Automated mapping of *Portulacaria afra* canopies for restoration monitoring with convolutional neural networks and heterogeneous unmanned aerial vehicle imagery

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Abstract

Ecosystem restoration and reforestation initiatives can operate at large spatial scales, whereas monitoring is often limited to spatially restricted field measures that are time- and -labour intensive and unable to accurately cover the hundreds to thousands of hectares under restoration. Recent advances in remote sensing technologies coupled with deep learning algorithms provide an unprecedented opportunity for monitoring changes in vegetation cover at spatial and temporal scales. Data generated in this manner can feed directly into adaptive management practices and provide insights into regeneration dynamics. Here we demonstrate that coupling imagery acquired using different models of Unoccupied Aerial Vehicles (UAVs), and under heterogeneous illumination conditions, with Convolutional Neural Network (CNN) segmentation algorithms accurately classified the canopy cover of *Portulacaria afra* Jacq. - the target species for the restoration of Albany Subtropical Thicket vegetation, endemic to South Africa. The model presented here is widely transferable to restoration monitoring as its application does not require any knowledge of the CNN model or specialist training, can be applied to imagery generated by a range of UAV models, and will reduce the sampling effort required to track restoration trajectories in space and time. This will contribute to more effective management or restoration sites and promote collaboration between scientists and practitioners.

Introduction

With the United Nations "Decade on Ecosystem Restoration" underway, there are likely to be global increases in the extent of restoration initiatives. These initiatives will require methods for accurately monitoring the trajectories of restoration efforts in an efficient and cost-effective manner (de Almeida et al., 2020; Méndez-Toribio et al., 2021; Murcia et al., 2016). Additionally, these methods should be easily transferable, allowing non-experts to collect data at large spatial and temporal scales. Recent advances in remote sensing technologies and deep learning algorithms may provide the tools required for restoration practitioners (Brodrick et al., 2019; Kattenborn et al., 2021; Zhu et al., 2017). The work presented here demonstrates that using standard and low-cost "out-of-the-box" Unoccupied Aerial Vehicles (UAVs) coupled with Convolutional Neural Network (CNN) algorithms allows for the detection and quantification of *Portulacaria afra* Jacq. in restoration plots established between 2007 and 2008. *P. afra* is regarded as an ecosystem engineer in the Albany Subtropical Thicket biome (van Luijk et al. 2013; Wilman et al. 2014), endemic to South Africa, and is the target species for large scale restoration initiatives (Mills et al., 2015; Mills and Cowling, 2006; van der Vyver et al., 2021a). It is estimated that up to 1.2 million hectares of the thicket biome exhibits some level of degradation (Lloyd et al., 2002) and in need of restoration intervention. With approximately 7000 ha of plantings completed by 2017 (Mills and Robson, 2017), it is likely that the scale of thicket restoration will reach the tens of thousands of hectares in coming years. Thus, the monitoring tool presented here could prove invaluable to the rapid monitoring and management of thicket restoration initiatives.

The thicket biome is largely confined to the Eastern Cape Province of South Africa and is characterized as a low growing, spinescent, dense woodland system with high standing biomass often dominated by a matrix of the succulent tree, *P. afra* (Vlok et al., 2003). Occurring within a semi-arid environment, the high productivity of thicket is globally unique, with litter production rates comparable to that of some temperate forest systems (Lechmere-Oertel et al., 2008). This productivity formed the basis for wool, and mohair production in the region (Beinart, 2008; Oakes, 1973; Stuart-Hill, 1992)s. While resistant to herbivory by indigenous browsers (Stuart-Hill, 1992, but see Landman et al., 2012), thicket vegetation is prone to *P. afra* denudation (due to the species' high palatability) when subjected to prolonged periods of browsing by domestic livestock (Hoffman and Cowling, 1990; Lechmere-Oertel et al., 2008). This results in a structural shift from a dense, closed-canopy woodland to an open habitat consisting of a handful of remnant and isolated woody species that occur within a matrix of bare soil, ephemeral herbs, grasses and dwarf shrubs (Lechmere-Oertel et al., 2008; Sigwela et al., 2009; Stuart-Hill, 1992).

The change in *P. afra* abundance due to unsustainable browsing practices pushes the system to a point where the natural regeneration (seed set and asexual reproduction via rooted lateral branches) of this species becomes insufficient to overcome rates of canopy reduction and mortality (Lechmere-Oertel et al., 2008). The environmental buffering effects of *P. afra* improves soil organic matter (Lechmere-Oertel et al., 2008) and water infiltration (Mills and de Wet, 2019; van Luijk et al., 2013) required for the recruitment of canopy tree species (Sigwela et al., 2009; Wilman et al., 2014), thus playing an important role in community assembly processes. The loss of *P. afra* cover, therefore, triggers a series of feedback loops that set the ecosystem onto a trajectory towards degradation: the lack of vegetation cover exposes the soils to erosion, depleting carbon stocks (Cowling and Mills, 2011; Lechmere-Oertel et al., 2008, 2005; Mills and Fey, 2004), which in turn disrupts hydrological processes such as water infiltration and retention (Cowling and Mills, 2011; Mills and de Wet, 2019; van Luijk et al., 2013), leading to further disruption of ecological functioning and ultimately biodiversity loss (Fabricius et al., 2003; Sigwela et al., 2009).

Active restoration of degraded *P. afra* thicket has been sponsored, at a landscape scale, by the

South African Government, in an initiative called the Subtropical Thicket Restoration Project (STRP). This aims to generate employment opportunities that will, ultimately, be funded by the global carbon market (Marais et al., 2009). The high productivity of *P. afra* thicket coupled with the ease of propagation (i.e. through the planting of unrooted *P. afra* truncheons into degraded habitat: Mills and Cowling, 2006; van der Vyver et al., 2021), lends the vegetation type well to carbon credit generation, sequestering up to 15.4 t CO_2 ha^{-1} yr^{-1} (Mills and Cowling, 2014). However, restoration success and carbon sequestration are measured over decades, while implementation success and restoration trajectories must be monitored over shorter time spans to allow for adaptive management. This monitoring is often limited to field measures that are time- and labour-intensive when having to cover hundreds to thousands of hectares. However, recent technological advancements have increased the availability of remote sensing data, providing solutions to this challenge in restoration (Almeida et al., 2021; Chen et al., 2021; Wang et al., 2021).

Novel aerial imagery platforms, such as UAVs, make the generation of high-resolution remote sensing data rapidly available with relatively little sampling effort (Colomina and Molina, 2014). These platforms require little specialist training and can provide high resolution data at spatial and temporal scales. Given the accelerated availability and volumes of such data, automated approaches are required to harness their full potential (Kattenborn et al., 2021). Convolutional Neural Networks (CNNs) are particularly well suited to the analysis of vegetation, due to this class of algorithms being designed to extract features in data (spatial features in the case of aerial imagery) that best describe the target object (e.g. leaf and canopy shapes, edges between individuals, and individual species spectral properties). Training the model to extract the desired features is particularly efficient as the algorithm itself is able to learn what patterns are important based on the reference material. This is done in sequential batches, enabling the model to cope with large amounts of data, which facilitates the training of models that are transferable across sites and remote sensing data conditions. CNNs have thus been applied in the identification of individual plant traits (e.g. growth form: Fromm et al., 2019 and Sylvain et al., 2019; and plant phenology: Hasan et al., 2018), species (Fricker et al., 2019 and Wagner et al., 2020), and communities (Kattenborn et al., 2019) from aerial imagery.

The growing interest in the global carbon market presents restoration initiatives with novel funding structures (Galatowitsch, 2009), that are likely to contribute to the upscaling of thicket restoration initiatives (Marais et al., 2009; Mills et al., 2015). This upscaling will require effective means of monitoring change in canopy cover, at a range of spatial and temporal scales, to inform adaptive management practices. By coupling imagery derived from readily available “out-of-the-box” UAV’s and CNN segmentation algorithms, this work successfully classifies canopy cover of reintroduced *P. afra* in experimental thicket restoration plots established between 2008 and 2009 (Mills et al., 2015). This demonstrates that commercially available UAVs coupled with CNN algorithms can provide rapid and accurate estimates of *P. afra* cover for restoration initiatives at low cost and without expert training. Implementation of this monitoring approach will allow for the rapid monitoring of changes in vegetation cover and facilitate adaptive management by allowing fine-scaled temporal monitoring of restoration sites.

Materials & Methods

Study site and UAV data acquisition

A total of 300 experimental restoration plots were established in degraded habitat across the global extent of *P. afra* dominated thicket vegetation (as delineated by Vlok et al., 2003). Each plot consisted of a 0.25 ha (50 x 50 m) herbivore exclosure that was fenced to a height of 1.2 m. These experimental plots tested a range of *P. afra* planting strategies (briefly described in van der Vyver et al., 2021), but produced highly variable results, with survival ranging between 0 - 100% between plots (Mills and Robson, 2017; van der Vyver et al., 2021b). Furthermore, the complete or partial removal of fencing exposed some experimental plots to herbivory (van der Vyver et al., 2021a), and differences in local climatic and soil conditions (Vlok et al., 2003) may have resulted in differences in the rate of *P. afra* growth. Thus, *P. afra* cover is highly variable between these plots. Aerial imagery for thirty-two experimental plots that reflect this variability in *P. afra* cover was aquired to train and test the CNN based segmentation models.

For this, RGB imagery was acquired in thirty-two individual flights in 2020-2021 using a DJI Phantom 4 Pro (n = 12) and DJI Mavic 2 Pro (n = 20). The imagery was acquired at different times and dates. This resulted in very diverse image properties, such as image brightness, contrast, or the presence, orientation and size of cast shadows. The flying height was 30 m above ground, with 10 m spacing between photographs, and this resulted in a Ground Sampling Distance (GSD) of ~0.9cm/pixel. Flight plans were generated using a custom script in R (V1.4.1717), and FlyLitchi (V4.22, www.flylitchi.com) was used to operate the UAV during flights. Imagery was stitched using Metashape (V1.7.2, Agisoft LLC). Examples of the images generated are provided in Figure 1.

Reference data was generated by visual interpretation of the orthoimagery in a GIS environment, where *P. afra* crowns were delineated by means of manually geocoded polygons. For each orthoimage and plot, the reference data acquisition targeted an area of approximately 12.5 by 12.5 m. After visual interpretation, the shapefiles were converted to a binary mask (presence vs. absence of *P. afra*) with a raster resolution corresponding to the respective orthoimage.

CNN model training and validation

For training the CNN, non-overlapping tile pairs of 128 by 128 pixels were seamlessly cropped from the orthoimages (predictors) and the masks (reference). For this, only the visually interpreted (*P. afra* cover) portion of the reference images was considered (cf. previous section). As a segmentation algorithm, we implemented the Unet architecture (Ronneberger et al., 2015). The Unet architecture is composed of an encoder and a decoder part, which are linked with skip connection. Both the encoder and decoder parts contain pooling operations, which reduce the spatial resolution of the feature maps. In the encoder part, the model extracts the image features for detecting *P. afra* at multiple spatial scales. The skip-connections transfer the activation maps of each spatial scale to the decoder part, which, hence, enables segmentation of the crown dimensions at the original spatial resolution of the input imagery. Here, we used encoder and decoder parts composed of 4 convolutional blocks, where each block consists of two convolutional layers followed by a batch normalization and max pooling operation. As activation functions, we used Gaussian Error Linear Units (GELU). Similar setups have been successfully applied in previous studies (Kattenborn et al., 2019; Schiefer et al., 2020).

To avoid optimistic model evaluation by spatially autocorrelated training and validation data (Ploton et al. 2021), we randomly split all available data on a plot basis, where a portion of plots was used for model training (n=24) and model testing (n=8). The training data was again split in training (7/8) and validation data (1/8), whereas the validation data was used to monitor the training process. The models were trained in 100 epochs and the final model used for further analysis was selected based on the lowest loss on the validation data. As a loss function, we used the binary cross-entropy. Training the model took about 457 minutes using an NVIDIA A6000. The final model performance for the tiles that were included in the training, validation and testing was reported using the F1-score (also known as dice coefficient). Additionally, we performed a t-Test to assess if F1-scores differed significantly between imagery obtained with the DJI Phantom 4 Pro and the DJI Mavic 2 Pro.

The final model was used to predict *P. afra* crowns in all orthoimagery. The prediction was performed using a moving window approach, in which individual tiles of the same size as used for model training (128 x 128 pixels) were seamlessly cropped from the orthoimagery. The final model was then applied on these tiles and the predictions were stored as a prediction raster containing the class probability (0 = absence & 1 = presence of *P. afra*). To reduce edge effects (potential mispredictions at the border of tiles), we applied this procedure two times, where the locations of extracting the tiles were shifted by 50 % of the tile size (64 pixels). The two resulting prediction rasters were averaged and a threshold of (0.5) was applied to produce a binary classification output.

Results

The model performance in terms of F1-score was 0.932 for the training data, 0.926 for the validation data and 0.936 for the test data obtained from the entirely independent plots. The F1-score for most individual plots was at least 0.9 (n = 29), 3 plots with F1-scores lower than 0.9 were observed. The lower accuracy of two of these plots resulted from misinterpretations of the reference data and in one case from false-positive predictions in very dark and large cast shadows. No significant difference in F1-scores was detected between predictions obtained for the DJI Phantom 4 Pro and the DJI Mavic 2 Pro ($t = 1.5283$, $df = 24.84$, p-value = 0.1391, Figure 2).

Discussion

The application of CNN machine learning models proved suitable for the classification and quantification of *P. afra* cover in the heterogenous RGB aerial imagery, generated from commercially available ‘out of the box’ UAV models (Figure 3). The method presented here proved to be transferable across different UAV models, sites and illumination conditions with no apparent loss of performance (Figure 2).

Where multiple UAV flights are required for data collection, it is common practice to limit flights to the same time of day and on clear days so as to minimize the potential effects of solar angle and radiance on model performance (Abdulridha et al., 2019; Adak et al., 2021; Eskandari et al., 2020; Guo et al., 2020; Lopatin et al., 2019). This was not the case here, UAV data acquisition was not restricted to specific illumination conditions, no image corrections or cross-calibrations were conducted, and the model was trained using images sourced under a range of conditions and using different models of UAV’s. Despite this, model performance was comparable to other studies (see studies reviewed in Kattenborn et al., 2021), highlighting the robust nature of the CNN model applied, which should, therefore, be easily transferable for the quantification of *P. afra* cover in restoration sites across the Albany Thicket biome in South Africa.

The ease of use and transferability of aerial image classification models presents new opportunities for defining and tracking restoration targets across a range of spatial and temporal scales. Loewensteiner et al. (2021) demonstrate the importance of temporal scale in defining restoration targets, applying CNN models to the classification of woody cover in a Savanna ecosystem over a 66 year time period. Woody cover was found to be variable over time, thus, restoration targets for the system should fall within a spectrum of woody cover and are not required to reflect the current state of the reference ecosystem. A similar approach could be applied to describe restoration targets and planting densities in thicket restoration, as the current practice aims to generate a dense closed canopy with individual *P. afra* reintroduced at high densities (1-2 m spacing). Additionally, it may be possible to detect return of ecosystem functioning using aerial imagery. This may include measures of structural complexity, indicative of biodiversity returns (Camarretta et al., 2020), or regeneration dynamics (e.g. measures of target species cover as presented here for *P. afra*) and seedling recruitment (Buters et al., 2019; Fromm et al., 2019).

The application of the model presented here will allow thicket restoration initiatives to rapidly collect data from a range of different UAV models for temporal monitoring of restoration trajectories, informing adaptive management practices (Camarretta et al., 2020). This currently presents a major challenge in thicket restoration as field-based monitoring often takes place in distant rural areas, where *P. afra* has coalesced to form a fairly impenetrable barrier of vegetation, and requires expert training in ecological monitoring techniques. Repeat aerial imagery can be generated, by almost anyone with a little training, for restoration sites with no increase in sampling effort over time. The data generated can potentially be sent to a centralised repository for analysis, bridging the science-practice gap (Dickens and Suding, 2013) and promoting further collaboration within the Albany Subtropical Thicket restoration community (Mills et al., 2015). This will provide managers with estimates of plant density (using blob detection, which separates individuals in the CNN classification: Kattenborn et al., 2021); accurate estimates of plant survival in the first year of implementation (comparing plant density changes between flights); and estimates of plant cover changes overtime to ensure interventions can be made if plant cover is lost due to disturbance (e.g. frost: Duker et al. 2015, or herbivory: van der Vyver et al. 2021). In such cases, actions can be informed by the scienftific community and implemented by managers and landowners to remediate the processes threatening the restoration initiative.

Aerial imagery-based monitoring is well suited to collecting data at spatial scales relevant to ecosystem restoration. The spatial extent to which a UAV can collect data is confined by the battery life (flight time), whereas the classification of these images using CNN models has the potential to classify vegetation dynamics at large spatial scales (Flood et al., 2019; Timilsina et al., 2020). Cloud computing provides a possible means of overcoming the computational load of processing large data (see Kattenborn et al. 2021 for a summary of available servers for CNN data analysis), making the classification of large spatial areas feasible for a greater number of practitioners. This may prove invaluable for the upscaling of thicket restoration in South Africa, with an estimated 1.2 million ha of degraded ecosystems having some restoration potential (Lloyd et al., 2002).

While we have presented the first CNN model relevant to the restoration of the Albany Subtropical Thicket biome, and that could be applied to monitoring restoration at scale, we do not harness the full capabilities of machine learning in this study. Here, we used the well-known

Unet algorithm (Ronneberger et al., 2015), while CNN-based segmentation algorithms are steadily advancing (Minaee et al., 2021). Likewise, UAV and sensor technology continue to advance, improved image resolution and spectral range of drone imagery are likely to come at lower prices, making detection of finer scaled patterns possible without having to decrease flight altitudes. Additionally, the three-dimensional mapping of vegetation cover using LiDAR technologies provides opportunities to estimate plant biomass without labour intensive fieldwork (Shendryk et al., 2020; ten Harkel et al., 2019). This may aid in estimating carbon sequestration in restoration sites to assist in carbon credit verification and issuing for the global carbon market. Harris et al. (2021) present an example of this, reporting a significant correlation between above-ground carbon estimates calculated from remote sensed *P.afra* canopies and field measures. Increased image resolution can provide novel insights into *P. afra* recruitment dynamics, and further developing the CNN model to classify multiple species (as per Fricker et al., 2019 and Kattenborn et al., 2019) can provide insights into biodiversity return with relatively low sampling effort (a laborious task to complete using manual field measures, last undertaken by van der Vyver et al., 2013). Thus, it is evident that the work present here should inspire future application of UAV imagery to the ecology and management of Albany Subtropical Thicket vegetation.

Conclusions

Recent advancements in machine learning and remote sensing technologies have provided unprecedented access to, and automated processing of earth imagery. This can potentially transform monitoring of ecosystem restoration practices, shifting protocols from time and resource exhaustive field measures to remote sensing approaches. Here we demonstrated the utility of standard 'out of the box' UAV data coupled with CNN models to classify and quantify *P. afra* cover in thicket restoration plots. The models were transferable across different plot properties, illumination conditions, and UAV models. The integration of this model in the monitoring of thicket restoration will aid in the planned upscaling of Albany Subtropical Thicket restoration and generate valuable temporal data for evaluating restoration trajectories and demographic processes. This will promote collaborative efforts between scientists and practitioners, strengthening the restoration community. Importantly, the integration of this monitoring approach does not require any technical knowledge of the CNN model, or special skill sets to fly commercially available UAVs, and can thus reduce the sampling effort required for monitoring restoration at scale.

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Figure 1

Photographs of three experimental restoration plots.

(A-C) Experimental restoration plots in context. Note the open woodland (degraded thicket) surrounding the plots in relation to the dense woodland (intact thicket) in the background. (D-F) Arial images of the above restoration plots used for *P. afra* canopy cover classification.

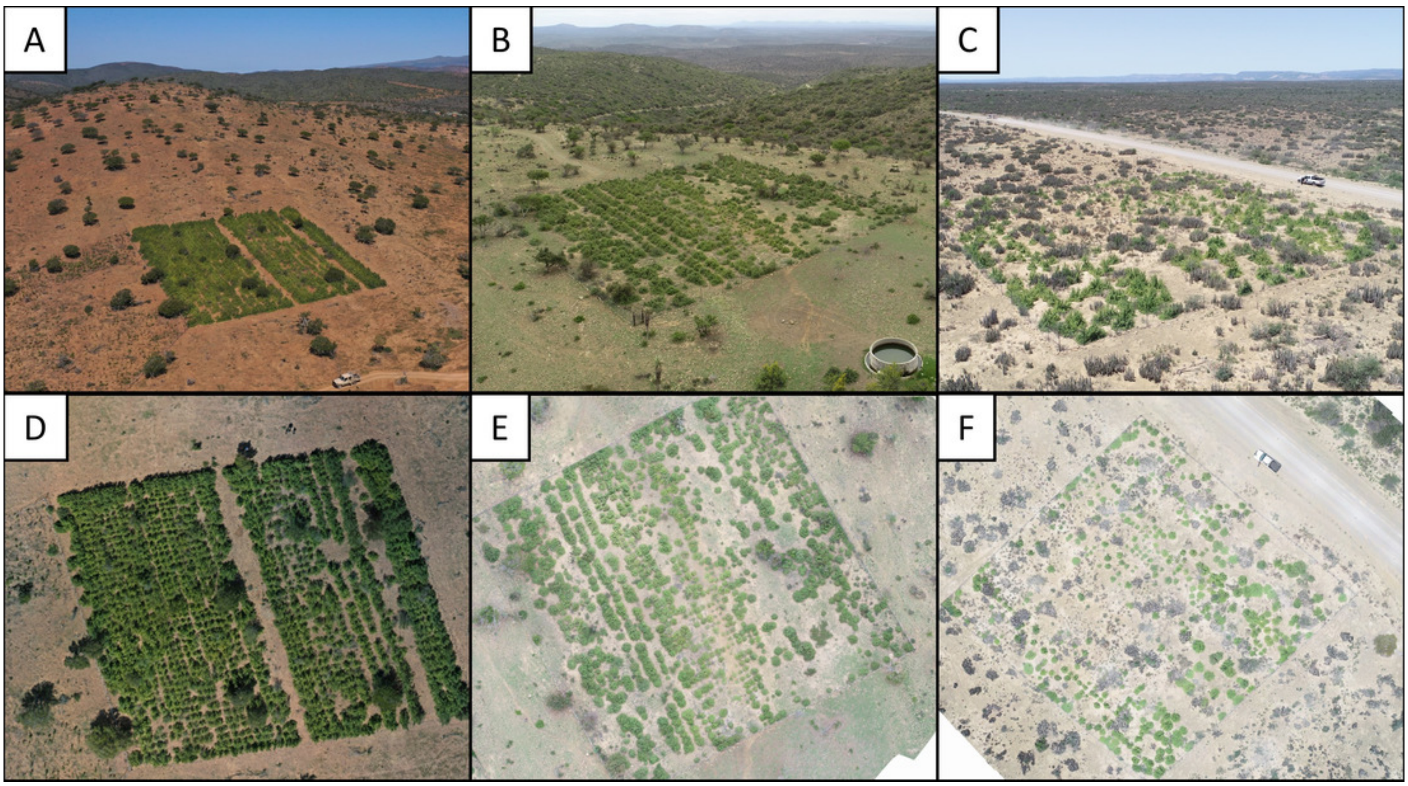

Figure 2

Model performance estimates using F1-scores, (train) Training data, (val) the validation data and (test) data of entirely independent plots.

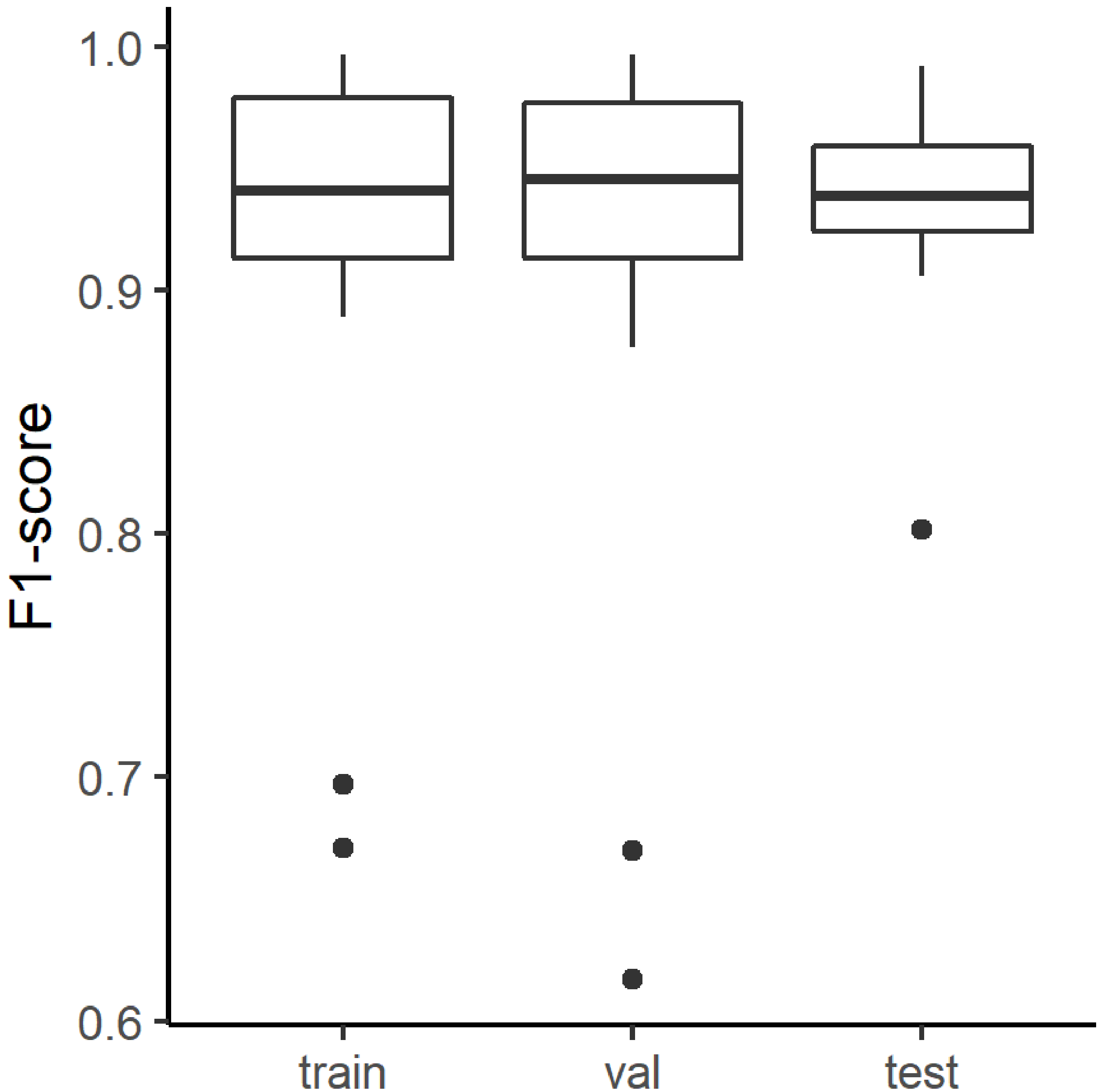

Figure 3

Prediction results of the final CNN model on the orthoimagery.

Top: The orthoimagery overlaid by the reference polygons (white). Bottom: Orthoimagery overlaid with reference polygons (white) and segmentation results (purple). EPSG: 32735.