TECHNICAL NOTES v1.4

MAPPING

MONARO TABLELAND COOL TEMPERATE GRASSY WOODLAND v1.4

WERRIWA TABLEANDS COOL TEMPERATE GRASSY WOODLAND v1.4

INTRODUCTION

The Monaro and Werriwa Tablelands Cool Temperate Grassy Woodlands (respectively Monaro and Werriwa) have been nominated by the NSW Scientific Advisory Committee as Critically Endangered Ecological Communities (NSW Threatened Species Scientific Committee (2019)

The Office of Environment and Heritage has produced map products for both Monaro and Werriwa to coincide with the final determinations by the end of June 2019.

Mapping was undertaken during the period March 2019 to June 2019.

APPROACH

The approach was to model the likely distribution of both communities based on identified sites and environmental variables. Following this work, the footprint comprising the highest likelihood of occurrence was used as a target for systematic aerial photographic interpretation in a 3D environment to identify the Werriwa and Monaro communities.

Following mapping of the woody areas of the Monaro and Werriwa communities, the woody polygons were extended by a 100m buffer out across any contiguous candidate native grassland terminating at the NSW cadastre Lot boundary.

PRESENCE-ABSENCE COMMUNITY MODELLING

A presence-absence (PA) distribution modelling approach was used to create an indicative (potential) distribution map of each TEC.

The modelling methodology is described in detail in OEH (2016). In brief, we used Random Forest (RF) and Boosted Regression Tree modelling (BRT) techniques to predict the potential extent of the communities in terms of their probability of occurrence across the South Eastern Highlands and South East Corner Bioregions.

The TECs were modelled separately and as single combined entity to test whether the two communities occupy a similar ecological niche across a range of environmental gradients. The NSW Threatened Species Scientific Committee (2018) notes that Monaro is replaced by Werriwa in areas with similar or slightly higher rainfall, but where average summer temperature maxima are approximately 2°C warmer. While little intergradation exists between Monaro and Werriwa due to the limited overlap in their respective temperature and rainfall envelopes, they still occupy the same

frost-hollow niche at a local scale. This effectively meant we were able to predict the combined potential extent of the two TECs in a single model.

To predict the distribution of the TECs, we needed to characterise the environmental conditions that are suitable for each to exist. The inclusion of presence and absence site data in the models allowed us to constrain the potential distribution of the TECs to a set of favourable environmental conditions which are not occupied by other existing vegetation communities. The models performed exceptionally well, with almost no overlap (>99%) between the predicted probability of occurrence values between presence and absence sites.

Collation and presence-absence assignment of vegetation plot data

The RF and BRT models used the same presence-absence (PA) data set comprised of 10,635 sites. Each of site was represented by full floristic vegetation plot that forms part of the OEH Vegetation Information System (VIS) database. All of the sites had been assigned a Plant Community Type (PCT) as part of the new East Coast Vegetation Classification (ECVC). In our case, Monaro is represented by the RCP group R4.42E (Monaro -Central-Tablelands frost hollow grassy woodland), which is historically linked to SCIVI Vegetation Types m31/p220 and UMC types m31/u118). Conversely, the Werriwa is represented by the RCP group R4.141 (Werriwa frost-hollow grassy woodland) which is linked to the SCIVI Vegetation Type p24. As part of the development of the ECVC, the floristic data of individual sites were checked and vetted, and sites strongly influenced by disturbance removed.

In addition to plots allocated by the East Coast Classification, an additional set of sites that are assumed to represent the TECs were also added. These sites came from surveys conducted by OEH threatened species ecologists and other experts that were not included in the ECVC. They include most, but not all sites identified by the Scientific Committee as representative of the TEC (Mark Tozer, Pers Comm). A total of 84 sites were included in the models as presence sites for Monaro and 59 for Werriwa (Fig 1). While these sets contain an adequate spread of sites over the presumed range of the TECs, the models are strongly influenced by the number of absence sites ascribed to PCTs that are not related to R4.42E and R4.141.

Environmental predictors used in the models

An initial set of 31 environmental predictors was identified through the information provided in the Determination and discussions with Mark Tozer and Rob Armstrong. Broad groups of environmental predictors were identified as moisture availability, drainage, soil waterlogging, valley floors, slope, relief, varied substrate, temperature, elevation, topographic exposure, soil texture, frost and wind. Various predictors and combinations of predictors (and correlations) were tested to determine the optimum set and best model performance. Climatic variables can be described in a number of ways e.g. mean annual, maximum, minimum, seasonality, warmest period, coldest period etc. Similarly, with topographic variables, soil properties etc.

BRT and RF are data driven models, whose purpose is to give the best possible predicted extent for the data available, and the complexity of spatial pattern. Variable selection is therefore a crucial step in the modelling process, and decisions around what predictors to include in a model should be ecologically based.

A final set of 13 predictors were selected as inputs to the BRT and RF models (Table 1). Both RF and BRT are robust to multicollinearity as far as predictions are concerned, but this can cause problems when it comes to interpretation. To avoid this uncertainty around model fit, we tested for multicollinearity between the site values across the predictors using the “multicollinear” function in

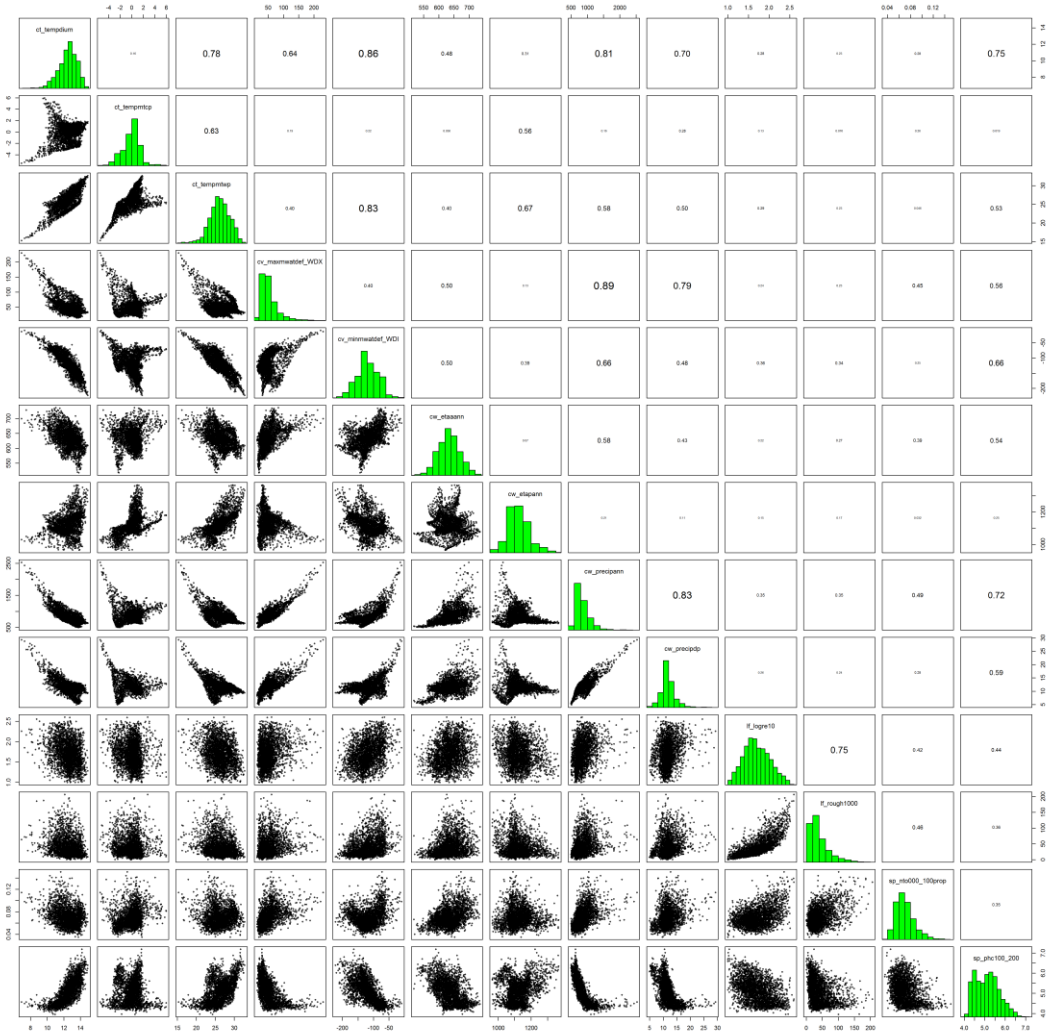
the rfUtilities library using a significance value of 0.001. To check whether the collinear variables were in fact redundant, we performed a "leave one out" test which identifies whether any variables are forcing other variables to appear multicollinear. Before running the models, we looked at pairwise correlations between variables and found that none were correlated by more than 0.9 (Fig 1).

All predictor surfaces are rasterised at 30x30m grid resolution, have a common extent and projection. These raster layers were stacked in R using the Raster Package. The values for each predictor at each site in the allocation file were extracted using a customised script in R, and the resulting csv file loaded into R.

Table 1. Environmental predictors used in the RF and BRT models.

Name	Description	Units
ct_tempdiurn	Mean Diurnal Range (Mean(period max-min)) (bio2)	^{o}C
ct_tempmtcp	Min Temperature of Coldest Period (bio6)	^{o}C
ct_tempmtwp	Max Temperature of Warmest Period (bio5)	^{o}C
cv_maxmwatdef_WDX	Maximum monthly atmospheric water deficit (precipitation - potential evaporation)	mm
cv_minmwatdef_WDI	Minimum monthly atmospheric water deficit (precipitation - potential evaporation)	mm
cw_etaaann	Average areal actual evapotranspiration - Annual	mm
cw_etapann	Average areal potential evapotranspiration - Annual	mm
cw_precipann	Annual Precipitation (bio12)	mm
cw_precipdp	Precipitation of Driest Period (bio14)	mm
lf_logre10	Cold air drainage	index
lf_rough1000	Neighbourhood topographical roughness based on the standard deviation of elevation in a circular 1000 m neighbourhood. Derived from DEM-S	index
sp_nto000_100prop	Total nitrogen proportionally combined depths from 0 to 100 cm	%
sp_phc100_200	pH (calcium chloride) (100 - 200cm)	pHCa

Figure 1: Correlations between the thirteen predictors used in the RF and BRT models.



Modelling approach

Boosted Regression Trees (BRT) and Random Forests (RF) are commonly used to predict the distributions of plant communities and individual fauna and flora species when presence-absence data are available. We implemented RF and BRT in R using the Random Forest and Dismo packages respectively.

All models were run with 10-fold cross validation, using held-out data to calculate performance measures which are used to select optimum model parameters and final model fit. Statistics were derived from a confusion matrix, calculating overall accuracy, user and producer accuracies and standard deviations.

We evaluate the response curves for each predictor to determine if the effect of the variable on the response makes ecological sense reran multiple iterations of models to look at the effects of sequentially removing predictors in an attempt to generate a more parsimonious model.

Six models where prepared and predicted back into geographic space (3 BRT and 3 RF) covering a Monaro only model, Werriwa only and Combined model. The models show a continuous probability of occurrence surface which varies between 0 and 1.

The spatial outputs of the BRT and RF models were reviewed by Allen Mcilwee and Rob Armstrong the and RF models were selected as the most preferred. Below we present the performance statistics, ecological interpretations and predictions of the three RF models.

Model Performance

To evaluate model performance, we plotted the predicted probability of occurrence (PO) values for all plots allocated to each TEC (in descending order) against the same number of highest ranked absence plots (Fig 2). We defined a good model as having high PoC values across the majority of TEC presence sites, dropping sharply at the end for those plots that occupy marginal environmental space (these are likely to be misclassified false positives).

In the case of the Monaro-only model we found no overlap in PoC values for the lowest ranked presence sites and the highest ranked absence sites. This meant there was no need to present a confusion matrix describing the percentage of sites correctly classified. For the Combined and Werriwa-only model, the marginal overlap between lowest ranked presence sites and the highest ranked absence sites was most likely due to the misclassification of a small number of presence sites.

Figure 2: Pattern of decline in predicted probability of occurrence at presence sites (ranked from highest to lowest value) and the corresponding number of highest ranked absence plots.

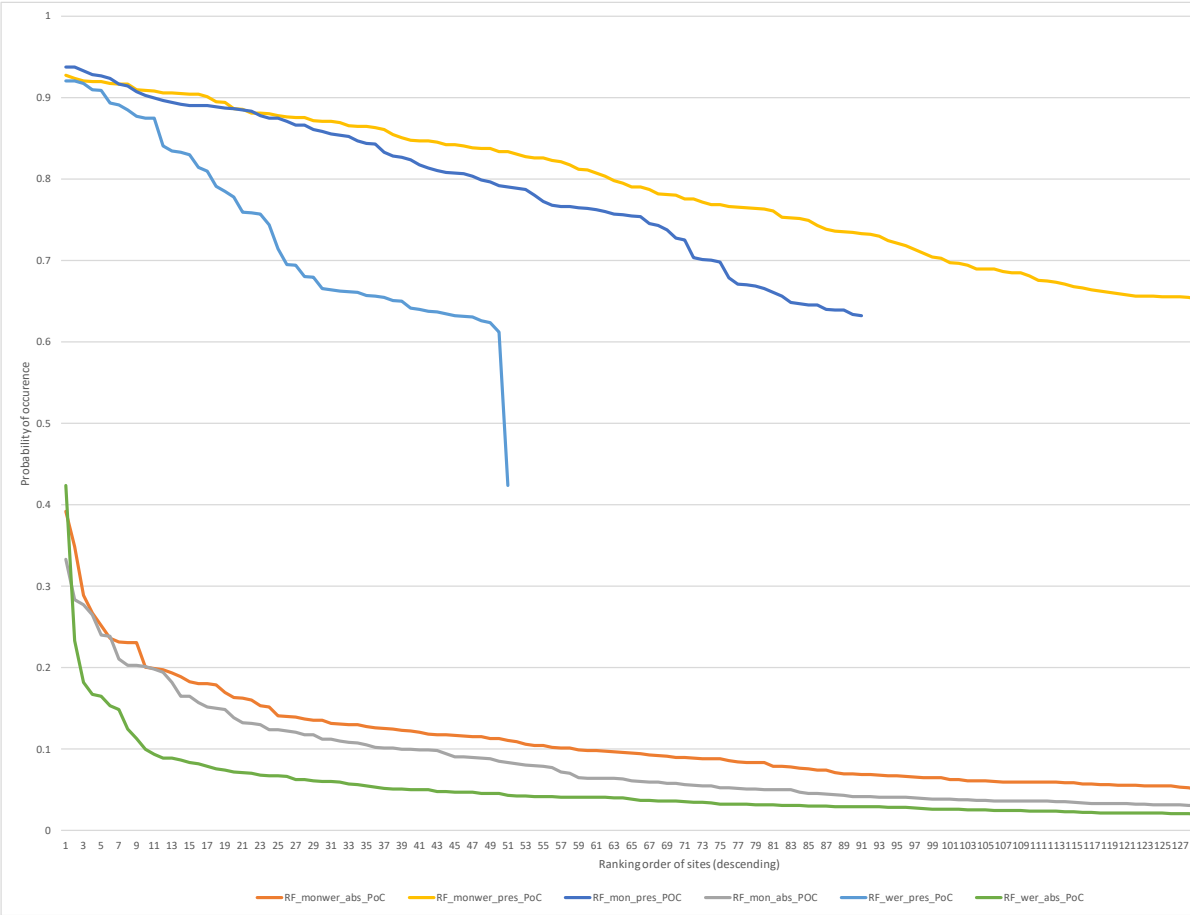


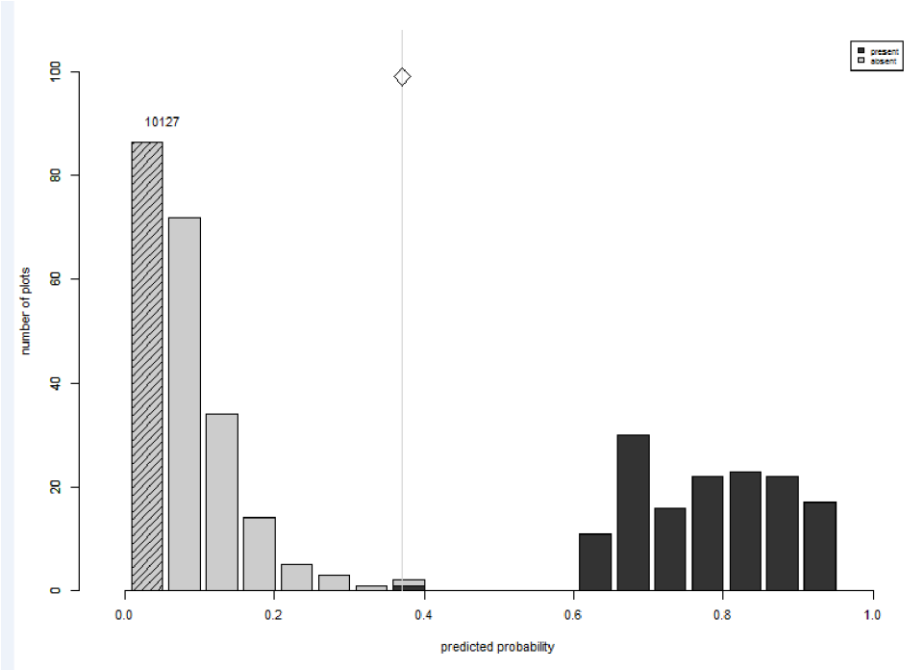
Figure three shows another away to represent the data above, this time through frequency histogram plots of PoC values across presence and absence sites. Almost all absence sites have PoC values below 0.4, with 10,127 sites in the Combined model, 10225 sites in the Monaro-only model and 10,307 sites in the Werriwa-only model containing PoC values below 0.05. Clearly one could expect from this that there is virtually no chance of misclassification (false absences) at this very low threshold, hence we can expect a threshold that represents maximum potential extent to occur above this threshold. The histograms show a clear separation between sites identified as the TEC (almost all have PoC values above 0.6) and sites that have been classified as other vegetation communities by the East Coast Vegetation Classification Team.

The lines on each of the histogram plots represent the sensitivity = specificity threshold, which balances the risk of making commission and omission errors. This is the threshold we have used to define what we have called “core” potential habitat – that was subject of further investigation by API. The sensitivity = specificity threshold is 0.4 for the Combined model, 0.48 for the Monaro-only model and 0.33 for the Werriwa only model.

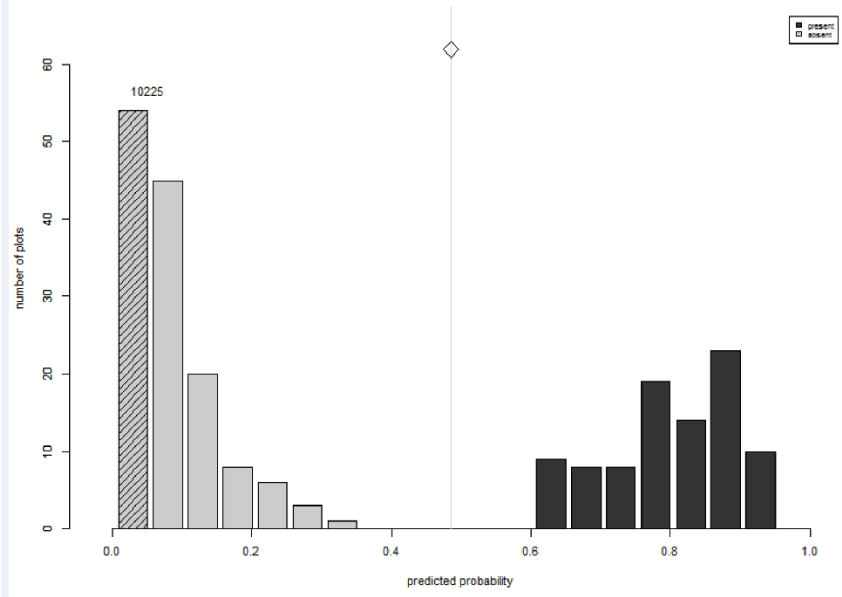
At the lowest end of the scale we manually selected a threshold of 0.75 to represent the area over which we believe covers the full extent over which the TEC made occur (on the basis of the currently known set of presence sites). This threshold was chosen by overlaying the models on high resolution SPOT and ADS40 images, and a DEM hillshade, and manually tweaking the threshold up and down until it best covered areas identified as frost hollows.

Figure 3: Accuracy statistics for the a) final Monaro-Werriwa combined model, b) Monaro only model and c) Werriwa only model.

a)



b)



c)

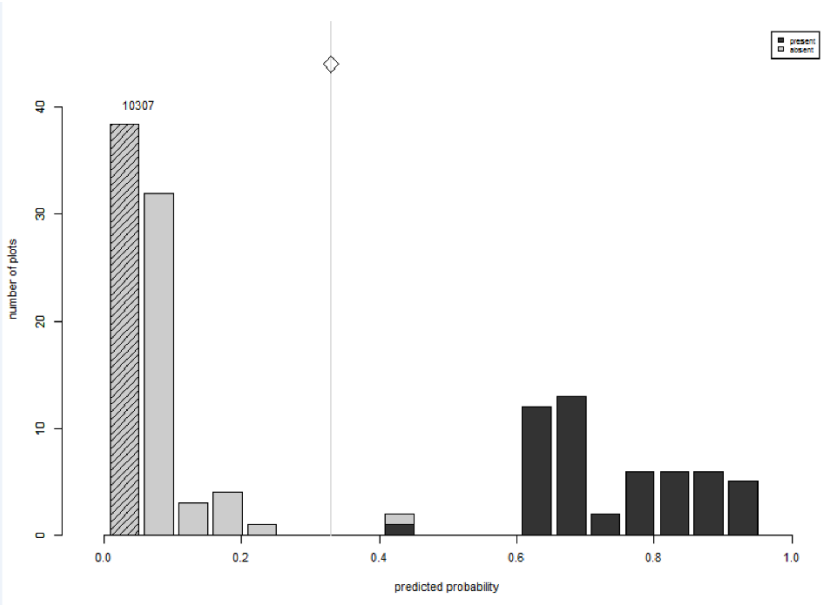
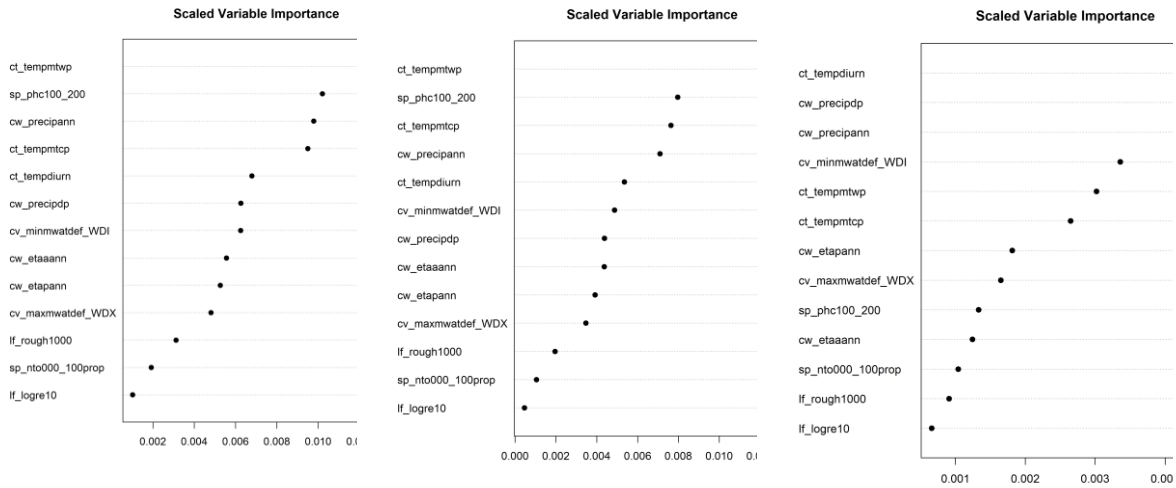


Figure four shows the scaled variable importance values for predictors included in the three models. The shape of the response curves is generally very similar across the combined and Monaro-only models. The shape of the local scale factors (soil pH and nitrogen, roughness and cold air drainage) are similar across the three models, while the Werriwa only model occupies a slightly warmer and drier (lower driest period rainfall) position along regional-scale environmental gradients relative to the Monaro-only model. Soil pH had a strong influence on the Combined and Monaro-only model suggesting this TEC may favour more fertile soils – but this predictor was of lower relative importance in the Werriwa only model.

Figure 4: Scale variable importance of predictors used to model the occurrence of the a) final Monaro-Werriwa combined model, b) Monaro-only model and c) Werriwa-only model.

a) b) c)



Figures 6, 7 and 8 show the spatial predictions of the Monaro-only, Werriwa only and Combined models. They show a very high level of overlap between the individual and combined models, hence the reason why the Combined model was selected over the individual to represent the distribution of the two TECs. The other main reason for selecting the combined was because we felt the ecological response curves made more sense when looking at the two TECs combined, even though their distributions do not appear to intergrade (as indicated by the individual TEC models). This the combined model better captures what is going on across multiple environmental gradients – some of which operate at a regional scale, while others are important at a local scale in a relative context.

Figure 6: Predicted potential extent of the Monaro with "core areas" above a threshold of 0.4 highlighted.

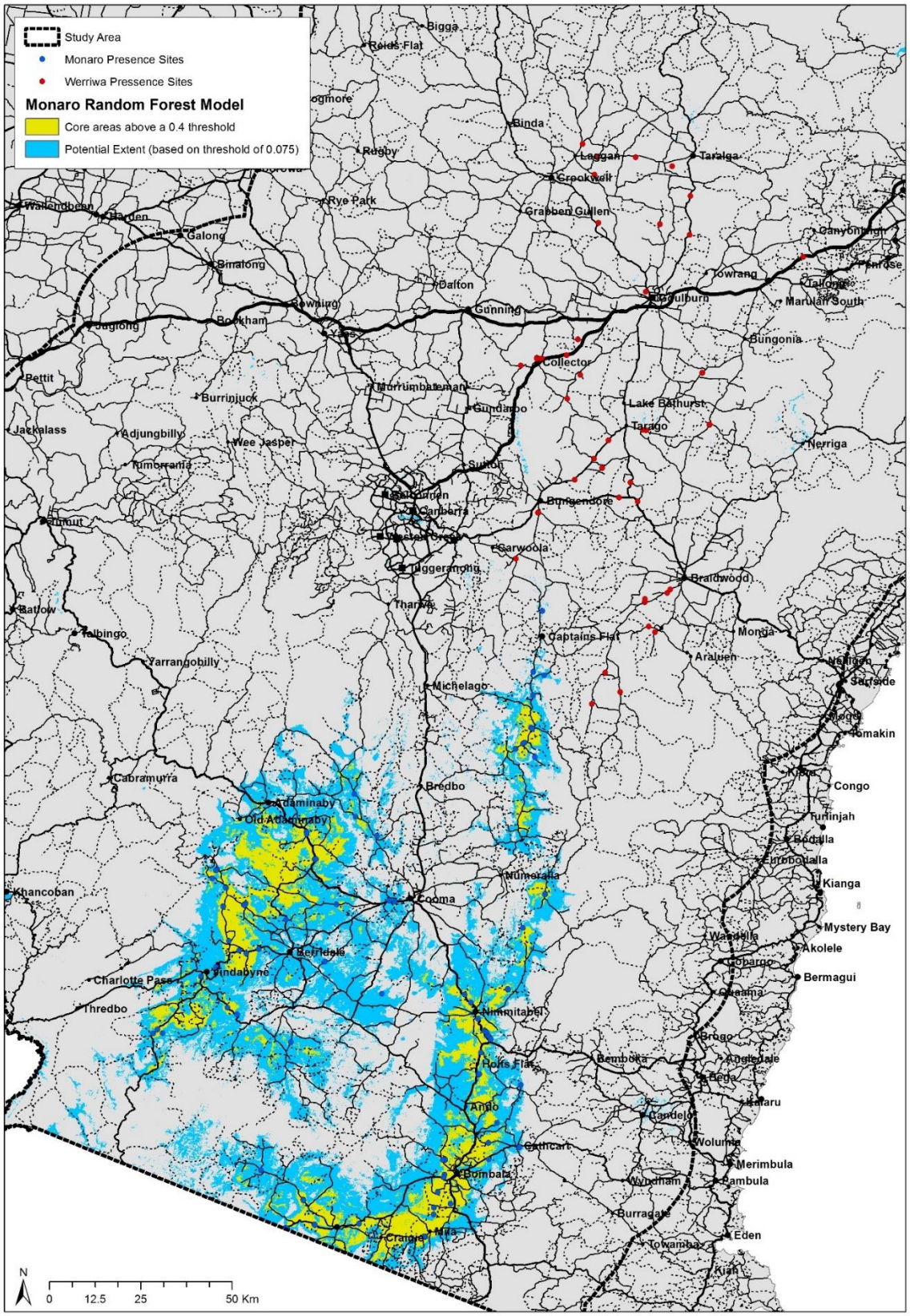


Figure 7: Predicted potential extent of the Werriwa with "core areas" above a threshold of 0.4 highlighted.

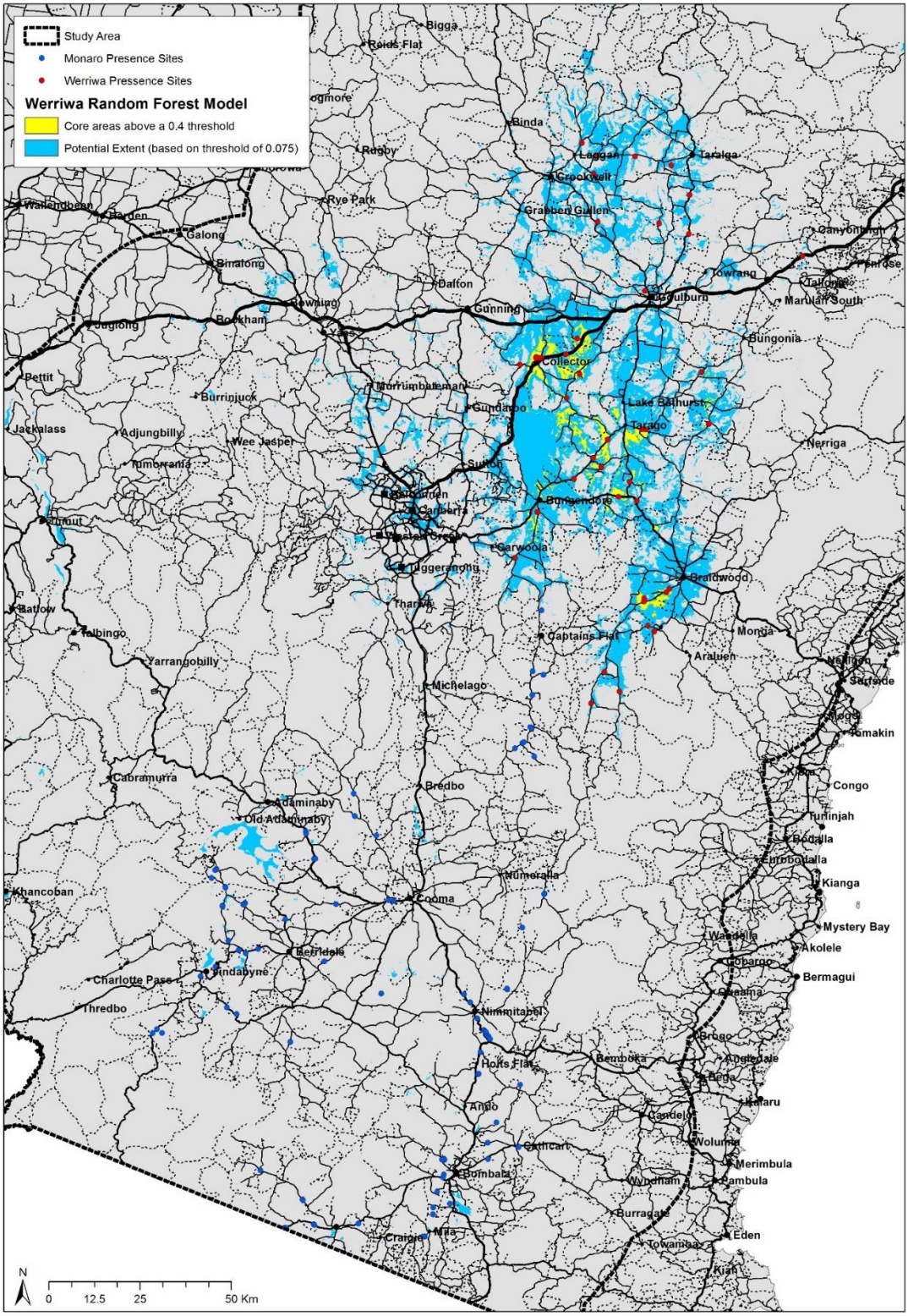
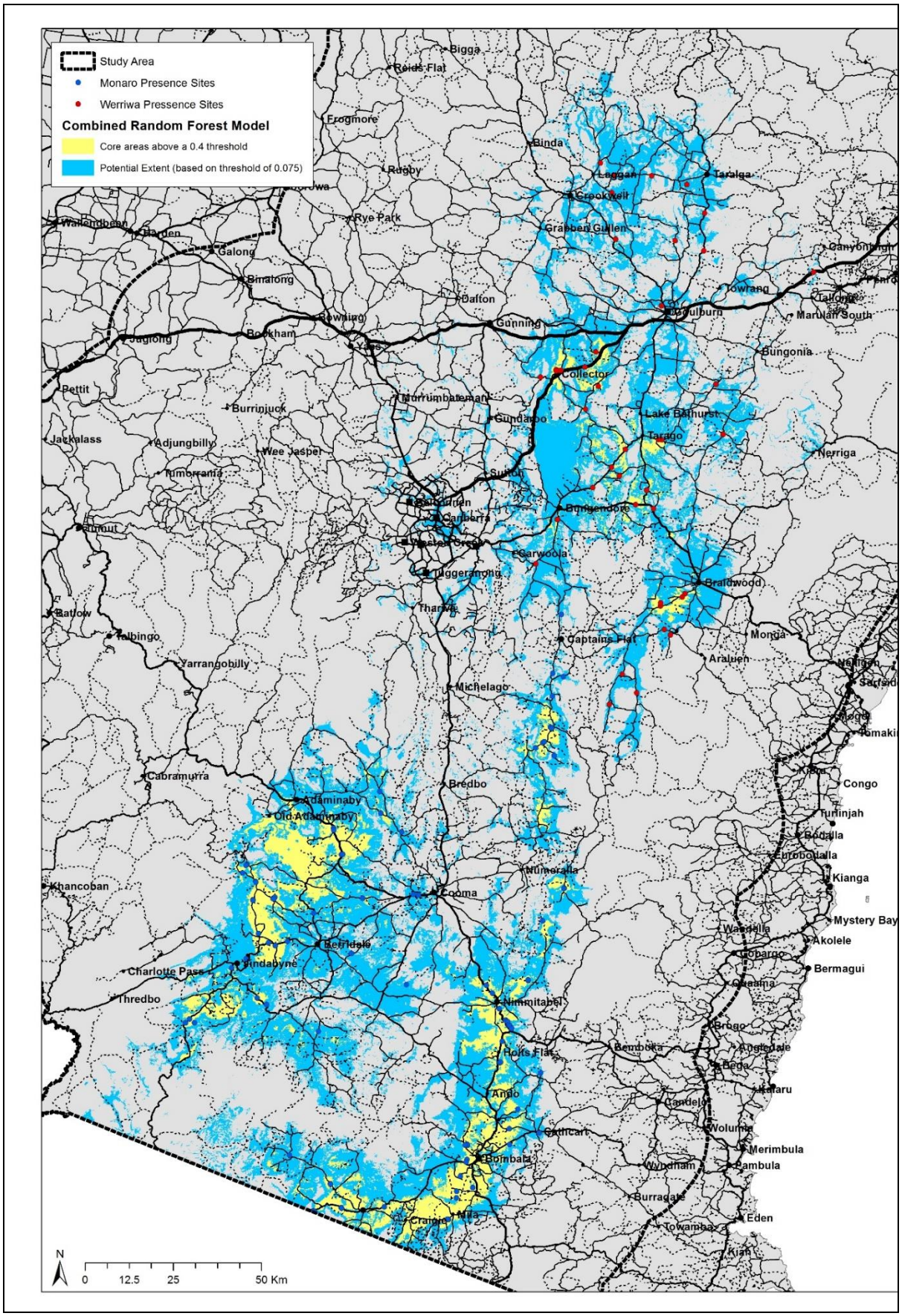


Figure 8: Predicted potential extent of the combined distributions of Monaro and Werriwa with "core areas" above a threshold of 0.4 highlighted.



FINE SCALE MAPPING

The approach to fine scale mapping was expert aerial photographic interpretation (API) using ADS40/80 imagery in a 3D viewer. API was undertaken in an ARCGis geodatabase environment.

Fine scale mapping was in the main applied to the high probability areas indicated by presence-absence modelling whist some locally adjacent areas where the community was found to occur where included.

Spatial Layers

API was supported by an array of environmental and data layers comprising:

- Google Street view: observing tree species and understorey (shrubby/grassy) conditions
- TEC_Edit_Surface_190326; contained polygons within the gross project area. This comprised segmentation created for regional scale mapping was used for the identification of homogenous image patches.
- rf_mon_p11_7150.tif; a raster representing probability of Monaro occurrence
- ADS40 photogrammetric data to enable viewing of imagery as 3D stereo models
- Field-measured botanical observation plots (PCT attribtion)
- A range of environmental and topographic data

The OEH Seasonal disturbance cover image (SDCI) was used to define candidate native grasslands. The SDCI was completed by OEH in 2017 and is used in the NSW state vegetation type map to classify areas of candidate native grassland. The SCDI combines information from images spanning seasons from summer 1988 to autumn 2013 and eliminates cropping and modified areas identified by the NSW Landuse Layer. Candidate areas are unioned with property boundaries.

API Attribution

As a rule the targeted community comprises at least 10% of the community in any polygon.

Polygons were classified into the following classes:

0 – not CEEC

1 – likely CEEC

2 – treeless areas that are likely to have been CEEC and have not been subject to significant alteration of ground-cover such as cropping and ploughing.

3 – treeless areas which have not been classified as 0 or 2.

Initially the intention was to classify all treeless areas as either 0 or 2, however this was demonstrated to be a time-consuming process and one that has relatively low accuracy due to inherent difficulty in attempting to determine small herbaceous species using API.

<u>Monaro</u>

The Edit Surface contained approximately 28 000 000 polygons, the majority of which had very low probability of Monaro occurrence. A subset of polygons with probability of Monaro occurrence

greater than or equal to 0.4 were selected for editing. These polygons are subsequently referred to as Monaro_p04.

For Monaro: API of woody vegetation occurring in the "blue zone" which occupies more than 10% of any (segmentation) polygon and is likely to comprise the dominant E.pauciflora and codominants E.stellulata, E.viminalis, E.Rubida or Acacia melanoxylon.

Polygon attribution utilised two software packages:

- ArcGIS Dektop 10.7
- DAT/EM Summit Evolution – Lite Edition, a photogrammetric package enabling 3D stereo viewing of ADS40 imagery

Monaro_p04 polygons were displayed in ArcGIS and 3D ADS40 imagery was displayed in Summit. ADS40 imagery is provided on a 1:100 000 map-sheet basis, which provided a framework for workflow. Several methods were used to gain familiarity with the topographic distribution and 3D appearance of Monaro as described in the Preliminary Determination (ref) including:

- Locating botanical plots within the map-sheet
- Viewing plot locations in 3D at high resolution (eg 1:500)
- Adjusting image colour display to highlight differences between eucalypt species.
- Use of Google Street View:
    - Some plot locations were close to roadsides and were visible in Google Maps Street View.
    - It became apparent that it is sometimes possible to identify some Eucalypt species from roadside pictures within Street View, and other times it is possible to exclude Eucalypt species, eg, if an area is dominated by rough-barked species it is not Snow Gum.

After familiarisation, Monaro_p04 polygons where grouped into working subsets and assigned a temporary code, to enable quick selection using "select by attributes" in ArcGIS. Within the working subset the code of the largest proportion of polygons was determined. For example it was common that the area to be classified was dominated by cleared grazing country, for which the code would be 3. Manual classification task then focussed on highlighting polygons which were not code 3. This was undertaken in several passes over the subset area. The first pass may focus on selecting and labelling polygons which were definitely not Monaro (Class 0). The second pass could then focus on selecting and labelling polygons likely to be Monaro (Class 1). The remaining polygons could then be selected using the temporary code, and labelled 3.

Once this general procedure had been implemented it became apparent that some of the ancillary information contained within the attribute table of the Edit Surface polygons could increase efficiency of classification. Specifically, coasteds1 and LU2017 could be used to identify polygons likely to be labelled 0. Similarly, the woody attribute was used to sort polygons into likely woody/non-woody and hence category 3 or not. These automated classifications are not accurate enough for the final product and did require manual review – they did however improve efficiency.

In summary the following method was utilised for assigning a class to polygons:

- Select a logical working subset of polygons
- Assign a temporary code
- Determine most common class (e.g. 3)
- Use existing data for provisional class

- Manually assign class to the least common classes (e.g. 0, 1)
- Assign class to the remainder of the working subset (3 in this example)

<u>Werriwa</u>

For Werriwa: API of woody vegetation occurring in the "blue zone" which occupies more than 10% of any (segmentation) polygon and is likely to comprise the dominant E.pauciflora and codominants E. rubida.

The procedure used for the Werriwa area was identical to that used in the Monaro, except:

- Edit Surface polygons with probability of Werrriwa occurrence greater than or equal to 0.4 where selected using the model rf_wer_p8_7150
- A second version of modelling was provided, identified as rf_monwer_p13
- Polygons with probability of Werriwa occurrence greater than or equal to 0.4 where selected using the model rf_monwer_p13
- These polygons were added to the rf_wer_p8_7150 polygons
- Two fields were added to the attribute table to identify the two model versions.
    - InV1Model: rf_wer_p8_7150 (p 0.4) polygon = 1
    - InV2Model: rf_monwer_p13 (p 0.4) polygon = 1
    - Many polygons are in both models

Within the Monaro there a relatively few eucalypt species, which made recognition of Snow Gum dominated patches comparatively quick and reliable. Within the Werriwa area, there are more eucalypts species including gums of similar growth form to Snow Gum, and hence Werriwa is more difficult, less efficient and probably less accurate.

Monaro and Werriwa Candidate Grasslands

For both communities, the SCDI candidate grasslands layers occurring in the 'blue zone' was used as the candidate grasslands surface. Where time permitted that surface was checked by API and classified as a likely or unlikely grassland.

- **Candidate Grasslands- Checked**

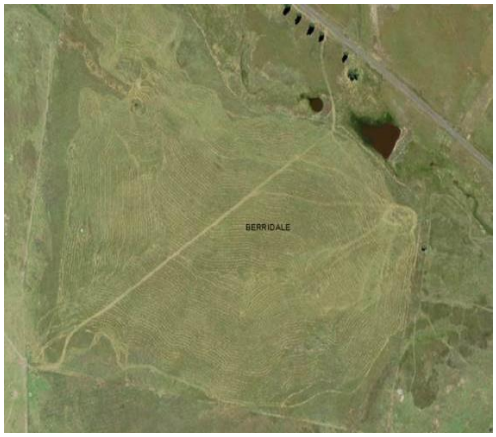
Areas checked by API and comprising likely candidate grasslands (absence of ploughing, absence of pasture improvements, absence of infrastructure -see following example images) were coded as '2'

Areas checked by API and not comprising likely candidate grasslands were coded '0'

- **Candidate Grasslands- Unchecked.**

Areas of SCDI candidate grasslands where there was insufficient time to undertake API checking were coded as '2'.

Examples of candidate areas coded as '0' due to high disturbance indicated in the imagery


BERRIDALE

Spatial Kit:

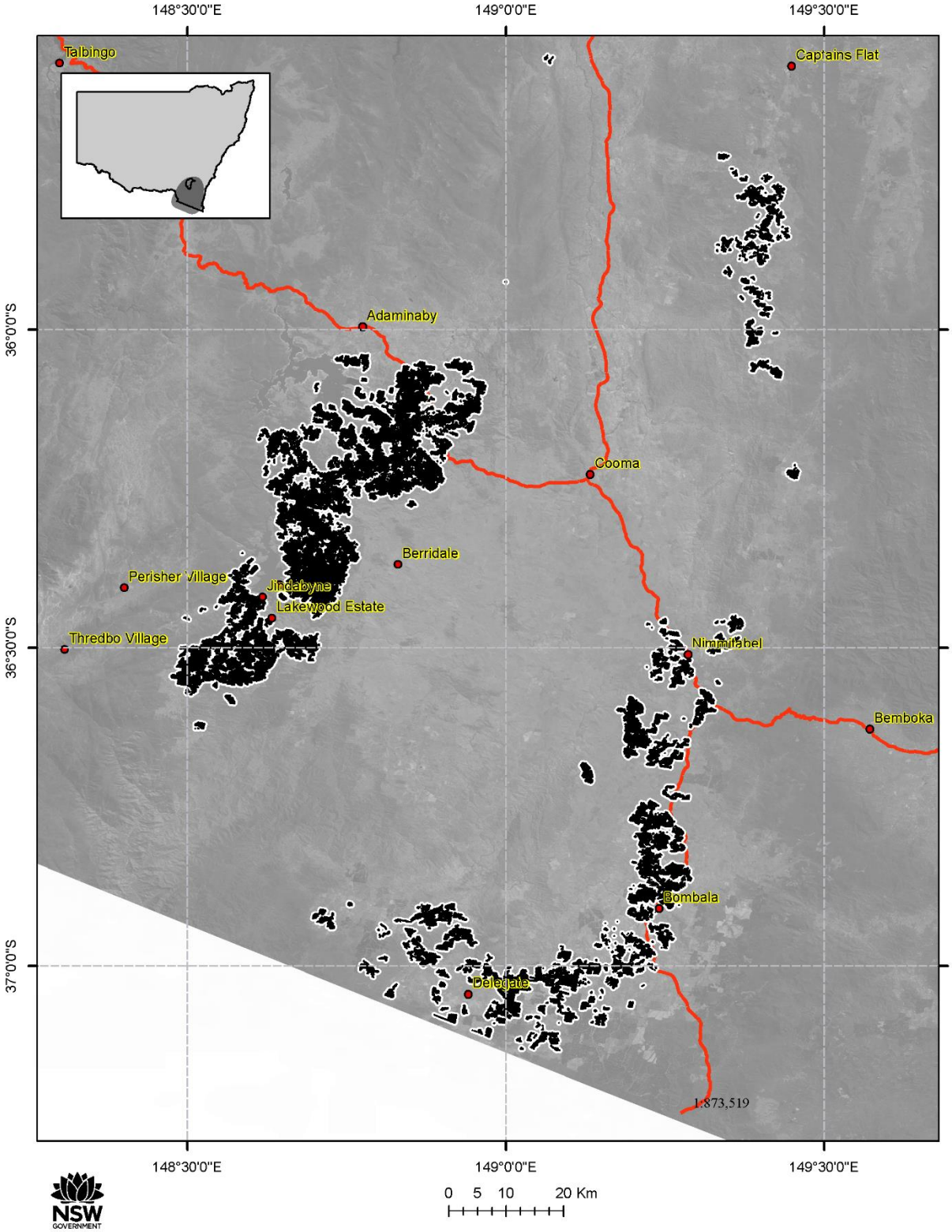
The spatial catalogue is shown below.

- MonaroWerriwa_CEEC_v1
  - Shapefiles
    - Monaro_CEEC_v1.shp
    - Werriwa_CEEC_v1.shp
  - Monaro_Werriwa_CEEC.gdb
    - Monaro_CEEC_v1
    - Werriwa_CEEC_v1
  - A3_MonaroCEEC_Illustration.png
  - A3_WerriwaCEEC_Illustration.png
  - Monaro_Werriwa_CEEC_v1.mpk
  - Monaro_Werriwa_CEEC_v1.mxd

The mxd and mpk package shalldepict the following layers. A primary extent accompanied by a secondary breakdown of classes for each community.

- ☑ Monaro CEEC
  - ☐ Monaro_CEEC_v1
    - CEEC Present
  - ☐ Monaro_CEEC_v1_Categories
    - CEEC
    - CEEC 100m Buffer into Grassland
    - TEC Connected Grassland Contrained By Lot
- ☑ Werriwa CEEC
  - ☐ Werriwa_CEEC_v1
    -
  - ☐ Werriwa_CEEC_v1_Categories
    - CEEC
    - CEEC 100m Buffer into Grassland
    - TEC Connected Grassland Contrained By Lot

Please see overall extent illustrations below. The spatial data provides discrimination at a finer property scale.

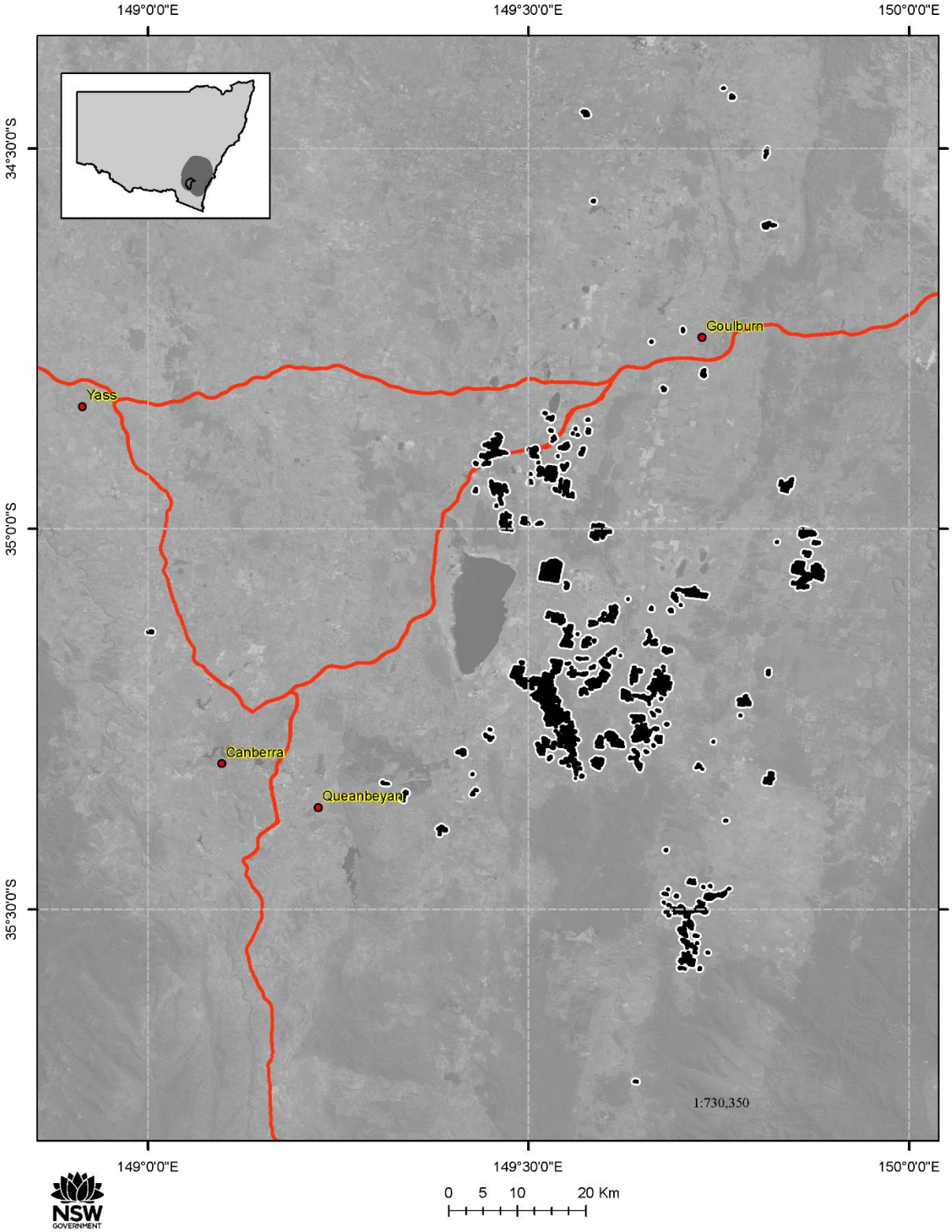


Monaro Tablelands Cool Temperate Grassy Woodlands Critically Endangered Ecological Community

Version 1.0

Native Vegetation Information Branch
Science Division
NSW Office of Environment & Heritage
Illustration only - not for spatial interpretation

Coordinate System: GCS GDA 1994
Datum: GDA 1994
Units: Degree



Werriwa Tablelands Cool Temperate Grassy Woodlands Critically Endangered Ecological Community

Version 1.0

Native Vegetation Information Branch
Science Division
NSW Office of Environment & Heritage
Illustration only - not for spatial interpretation

Coordinate System: GCS GDA 1994
Datum: GDA 1994
Units: Degree

Versioning:

v.1.1: Restricted coverage to the 100m buffer of core attribution (categories 1 & 2 only).

V1.2: A single merged and dissolved coverage of both Monaro and Werriwa CEEC's for NVR.

V1.3: A single merged and dissolved coverage of both Monaro and Werriwa CEEC's for NVR. Categories 1,2 & 3 included.

V1.4: Manual high resolution API correction to buffer induced commission errors

References

Office of Environment and Heritage (2016) Assessment of Tablelands Snow Gum, Black Sallee, Candlebark and Ribbon Gum Grassy Woodland TEC on NSW Crown Forest Estate: Survey, Classification and Mapping Completed for the NSW Environment Protection Authority. Published by Environment Protection Authority, Sydney, NSW. (https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/forestagreements/assessment-tablelands-snow-gum-tec-160623.pdf?la=en&hash=E4953EB1E7DE37DB5A80BAF0351525ECA25E3CE1)

NSW Threatened Species Scientific Committee (2019) Werriwa Tablelands Cool Temperate Grassy Woodland in the South Eastern Highlands and South East Corner Bioregions – critically endangered ecological community listing (https://www.environment.nsw.gov.au/-/media/OEH/Corporate-Site/Documents/Animals-and-plants/Scientific-Committee/Determinations/2019/werriwa-tableland-final-determination-CEEC.pdf?la=en&hash=92C6D495486B7F36D0F15C133F93E8B5DE5141E8)