types of terrace in the Colca Valley alone (largely shaped by their ecological context), and Langlie [21] demonstrated that the morphology of terraces within a complex can reveal patterns of social resistance, in addition to those of social control commonly attributed to Inka terraces. Future models may be designed to map the boundaries of individual fields [56], rather than those of field complexes, allowing for this kind of morphological analysis at trans-regional scales. In each of these applications, AI-assisted survey methods promise transformational research at previously impossible archaeological scales. The inventory of agricultural features has shown that rates of field abandonment, and the relationship of field production and abandonment to environmental variables, is non-stationary across the study region. That is, local populations have made different choices and possibly been offered different affordances about how to manage agricultural resources. Mapping these variations and incorporating more social and human experiential variables into the modeling process will be vital to developing new, better, and more sophisticated hypotheses about how these variations arose. This research can then guide future studies in the field to test hypotheses and “ground truth” the data produced through trans-regional satellite surveys.

6. Conclusions

Despite their importance, agricultural fields (particularly terracing) in the Andes have attracted less attention from archaeologists than other features of archaeological interest. The underlying infrastructure that sustained both Tawantinsuyu and the subsequent viceregal economy has remained under-appreciated in large measure because fields are dispersed across thousands of hectares, while settlement information is much more concentrated. Nevertheless, these monumental-scale infrastructure projects were vital to the economic, social, and political lives of Andean people throughout prehistory and following the Span-

ish conquest, and deserve further examination. This research represents the first step on this path, mapping where these features are, and their current state of use or abandonment. This work complements “brute force” (manual) surveys of satellite imagery such as those conducted by GeoPACHA [33,43] and other satellite archaeological surveys [31], or by the Peruvian Ministry of Agriculture [32], by affording the timely expansion of analyses to new regions and imagery.

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