Applying replicable open-source workflows to identify invasive flora: *Spathodea campanulata* in a small-scale forest plot in Korotari, Fiji.

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Abstract

Deforestation in the Pacific is increasingly driven by land clearing due to agriculture and developments and natural disasters such as tropical cyclones. These disturbances have accelerated the spread of invasive species, particularly across exposed and degraded landscapes, where they outcompete native vegetation. One of the most pervasive species, *Spathodea campanulata* (African tulip), along with other invasive flora , has emerged as a significant environmental stressor across many Pacific Island Countries and Territories (PICTs). Monitoring their spread remains a major challenge due to the scale and rate of invasion (Pacific Community, 2025). This study explores the use of free and open-source software (FOSS) workflows combining QField, QGIS, Digital Earth Pacific Earth observation workflows and machine learning outlined in Metherall et al., (forthcoming). Within this paper, these workflows are applied towards the practical application of mapping and monitoring the distribution of invasive tree species. As a case study, the research focuses on mapping *Spathodea campanulata* in Korotari, Vanua Levu, Fiji. Field data were collected through QField GPS-based surveys to identify confirmed locations of invasive species, which were then analysed using time-series satellite data in Digital Earth Pacific. Phenological signatures determined through seasonal patterns in vegetation were incorporated and used to train models to detect and track invasive species over time (Sultana et al., 2025). The results demonstrate promising potential for monitoring of invasive flora. These methods provide a valuable foundation for understanding spatial trends in invasion from as early as 2017, supporting more targeted ecosystem management and informing policy responses to land degradation and biodiversity loss in PICTs (Ekka et al., 2023)

1. INTRODUCTION

1.1. Invasive Species in Pacific Island Countries and Territories (PICTs)

Within PICTs, there are challenges in monitoring the distribution and thus managing and mitigating the expanding invasive flora such as *Spathodea campanulata and Cordia Alliodora*. Earth observation dataset and models have emerged as a potential option to support the ongoing monitoring of vegetation and the distribution of invasive flora. Yet within PICTs there is often limited access to datasets, tools, software and computational processing capacity to enable monitoring workflows. This paper draws on the free and open source software (FOSS) methods outlined in Metherall et al., (Metherall, forthcoming) providing a case study of how these approaches have been applied to ongoing monitoring of invasive tree species with a specific focus on *Spathodea campanulata* (figure 1a).

1.2. Spathodea campanulata (African tulip tree)

Spathodea campanulata is commonly known as the African tulip tree. The plant is widely distributed in Nigeria and other West African countries (Adeneye, 2014). Spathodea campanulata is a medium dimension tree which commonly ranges in height between 10-35 m (Orwa et al., 2009). It is deciduous, with a round, heavy crown of dense, dark foliage, smooth pale grey to brown bark which scales and cracks with age (Adeneye, 2014). One of the main characteristic features of *S. campanulata* are the large red, orange flower buds which are curved and contain a red sap (Adeneye, 2014). S. campanulata grows rapidly colonising within secondary forests, in high forest zones and in deciduous, transition, and savannah forests (Adeneye, 2014). *S. campanulata* usually blooms and fruits during the dry season and with the help of pollination from bees and

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birds, it is able to release large seed crops which are small, light, and winged seeds that dispersed through wind (Rangaiah et al., 2004). In Fiji, S. campanulata has become a dominant invasive tree in the wet zone and slowly spreading to the dry zones of Viti Levu and Vanua Levu. *S. campanulata* is most prevalent in warmer climates including in Fiji. The ability for *S. campanulata* to propagate rapidly is also influenced by the Southeasterly trade winds that are common throughout Fiji (Pacific Soils Portal, n.d.).

African Tulip Tree

Figure 1a (O'briens Tree care and Landscaping, 2023), 1b) Figure 2: (TanzaniaPlantCollaboration, 2013), Figure 1c) (UrbanTropicals, n.d.)

1.3 The need to map and monitor invasive forest species

The Large Ocean States (LOS) of the Pacific face dual existential threats. From the ocean, storm surges and sea level rise threatens communities' access to land. From the land, the rapid rate of expanding sprawls of invasive flora and fauna also encroach upon the remaining land available for Pacific Island communities (Adeneye, 2014). Indeed, invasive plant species pose a risk to ecosystems across the Pacific. With rapid changes in land use and land cover (LULC) often involving the clearing of native forest and other vegetation, the land becomes especially vulnerable to encroaching invasive plant species (Epie & Hull, 2025). These invasive florae are highly competitive leading to rapid expansion over landscapes faster than other vegetation.. These species often opportunistically take over disturbed lands where there has been a history of crops, grazing and other forms of disturbance (Terrain, 2025).

In 2024, SPC's Geoscience, Energy and Maritime Division (GEM) and the Land Resources Division (LRD) Sustainable Forest Management Section collaborated with national forestry stakeholders in Fiji and Tonga, along with industry partners such as Fiji Pine Ltd, Fiji Hardwood Coorporation, and Fiji Sugar Corporation, to map the extent of invasive forest species. Using Sentinel-2 satellite imagery, field-verified training data, and a Random Forest machine-learning classifier, the project produced spatial maps showing the distribution of invasive trees across selected Pacific islands. This initiative represents a major step forward in providing accurate, science-based data on invasive species in regions where forest degradation has historically been poorly quantified.

Invasive species are capable of causing extinctions of native plants and animals, reducing biodiversity, competing with native organisms for limited resources, and altering habitats (National Oceanic and Atmospheric Administration, 2024). Invasive plants already have many negative impacts on forest and landscape health, including, loss of biodiversity, habitat destruction, soil degradation, reduced ground water levels, genetic changes, and changes to ecosystems processes. Expansion of invasive species also has economic impacts like the loss of grazing and farmlands, reduction in land value and loss of forest and landscape productivity.

Increases in land clearing and natural disasters including tropical cyclones have been some of the core drivers of deforestation and forest degradation in the Pacific (Cook and Goyens, 2008; Ibanez et al., 2019; Metherall et al., 2026). Tropical cyclones have also led to dramatic changes in landscape ecology within agricultural lands (Shamsuzzoha et al., 2021). Invasive species have rapidly expanded throughout many of these disturbed lands: colonizing these bare soils and outcompeting native species (Kinhal, 2025). It has been challenging to map and monitor the extents of these invasive species as well as the rates of change over time. This particular project focuses on *Spathodea campanulata* or African tulip as well as Cordia alliodora to provide the first proof of concept. If found to be effective, the workflows may be expanded to cover other invasive tree species that have become environmental stressors throughout many Pacific Island Countries and Territories (PICTs) particularly within locations that are highly exposed to human and climatic drivers of land degradation. Addressing this, may have significant implications for both environmental and economic outcomes in these countries.

Through this study, earth observations workflows are applied to map and monitor invasive species focusing on the example of *Spathodea campanulata* and *Cordia Alliodora*. This study sheds light on the methods to monitor these ecological and landscape processes This process requires field data collection to calibrate machine learning models for the mapping and monitoring of these invasive species. In the Pacific, there is often limited resourcing and access to the software, tools and data required to enable this monitoring capability. As a result, this paper highlights free and open-source software options to support access to datasets, tools, software and computational processing capacity to enable monitoring workflows. This paper draws on the free and open source software (FOSS) methods outlined in Metherall et al., (2026) and provides a case study of how this has been applied to monitoring invasive flora.

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2. CONCEPTS AND SIMILAR WORK

2.1. Monitoring of invasive species using satellite data

The recent advancements made in remote sensing and the application of machine-learning methods have significantly increased the capability of detecting and monitoring the presence of invasive species like the African tulip (*Spathodea campanulata*) through the use of their spectral and phenological attributes (Dixon et al., 2021). The flowering events can be detected with quite an accuracy when the analysis is done on the temporal changes of the greenness and flowering indices that have been obtained from either high-resolution drone imagery or PlanetScope CubeSat time series, thus making it possible to predict the flowering proportions on a pixel level within diverse forest landscapes with high accuracy (Dixon et al., 2021). The framework based on their modeling displays that spectral signals connected with bud emergence, maximum flowering, and senescence (biological aging and decay) give strong support to the mapping of those species with conspicuous florals. This approach has also been applied to the case of invasive flowering trees (Dixon et al., 2021). Alongside this, phenological method, Ramoncito and Jawani demonstrate that the combination of the multispectral Sentinel-2 imagery and the use of machine-learning algorithms includingSupport Vector Machines (SVMs) has led to the successful classification and mapping of *S. campanulata* distributions, with the key spectral bands (blue, green, red, red-edge, NIR) proving to be very effective in differentiating the species from the nearby plants due to its unique canopy reflectance characteristics (Ramoncito & Jawani, 2024). The study results openly indicate invasion patterns together with the dense infestation areas. Such studies highlight the usefulness of supervised classification for the purpose of monitoring and management. To sum up, the research done by these authors shows some examples of how researchers might combine phenology-based spectral detection with multispectral classification models to detect invasive species to track their movement and expansion. This was seen in the case of *S. campanulata* over different landscapes. This study seeks to build on the existing literature, learning and adapting to the local context and invasive species found in a forest study area within Korotari, Fiji.

3. METHODOLOGY

3.1. Study area

Korotari is located in Macuatu Province of Vanua Levu, the second largest island of Fiji located in the South Pacific. Korotari is located within a mosaic landscape composed of forested landscapes, agricultural plains, and waterways. It is situated close to the township of *Labasa* in the Northwest rainshadow sugarcane belt interior of Vanua Levu. This study site was selected as part of an ongoing collaboration with the Ministry of Forestry. Adjacent to the Korotari forest invasive monitoring plot established by the MoF, is a Forestry Station which has established hardwood plantations within adjacent leased areas. *Cordia alliodora* was one of the species planted but has since been displaced by the higher-priority and demand for *Swietenia* spp. (Mahogany) which has performed exceptionally well in Fiji (Pine Timber Products, n.d.). *C. alliodora* has since spread outside of the leased areas and is now threatening nearby low-lying croplands. Although the region is important for its ecological value and supports native plant and animal species, invasive plants like *Cordia alliodora* and *Spathodea campanulata* are having an increasing negative impact: posing ecological threats to the biological diversity of the region of Korotari. Because they outcompete native plants and change habitats, these invasives pose a threat to natural ecosystems. Preserving Korotari's natural heritage and ecological resilience requires proactive management that includes reforestation, sustainable agriculture, and community involvement. Within this study the field plot is made up of 27 hectares and is located at Korotari Forest area just beside Korotari village as shown on *Figure 2*.

Figure 2. Map of Korotari near Labasa Town within Vanua Levu, Fiji.

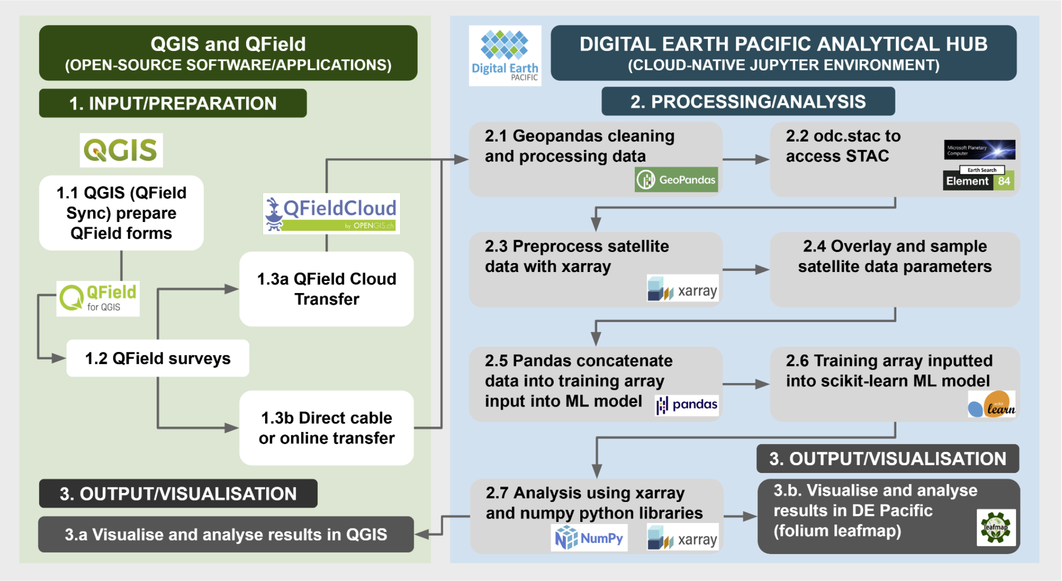
3.2. Free and open-source software, tools, datasets and workflows

The overarching software and tools used in this study for the GIS data collection are outlined at a high level in Metherall et al., (2026). This can be summarised as workflows within QGIS and QField as well as within the Digital Earth Pacific Analytical Hub Jupyter Environment (figure 2). These steps are outlined as follows:

Table 1. General free and open-source software machine learning workflows used in Digital Earth Pacific (Metherall et al., 2026):

1. QGIS to prepare QField forms
2. QField to collect field data
3. Geopandas / pandas to process / clean / training data
4. odc.stac library to load satellite imagery datasets from spatio-temporal asset catalogues

5. Mask and preprocess satellite imagery using xarray python package
6. Overlay training data over satellite imagery into sample satellite data parameters at the locations of each training data point.
7. Pandas concatenate the data into a training data array input into machine learning
8. Data inputted into scikit-learn Random Forest Classifier machine learning library for Python.
9. Export COG predictions
10. Analyses of results using xarray and numpy python libraries
11. Visualise results in a folium leafmap python package or export into QGIS for further visualisation and analyses.



Free and Open-Source Software (FOSS) workflows within QGIS, QField and Digital Earth Pacific (Metherall et al., 2026). These workflows can be replicated via GitHub: https://github.com/nicholasmetherall/digitalearthpacific-tonga-lulc and broader Digital Earth Pacific earth observations products can be accessed via: https://github.com/digitalearthpacific.

In terms of the steps to calibrate the classification approach of the machine learning models to detect invasive flora. This was primarily achieved through the field survey stages.

3.3 Survey methods:

There were eight main steps within the methods used in this study:

1. Field surveys to collect GPS data points at locations of invasive species
2. Data cleaning and validation
3. Ingesting data into Digital Earth Pacific (DE Pacific)
4. Calibration of satellite data querying inputs including timeframes of flowering / other phenological processes
5. Running machine learning model predictions of classification
6. Participatory accuracy assessments through consultation and collaboration with local forestry and botany experts.
7. Revisiting field sites to ground truth results while collecting more field data points
8. Revision of model based on findings

These 8 steps are undertaken in cyclical sequence over time to improve upon results through each iteration.

Overview of field surveys in Korotari:

A. Data collection and survey was done on the 18th September, 2024 which lasted about three hours between 10am-1pm.
B. There were about 5 surveyors which included representatives from the Ministry of Forestry and Fiji Hardwood Corporation.
C. At Korotari Forest Area, just outside of Labasa town area near the Labasa Water catchment
D. Surveyors included Jalesi Mateboto (GIZ), Adi Loraini Baleilomaloma (SPC), Elenoa Biukoto (SPC), Viliame Tupua (MoF), and Sevanaia (Fiji Hardwood Corporation)
E. Elevation Estimate
Min: 35.07 m | Median: 123.59 m | Max: 189.6 m
F. Slope estimate
Min: 0.2° | Median: 14.3° | Max: 17.3°

G. Since the team were working with QField, equipment was limited to Mobile phones with Positioning settings activated.

Field surveys to collect GPS data points

Invasive species were mapped using QField: an open-source mobile application that is compatible with QGIS software. QField is used by filling in a form that also collects GPS data in the field and can be customized for data collection depending on the objectives of the study. QField has been widely documented as a useful tool for field data collection across various disciplines including archaeology (Pažout, 2023), agriculture (Dzulfansyah et al., 2024), ecology (Oh et al., 2024), geology (Stephan-Perrey et al., 2025), emergency response (Fedosov et al., 2025). In this paper, we document how QField can be used in forestry, ecology and invasive species surveys while also examining its interoperability with other FOSS workflows to allow for replicability as documented in Metherall et al., (2026). The field data collection forms were designed to collect data on the following parameters: 1) date, 2) species, 3) landcover type, 4) GPS location. Data was collected either by line of sight or by locked location. This means the surveyor had to either locate the trees they viewed from the field on the map or stand directly under them and record the location while the accuracy and precision of their GPS was within a certain range (usually aiming for less than 5m). In other cases, the sites were labelled by locking the location to the mobile device (TDC 650) with 3-m to sub-metre accuracy depending on satellite availability and canopy cover over the location of the surveyor. It was also important to record points for non-invasive species and other vegetation types to have training datasets to teach machine learning how to distinguish between invasive and other species. This stage of data collection was conducted in collaboration with the Ministry of Forestry in Fiji and Tonga.

3.4 Data cleaning and validation

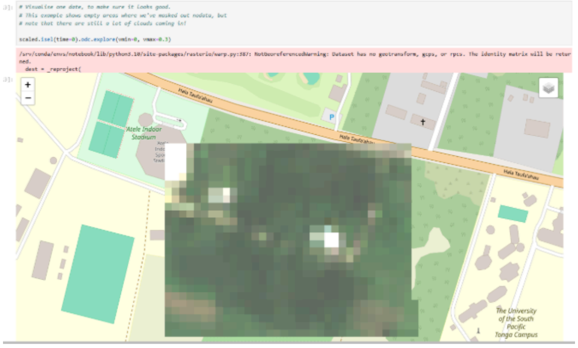
Once all the field datasets were collected, they were then collated within a geodatabase, cleaned and validated. Subsequently, data was overlaid on top of a Sentinel 2 satellite composite image with 10-m pixel resolution for the year 2024.

3.5 Ingesting data into Digital Earth Pacific (DE Pacific)

The training data points were then ingested into Digital Earth Pacific platform. The points (vector data) then sampled the values of the sentinel imagery (raster) data for each of the following sentinel 2 bands and indices: red, green, blue, near infrared, normalised difference vegetation index, short wave infrared, enhanced vegetation index, change in vegetation index, chlorophyll index, near red band and a range of other band ratios and spectral indices.

3.6 Random Forest Classification

Using the DE Pacific Random Forest Invasive classifier script, the odc-stac library and various processing tools were exported into the DE Pacific Jupyter interface to lead the classification. Establishing the STAC catalog and then sampling satellite parameter data at the latitude and longitude of each training data point within the perimeter of the area of interest (Metherall et al., 2026).



```
# Visualise one date, to make sure it looks good.
# This example shows empty areas where we've masked out nodata, but
# note that there are still a lot of clouds coming in!

scaled.isel(time=0).odc.explore(vmin=0, vmax=0.3)
```

```
/srv/conda/envs/notebook/lib/python3.10/site-packages/rasterio/warp.py:387: NotGeoreferencedWarning: Dataset has no geotransform, gcps, or rpcs. The identity matrix will be retur
ned.
  dest = _reproject(
```

Figure 4. Cloud free imagery of AOI after cloud masking using the sentinel 2 satellite imagery with 10x10m pixel resolution - this masking was done in the year 2024.

The Python library odc-stac is a vital metadata translation layer between the SpatioTemporal Asset Catalog (STAC) specification and the Open Data Cube (ODC) framework (Killough, 2018). This connection establishes a two-step procedure:

- Discovery via STAC: Initially, users take advantage of the STAC API to quickly discover and describe the geospatial data they are interested in (for example specific cloud-optimized GeoTIFFs or COGs), by standard parameters such as location (bounding box), time range, and product type (STAC, n.d.).
- Analysis using ODC: The next step, once the assets are identified, is for odc-stac to take the STAC metadata and turn it into the structured ODC data model that is denoted as an xarray.Dataset (Tayer, 2024). The formed structure allows ODC to manage the expensive task of performing high-speed analysis that is scalable through providing the features like lazy-loading and parallel computation using technologies such as Dask (Digital Earth Africa, 2021).

The collaboration between these different programming approaches leads to the creation of a seamless and speedy data handling workflow for the huge Earth observation data archives.

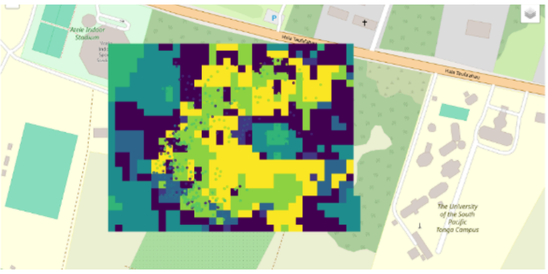


Figure 5. Examples of preliminary classification of AOI with training data overlaid onto prediction in the year 2024 with Sentinel 2 10x10 pixel resolution - Pale green (settlement), pale dark blue (Artocarpus Lacucha Monkey Jack), yellow (cropland), dark blue (grassland), and blue (African Tulip).

An illustration of the example classification result produced for the Area of Interest is shown along with the training data points that were used during model development. The map demonstrates a distinct separation of the predominant land-cover types, whereas it also indicates regions where the model might need additional refinement because of mixed or uncertain predictions. This visual inspection assists in the model performance evaluation which is to be conducted later on and directs to the areas where the training data balancing and spatial coverage improvements are needed.

4. RESULTS

4.1. Results visualised

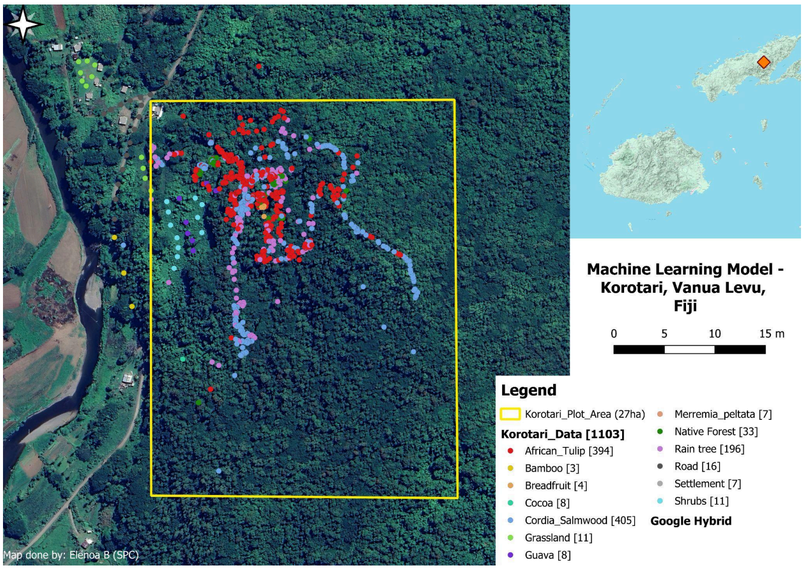


Figure 6: Field data collection conducted at Korotari, Labasa with five manpower collecting 1103 points of different tree and landcover species focusing on African Tulips and Cordia Salmwood collected in September, 2024. (Biukoto et al., 2026 forthcoming).

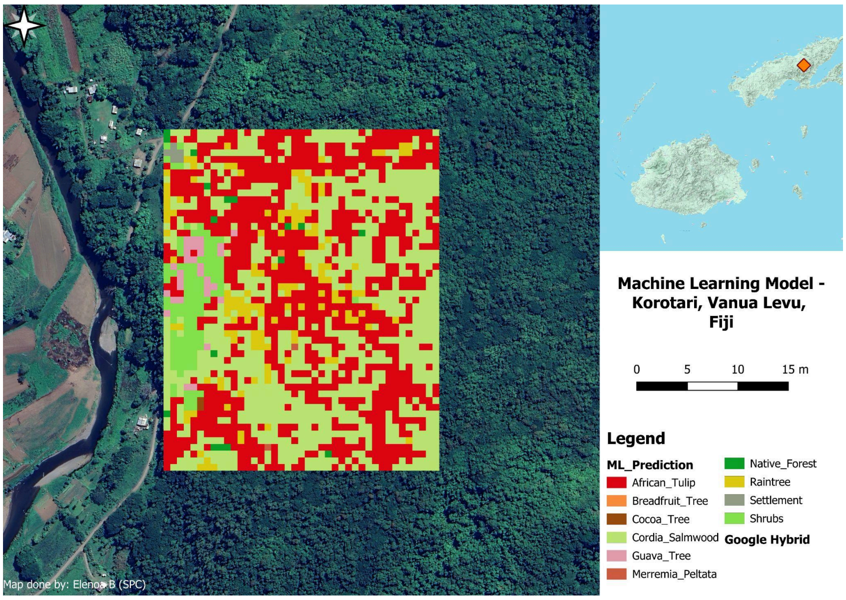


Figure 7. Results of prediction of species distribution for Korotari, Vanua Levu, Fiji with the date range between May-November 2024 using the Sentinel 2 10x10 resolution imagery. Note, *S. campanulata*

4.2 Results of field data collection:

- 1103 points were collected by 5 surveyors.
- 13 classes were assigned to these points in Korotari Forest.
- After data cleaning - data was collated as shown below:

Table 2. Shows the classes that were collected from the Korotari Forest plot area.

Classes	Number of Points
1) African_Tulip	394
2) Bamboo	3
3) Breadfruit_Tree	4
4) Cocoa_Tree	8
5) Cordia_Salmwood	405
6) Grassland	11
7) Guava_Tree	8
8) Merremia_Peltata	7
9) Native_Forest	33
10) Raintree	196
11) Road	16
12) Settlement	7
13) Shrubs	11

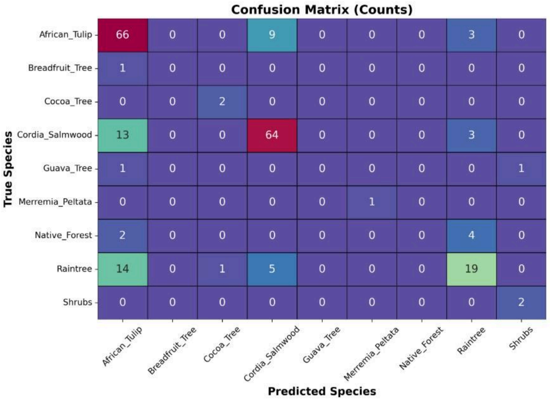
4.3 Digital Earth Pacific Korotari Forest Classification prediction results

10 classes were predicted within the plot area as shown in *Table 3* below. The results of figure 7 highlighted the prevalence of *S. campanulata* close to the roads and man-made land covers highlighting the correlation between anthropogenic land degradation and the spread of this species.

Table 3. Shows the classes that were predicted within the area of interest.

Class	count	Area(HA)	%
African_Tulip	895	8.95	42.80
Breadfruit_Tree	1	0.01	0.05
Cocoa_Tree	2	0.02	0.10
Cordia_Salmwood	883	8.83	42.23
Guava_Tree	31	0.31	1.48
Merremia_Peltata	2	0.02	0.10
Native_Forest	17	0.17	0.81
Raintree	143	1.43	6.84
Settlement	6	0.06	0.29
Shrubs	111	1.11	5.31

4.4 Accuracy assessment

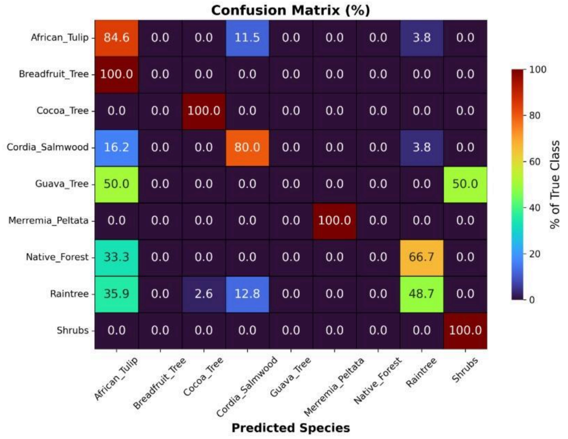


	African_Tulip	Breadfruit_Tree	Cocoa_Tree	Cordia_Salmwood	Guava_Tree	Merremia_Peltata	Native_Forest	Raintree	Shrubs
African_Tulip	66	0	0	9	0	0	0	3	0
Breadfruit_Tree	1	0	0	0	0	0	0	0	0
Cocoa_Tree	0	0	2	0	0	0	0	0	0
Cordia_Salmwood	13	0	0	64	0	0	0	3	0
Guava_Tree	1	0	0	0	0	0	0	0	1
Merremia_Peltata	0	0	0	0	0	1	0	0	0
Native_Forest	2	0	0	0	0	0	0	4	0
Raintree	14	0	1	5	0	0	0	19	0
Shrubs	0	0	0	0	0	0	0	0	2

Figure 8. Pixel count confusion matrix

Figure 8 presents the raw prediction counts from the Random Forest classifier based on an 80/20 train-test split. Diagonal cells contain correctly classified samples, while aligned cells where the classes match show the count of true positives. Whereas unaligned or mismatched rows and column cells show the count of misclassifications among different classes. The model demonstrates 66 true positives for S. campanulata and 64 for cordia demonstrating a relatively effective predictive capability for the major classes (e.g., Class African_Tulip and Class Cordia_Salmwood).

The model predicts these classes closely together so that Class African_Tulip, Class Cordia_Salmwood, and Class Raintree are often mixed up. This indicates that these classes may have similar features and can hence be mistaken for one another. The classes that are less frequent, namely Breadfruit_Tree, Guava_Tree, Merremia_Peltata, Native_Forest, and Shrubs.Some of these features have only a very small number of samples in the test set which leads to less accurate classifications. This underscores the effect of class imbalance on model performance, wherein the minority classes are not well learned and hence more likely to be confused with other classes.



	African_Tulip	Breadfruit_Tree	Cocoa_Tree	Cordia_Salmwood	Guava_Tree	Merremia_Peltata	Native_Forest	Raintree	Shrubs
African_Tulip	84.6	0.0	0.0	11.5	0.0	0.0	0.0	3.8	0.0
Breadfruit_Tree	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Cocoa_Tree	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0
Cordia_Salmwood	16.2	0.0	0.0	80.0	0.0	0.0	0.0	3.8	0.0
Guava_Tree	50.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	50.0
Merremia_Peltata	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0
Native_Forest	33.3	0.0	0.0	0.0	0.0	0.0	0.0	66.7	0.0
Raintree	35.9	0.0	2.6	12.8	0.0	0.0	0.0	48.7	0.0
Shrubs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0

Figure 9. Show the percentage matrix of the Korotari random forest invasive classification

Figure 9 shows the confusion matrix which is normalized and presented as a percentage of the true number of samples per class. This visualization makes it easier to compare classifiers without taking class size into account. The main classes still have high classification accuracy, with Class African_Tulip getting around 85% and Class Cordia_Salmwood getting 80% correct predictions. On the other hand, minority classes (like Class Breadfruit_Tree, Guava_Tree, and Native_Forest) show either 0% recall or very low percentage performance, and this means that the classifier cannot reliably identify these categories. Besides, the high variability across classes in prediction rates points to the limited learning of minority classes due to lack of training data, while, at the same time, it shows that the model is effective where proper sample representation is available.

Classification Report (Species-Level, Color-coded Table)

Species	precision	recall	f1-score	support
African_Tulip	0.68	0.82	0.74	78.00
Breadfruit_Tree	0.00	0.00	0.00	1.00
Cocoa_Tree	0.67	1.00	0.80	2.00
Cordia_Salmwood	0.82	0.80	0.81	80.00
Guava_Tree	0.00	0.00	0.00	2.00
Merremia_Peltata	1.00	1.00	1.00	1.00
Native_Forest	0.00	0.00	0.00	6.00
Raintree	0.61	0.49	0.54	39.00
Shrubs	0.67	1.00	0.80	2.00

Figure 10. Classification report of the species distribution.

Figure 10 displays the color-coded classification report which indicates precision, recall, F1-score and the number of samples (support) for each of the classes. The major classes (African_Tulip and Cordia_Salmwood) perform very well wherein high precision, recall, and F1-score are achieved as they are the most represented classes in the dataset. On the other hand, quite a few minority classes (Breadfruit_Tree, Guava_Tree, Merremia_Peltata, Native_Forest, Shrubs) exhibit low or non-existing values thus, the classifier is unable to correctly identify categories with very few samples. In general, the table suggests that the model is dependable for the classes that are well sampled but it will fail to spot the rare partially in response to the class imbalance issue.

5. DISCUSSION

This area of Korotari is particularly close to the *Cordia alliodora* Plantation for Fiji Hardwood where it was planted around the same time as the Nadala Cordia Plantation area. The establishment of this plantation has correlated with a significant increase in Cordia species infiltrating the natural forest areas and the permanent sample plots around the Labasa water catchment area established by the Ministry of Forestry. This area has since been closely monitored by the forestry officers enabling the research team to verify these changes. Through the ML processing, the classification for Korotari in 2025 managed to detect approximately 40% coverage of African Tulip and 43% coverage of Cordia Salmwood which covers most of the natural forest areas. This expansion of invasive species decreases the habitat areas of native species and their overall chances to thrive.

Combining forestry, ecology and machine learning disciplines -into FOSS workflows can support Pacific Island Countries with mapping, local building capacity-building, and practical management interventions of invasive species. Pacific island countries need to act rapidly to reduce ecological and economic impacts, strengthen climate resilience, and protect livelihoods dependent on healthy forests and agricultural landscapes. The FOSS workflows shared in this paper may be part of a longer-term solution.

The next phase should focus on operationalizing these workflows, fostering multi-stakeholder collaboration, and ensuring sustainable, long-term invasive species control across the region. The mapping results can inform spatial prioritisation for spraying herbicides, managed forest clearing and other methods to stopping the spread of invasive species

6. CONCLUSIONS

The study provides a case study precedent of how the FOSS workflows using QField and Digital Earth Pacific documented in Metherall et al., (forthcoming 2026) may be applied to the detection of invasive flora: S. *campanulata*. The results indicated 42.80% percentage of S. *campanulata* was for the plot of 27 ha. The validation process indicates a precision score of 0.701, F1 score of 0.709, recall of 0.730 and overall accuracy of 0.73.

While the study is limited to a small-scale plot case study of Korotari, it highlights the potential for wider monitoring across landscape scales. However, as discussed, further research will be needed to demonstrate the feasibility of monitoring capabilities across wider spatial and temporal scales. Alongside the potential to monitor across broader ranges of time and space, there may also be further potential to monitor other species including other invasive flora as well as broader species including vegetation that provides valuable ecosystem services including timber, biodiversity and CO_2 stocks. To address these broader areas of potential, ongoing research and development is being undertaken with SPC, Digital Earth Pacific and various Ministries of Forestry and Forest Divisions across Pacific Island Countries and Territories (PICTs) and Large Ocean States.

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