Assessment of White Gum Moist Forest TEC on NSW Crown Forest Estate

Survey, Classification and Mapping Completed for the NSW Environment Protection Authority

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Contents

1 Overview

White Gum Moist Forest is a threatened ecological community (TEC) found in the NSW North Coast Bioregion. The tree *Eucalyptus dunnii* (White Gum) is a primary diagnostic attribute of the TEC as its distribution underpins both the spatial extent, threat assessment and floristic descriptors included in the final determination (the determination). The assemblage includes other eucalypts and brush box (*Lophostemon confertus*) found in the upper stratum but is otherwise characterised by a mesic understorey that includes rainforest trees and shrubs, vines palms and ferns. It is currently known from two populations, one north of the Bruxner highway near Casino and a southern population west of Coffs Harbour on the foothills of the Dorrigo escarpment.

Our interpretation of White Gum Moist Forest (WGMF) relied on the occurrence of *Eucalyptus dunnii* to diagnose the presence of the TEC. We reviewed existing maps, predictive models and observation records of *Eucalyptus dunnii* to target state forests either known or likely to include stands of the species. We designed a stratified survey within state forests known to support the species but we abandoned the survey effort after 21 sites due to access constraints and traverses encumbered by dense lantana and vine thickets.

We generated a new predictive model based on existing records to guide the identification of suitable environments and habitats known to support the species. We assessed the utility of aerial photograph interpretation to discriminate crown signatures of target eucalypts using intensive localised field survey in Kangaroo River State Forest. We used these findings as a basis for extrapolation across state forests and as a method to review existing maps of *E. dunnii* including forest type maps and detailed mapping in the Coffs Harbour LGA (OEH 2012).

We supported our API mapping effort using targeted field-based reconnaissance and iteratively reviewed the performance of our interpretations. We mapped 980 hectares of forest likely to be dominated or co-dominated by *E. dunnii* across 16 state forests. Two thirds of the area is associated with the northern populations of *E. dunnii*. The largest areas were mapped in Beaury, Donaldson and Yabbra State Forests. In the southern area, Kangaroo River State Forest includes the largest representation in state forests.

Validation of our maps produced mixed results. At best in Edinburgh Castle State Forest we found 75% of sites visited within our mapped polygons included *E. dunnii* although it was dominant at only half these sites. However, in parts of Bagawa and Gundara State Forests we found *E. dunnii* absent from our mapped polygons. At present, we consider that we overestimate the extent of *E. dunnii* and its dominance; however, it is unlikely that extensive stands exist outside mapped areas. We also conclude that existing mapping (including both forest type mapping and OEH (2012)) significantly underestimates the likely true extent.

We demonstrate that API is capable of separating *E. dunnii* from other related eucalypts but only where it is supported by field reconnaissance. Further work is required to increase interpreter confidence throughout its range before maps are suitable for operational applications. We provide a list of state forests that include mapped areas of *E. dunnii* and identify the area that has corroborating field based evidence of *E. dunnii*. We recommend that all forests with mapped areas of *E. dunnii* be assessed using field based protocols until further mapping work is complete.

2 Introduction

2.1 Project rationale

The NSW Environment Protection Authority (EPA) and Forest Corporation NSW (FCNSW) initiated this project as a coordinated approach to resolve longstanding issues surrounding the identification, extent and location of priority NSW Threatened Ecological Communities (TECs) occurring on the NSW state forest estate within eastern Regional Forest Agreements.

2.2 Final determination

White Gum Moist Forest (WGMF) in the NSW North Coast Bioregions was gazetted as an Endangered Ecological Community on July 2008. The final determination provides a list of 51 species that characterise the assemblage in Paragraph 1.

Paragraph 4 of the determination (NSW Scientific Committee 2008) characterises the forest as dominated by *Eucalyptus dunnii* (White Gum) sometimes with *Eucalyptus saligna* (Sydney Blue Gum), *Eucalyptus microcorys* (Tallowwood) and/or *Lophostemon confertus* (Brush Box). A diverse and prominent stratum of rainforest tree and shrub species are described as being associated with the dominant eucalypt species. The forest is 'typically a tall open forest or open forest but may take on the structure of a low closed forest or scrub' (NSW Scientific Committee 2008) in disturbed situations.

Paragraph 6 indicates that WGMF occurs at elevations between 400 and 650 metres on fertile soils derived from basalt or fine-grained sediments and with a mean annual rainfall exceeding 1000 millimetres. It is typically found in gullies and lower slopes and uncommonly on west facing slopes.

Paragraphs 6 and 9 provide information on the known extent of WGMF. It describes two disjunct areas; one in the upper northern reaches of the Richmond River catchment and the other in the north-eastern foothills of the Dorrigo Plateau.

Paragraph 8 provides a list of vegetation communities that are included within the definition of WGMF. Dunns White Gum (Forest Type 51) of Benson and Hager (1993) is wholly included, 'Eucalyptus dunnii' (Floristic Group 73) of National Park and Wildlife Service [NPWS] (1994), 'Eucalyptus dunnii' Community (URBov8) of Binns (1995) and 'Dunn's White Gum Community' - Forest Ecosystem 45 of NPWS (1999). The latter reference is used in Paragraph 9 to estimate the extent of WGMF in north-eastern NSW.

2.3 Initial TEC Reference Panel interpretation

Under the *Threatened Species Conservation* (TSC) *Act* 1995, TECs are defined by two characteristics: an assemblage of species and a particular location. The TEC Project Reference Panel (the Panel) agreed that the occurrence of WGMF is constrained to the IBRA Bioregions stated in the final determination. The Panel agreed that while the determination provides a list of characteristic species the primary diagnostic attribute is the dominance of *Eucalyptus dunnii* in the over storey with a diverse assemblage of mesophyll flora in the shrub and small tree layer. From the final determination, Table 1 summarises the key determining features of WGMF and how they have been used in this assessment based on the interpretation of the features by the Panel.

<u>Table 1:</u> Key features of White Gum Moist Forest of potential diagnostic value. Numbers in the left-hand column refer to paragraph numbers in the final determination.

	Feature	**Diagnostic value and use for this assessment**
1	NSW occurrences fall within the North Coast Bioregion	Explicitly diagnostic.
1, 4	Dominated by White Gum, *Eucalyptus dunnii*, either in pure stands or with *E. saligna*, *E. microcorys* and/or *Lophostemon confertus*.	Explicitly diagnostic. The Panel noted that the *E. dunnii* must be the dominant species (>/=50%) of the overstorey cover across an area, although co-dominant or associated species are likely to include additional tree species than those stated in the determination. The Panel noted that crown cover may be a more effective measure to counter against foliage decline associated with dieback in *E. dunnii*.
1,4	Has a tall open canopy of eucalypts with a structurally complex understorey of rainforest trees and shrubs, vines, palms and ferns.	Indicative, not used. The panel noted that dominant stands of *E. dunnii* should not be excluded based on structural characteristics alone.
2	Characterised by the listed 51 plant species	Potentially diagnostic, however the Panel noted that the dominance of *E. dunnii* is an indicator for the assemblage.
6	Typically occurs on the escarpment slopes and foothills of the north east of NSW most commonly between 400-650m in elevation and where mean annual rainfall exceeds approximately 1000mm...	Indicative only, used to define an assessment area within the North Coast Bioregion.
6	Soils that support the community are relatively fertile and derived from basalt or fine-grained sediments, or colluvium or alluvium influenced by the presence of these substrates upstream. The community is typically found in gullies and on lower slopes, but has been recorded on upper slopes and basalt ridges.	Indicative only, not used
7	In NSW is currently known from the local government areas of Clarence Valley, Coffs Harbour, Kyogle and Tenterfield, but may occur elsewhere within the bioregion. In addition, suitable habitat for the community is predicted to occur within the LGAs of Bellingen, Glen Innes-Severn and Tenterfield.	Indicative only, not used.
8	White Gum Moist Forest includes 'Dunn's White Gum' (Forest Type 51) habitat of *Eucalyptus dunnii* is described by Benson and Hager (1993), '*Eucalyptus dunnii*' (Floristic Group 73) of NPWS (1995), '*Eucalyptus dunnii'* Community (URBov8) of Binns (1995) and 'Dunn's White Gum Community' (Forest Ecosystem 45 of NPWS (1999).	Potentially diagnostic. The Panel noted that Forest Type 51 is mapped on state forest and is likely to indicate dominant stands of *E .dunnii*. The panel noted that the mapping of Forest Type 51 underpins the survey effort of Benson and Hager (1993) and Binns (1995) and mapping of NPWS (1994, 1999).
9	All known records of White Gum Moist Forest occur within two disjunct areas: one in the upper reaches of the Richmond River Catchment; and the other in the north-eastern foothills of the Dorrigo Plateau	Indicative only, used to target survey effort.

2.4 Assessment area

2.4.1 State forests subject to assessment

The study area includes all Crown Forest estate situated within the Upper North East (UNE) Integrated Forestry Operations Approval (IFOA) region and the North Coast Bioregion (Map 1). A total of 180 state forests were included in this assessment (Table 2). State forests excluded from the assessment include those areas defined as Forest Management Zones 5 (Hardwood Plantations) and Zone 6 (Softwood Plantations). Small areas of native forest wholly enclosed or adjoining Forest Management Zone 6 (Softwoods) are also excluded from this assessment as they are considered to be outside of the authority of the IFOA.

Map 1: **Candidate state forests assessed.**

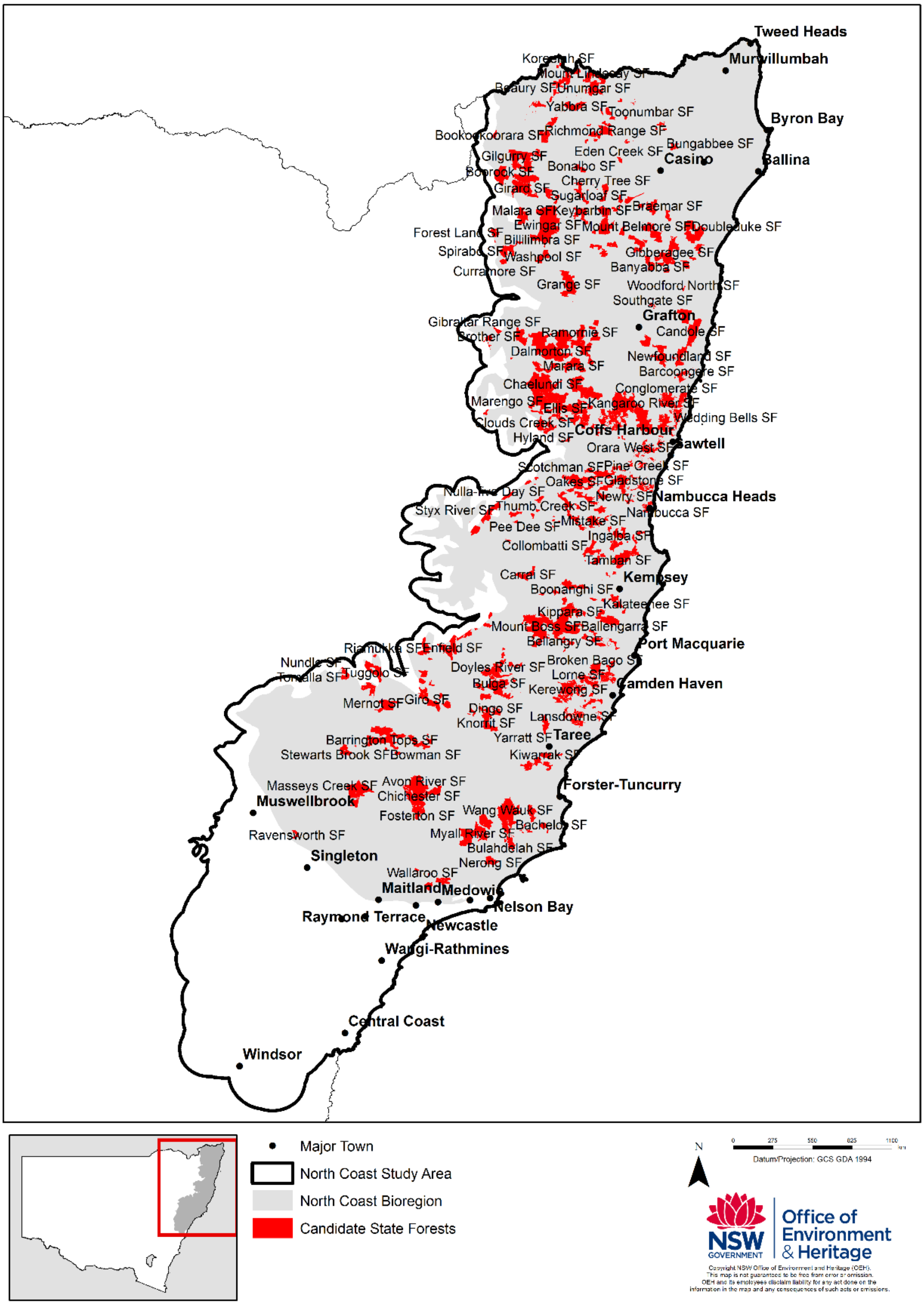


Table 2: List of candidate state forests assessed.

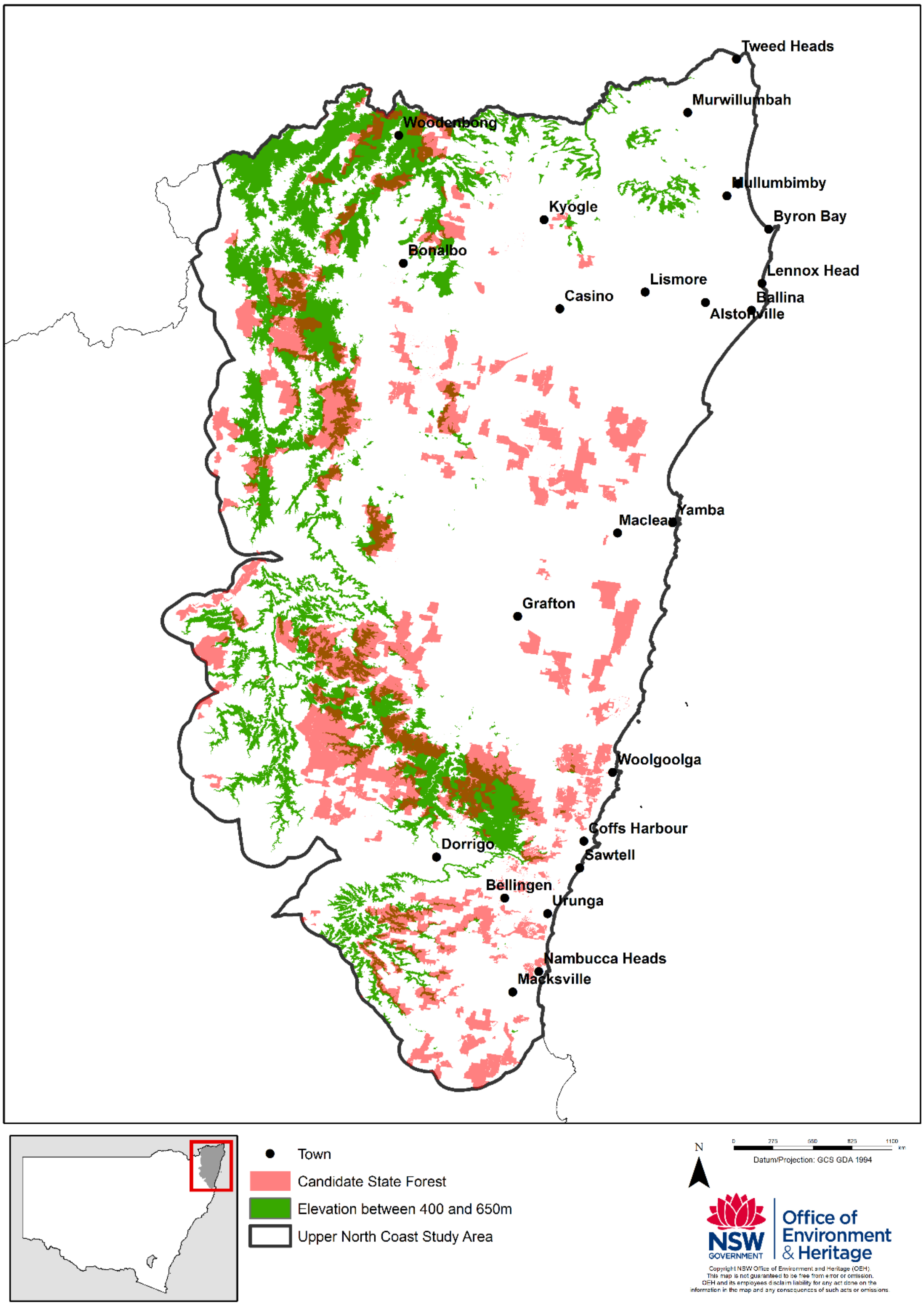
State Forest (SF)	Area (Ha)	State Forest (SF)	Area (Ha)	State Forest (SF)	Area (Ha)
Avon River SF	5,061	Edinburgh Castle SF	949	Nerong SF	2,173
Bachelor SF	2,642	Ellangowan SF	1,179	Never SF	3
Bagawa SF	5,384	Ellis SF	9,736	Newfoundland SF	5,939
Bald Knob SF	1,695	Enfield SF	6,798	Newry SF	2,841
Ballengarra SF	6,106	Ewingar SF	18,433	North Branch SF	796
Banyabba SF	2,674	Forest Land SF	1,527	Nowendoc SF	2,058
Barcoongere SF	320	Fosterton SF	823	Nulla-five Day SF	3,370
Barrington Tops SF	12,588	Fullers SF	1,053	Nundle SF	145
Beaury SF	4,568	Gibberagee SF	10,574	Nymboida SF	6,400
Bellangry SF	6,411	Gibraltar Range SF	761	Oakes SF	7,639
Billilimbra SF	3,853	Gilgurry SF	9,531	Old Station SF	230
Boambee SF	821	Girard SF	16,580	Orara East SF	3,983
Bom Bom SF	872	Giro SF	7,090	Orara West SF	4,459
Bonalbo SF	1,456	Gladstone SF	6,230	Paddys Land SF	452
Bookookoorara SF	712	Glenugie SF	4,952	Pappinbarra SF	1,181
Boonanghi SF	3,817	Grange SF	7,802	Pee Dee SF	62
Boonoo SF	2,406	Gundar SF	119	Pine Brush SF	3,966
Boorabee SF	914	Hyland SF	4,385	Pine Creek SF	1,219
Boorook SF	2,990	Ingalba SF	6,632	Queens Lake SF	576
Boundary Creek SF	2,539	Irishman SF	2,733	Ramornie SF	6,175
Bowman SF	3,187	Johns River SF	725	Ravensworth SF	901
Braemar SF	2,002	Kalateenee SF	1,344	Riamukka SF	3,453
Bril Bril SF	2,333	Kangaroo River SF	11,399	Richmond Range SF	6,340
Broken Bago SF	3,543	Kendall SF	354	Roses Creek SF	1,790
Brother SF	1,217	Kerewong SF	3,665	Royal Camp SF	2,203
Buckra Bendinni SF	1,766	Kew SF	897	Scotchman SF	4,158
Bulahdelah SF	7,799	Keybarbin SF	3,707	Sheas Nob SF	4,333
Bulga SF	14,254	Kippara SF	5,554	Skillion Flat SF	5
Bulls Ground SF	2,010	Kiwarrak SF	6,535	South Toonumbar SF	410
Bungabbee SF	1,097	Knorrit SF	5,081	Southgate SF	628
Bungawalbin SF	1,204	Koreelah SF	673	Spirabo SF	3,182
Burrawan SF	2,040	Lansdowne SF	4,118	Stewarts Brook SF	2,417
Cairncross SF	4,487	Little Newry SF	189	Styx River SF	7,931
Camira SF	4,009	London Bridge SF	118	Sugarloaf SF	3,151
Candole SF	6,574	Lorne SF	3,257	Tabbimoble SF	2,627
Carrai SF	3,028	Lower Bucca SF	2,621	Tamban SF	7,632
Carwong SF	603	Lower Creek SF	1,270	Tarkeeth SF	530
Chaelundi SF	18,238	Malara SF	3,334	Thumb Creek SF	3,944

State Forest (SF)	Area (Ha)	State Forest (SF)	Area (Ha)	State Forest (SF)	Area (Ha)
Cherry Tree SF	1,636	Marara SF	5,351	Tomalla SF	1,734
Cherry Tree West SF	321	Marengo SF	10,128	Toonumbar SF	1,528
Chichester SF	20,539	Maria River SF	1,815	Tuckers Nob SF	1,885
Clouds Creek SF	10,241	Masseys Creek SF	3,127	Tuggolo SF	7,681
Cochrane SF	231	Medowie SF	50	Uffington SF	325
Collombatti SF	4,126	Mernot SF	4,338	Unumgar SF	3,563
Comboyne SF	2,576	Middle Brother SF	2,131	Upsalls Creek SF	923
Coneac SF	777	Mistake SF	5,638	Urbenville SF	3
Conglomerate SF	5,162	Moonpar SF	1,821	Viewmont SF	702
Coopernook SF	871	Mororo SF	379	Wallaroo SF	3,487
Cowarra SF	1,687	Mount Belmore SF	9,181	Wallingat SF	1,240
Curramore SF	84	Mount Boss SF	17,165	Wang Wauk SF	8,330
Dalmorton SF	27,937	Mount Lindesay SF	3,045	Washpool SF	2,961
Devils Pulpit SF	1,484	Mount Marsh SF	3,636	Way Way SF	1,268
Diehappy SF	1,275	Mount Mitchell SF	54	Wedding Bells SF	4,645
Dingo SF	3,555	Mount Pikapene SF	553	Whiporie SF	1,109
Divines SF	1,524	Mount Seaview SF	1	Wild Cattle Creek SF	9,667
Donaldson SF	2,328	Muldiva SF	687	Woodenbong SF	306
Doubleduke SF	5,824	Myall River SF	13,611	Woodford North SF	219
Doyles River SF	5,807	Myrtle SF	4,303	Yabbra SF	8,417
Dyke SF	6	Nambucca SF	1,510	Yarratt SF	2,381
Eden Creek SF	1,179	Nana Creek SF	1,793	Yessabah SF	1,887
				Total	682,998

2.4.2 Location and study area boundaries

Map 2 shows the elevation thresholds described in the WGMF final determination within the upper north coast region. Elevation thresholds of 400 to 650 metres above sea level (asl) referenced in the determination are shown within Map 2.

<u>Map 2</u>: **Assessable state forests within the primary region described by the White Gum Moist Forest final determination. Elevations 400-650 metres above sea level are also illustrated.**



2.5 Project team

This project was completed by the by the Ecology and Classification Team in the OEH Native Vegetation Information Science Branch. It was initiated and funded by the NSW Environment Protection Authority under the oversight of the Director, Forestry Branch.

Daniel Connolly managed the project. Doug Binns reviewed *E. dunnii* records, calibrated observers and constructed sampling strategy to support mapping and validation. Allen McIlwee performed the spatial analysis and broad scale predictive distribution modelling. Owen Maguire undertook API mapping using 3D stereo imagery across the study area. Matt Potter, Paula Pollock, Owen Maguire and Daniel Connolly completed field survey.

3 Methodology

3.1 Approach

Analysis and mapping were guided by the general principles and particular interpretation of WGMF adopted by the TEC Reference Panel, described in Section 2.3. For the purpose of this project, WGMF was defined primarily by the dominance of *Eucalyptus dunnii*. A major part of our assessment was to identify a mapping method that could reliably discriminate the species from other related eucalypts and to assign stands to one of several classes of crown cover to assess dominance criteria.

We reviewed existing maps, predictive models and observation records of *Eucalyptus dunnii* to target state forest either known or likely to include stands of the species. A new predictive model based on existing records was used to refine the list of state forests likely to support the species. We used several different approaches to sampling and mapping *E. dunnii* using ground based surveys, predictive modelling and aerial photograph interpretation.

3.2 Existing vegetation data

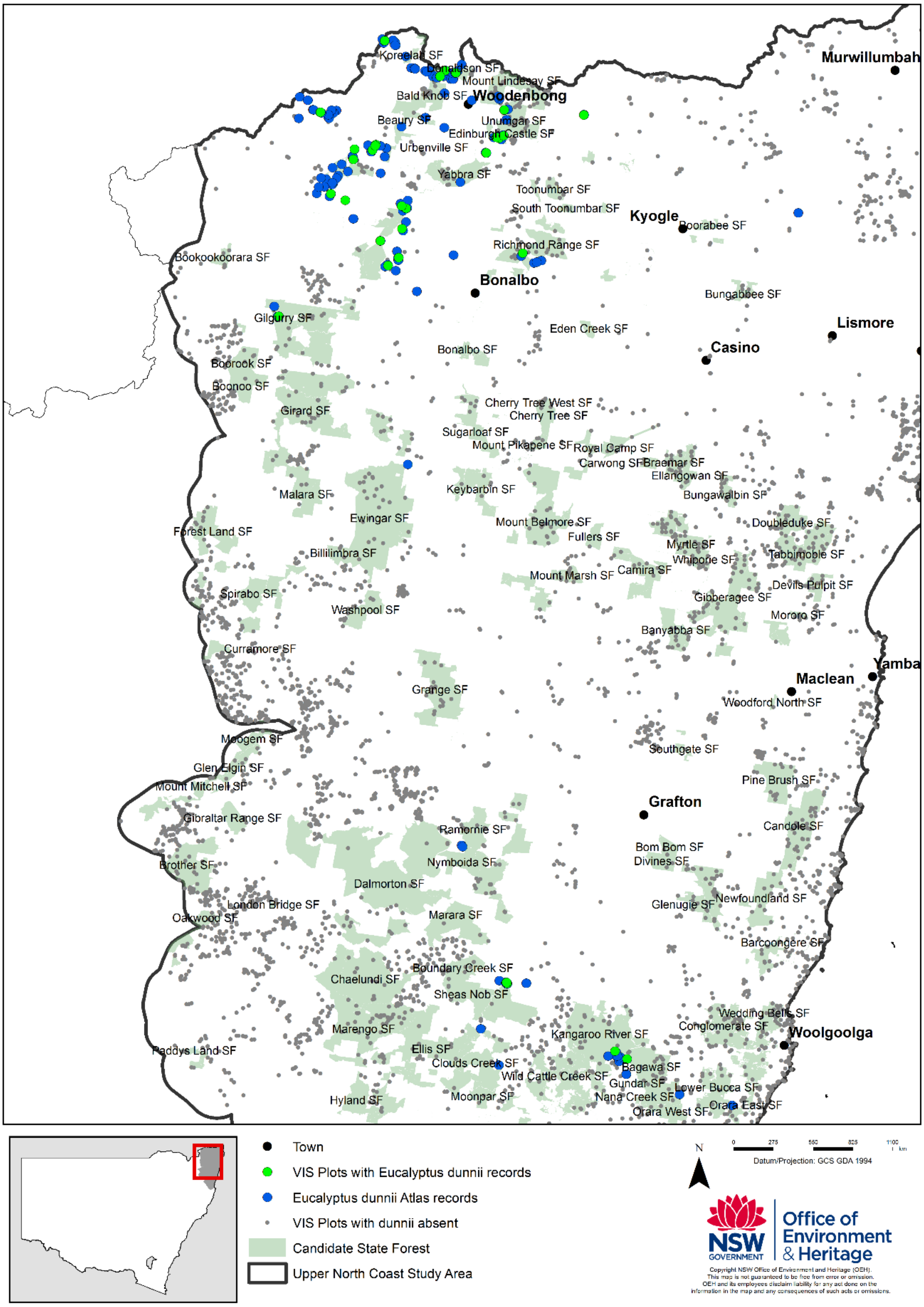
3.2.1 *Eucalyptus dunnii* location data

All records of *Eucalyptus dunnii* were extracted from Bionet (OEH accessed 20/8/2015) and plotted against state forest boundaries using a geographic information system (GIS). Map 3 shows the distribution of the species within our study area. We reviewed the distribution and accuracy of records and removed locations that identified known hardwood plantations or spatial outliers that supported a conflict between location description and spatial reference data.

3.2.2 Systematic VIS plot data

OEH maintains an archive of flora survey data within the Vegetation Information System (VIS) Flora survey module. We used the systematic plot data to provide confirmed locations where *E. dunnii* is both present and absent across our study area (Map 3). The purpose of this data was to provide the foundation for our predictive models for WGMF.

<u>Map 3:</u> **Existing *Eucalyptus dunnii* records**



3.2.3 Vegetation maps

Vegetation maps that provided coverage across our study area were sourced from the OEH VIS map catalogue (Map 4). We accessed the complete coverage of Forest Type Mapping, RN17, (FCNSW, undated) across northern NSW including coverage across areas now designated as National Parks and Nature Reserves. We also obtained the Forest Ecosystem mapping compiled for the North-east Comprehensive Regional Assessment process (NPWS 1999) and reviewed the predictive distribution maps for *Eucalyptus dunnii* during the North East Biodiversity Surveys (NPWS 1994). Recent mapping in the Coffs Harbour LGA (OEH 2012) was also used to locate *Eucalyptus dunnii* populations in the southern extent of its range.

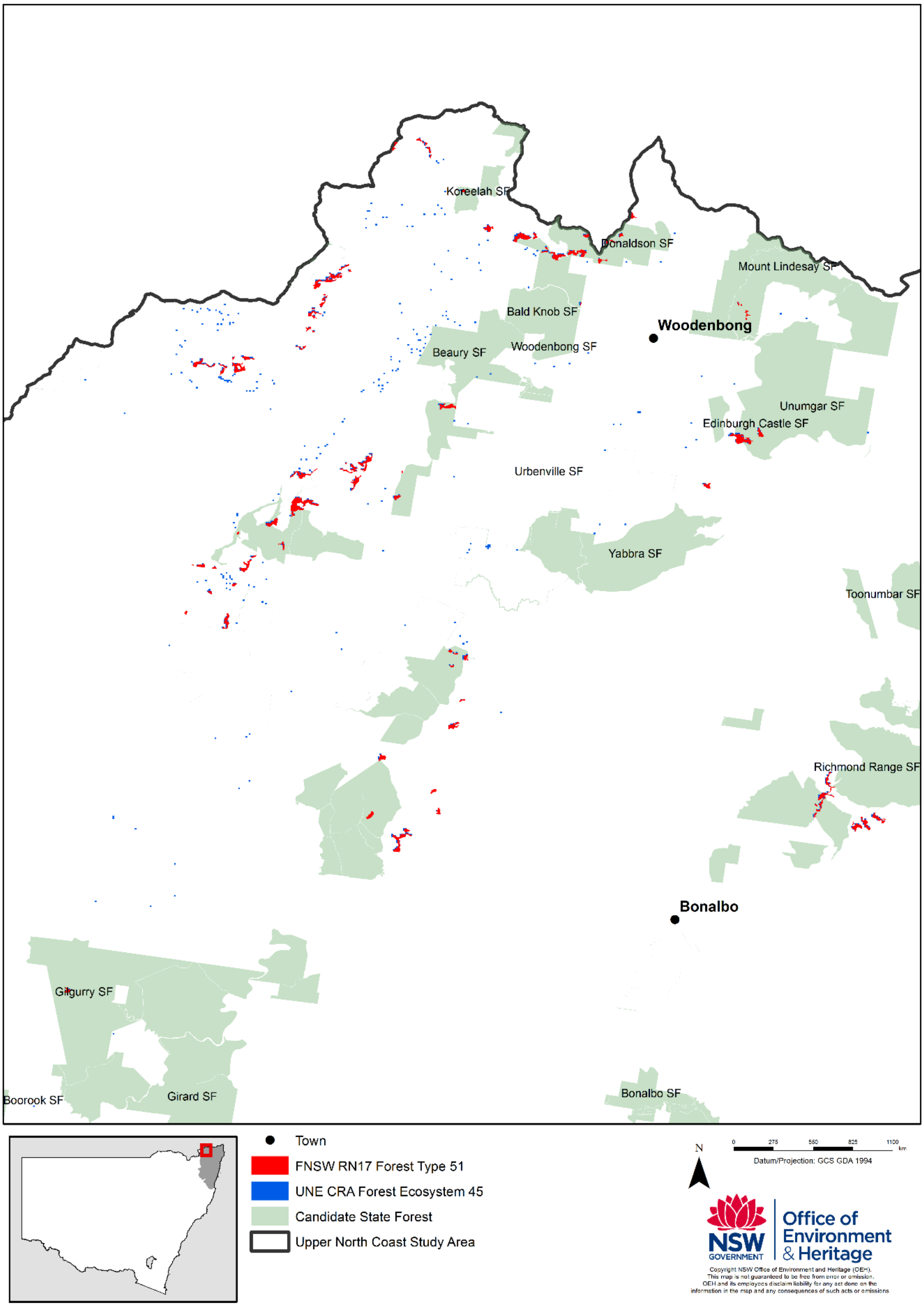
Table 3 Existing vegetation mapping and records of *E. dunnii* within state forests.

State forest (SF)	Area (ha)	Atlas records E dunnii (incidental records)	Recorded within OEH Plot data	Total number of E dunnii records	Number FT51 Polys	Area FT51	Area mapped within Coffs Harbour LGA (OEH 2012)
Bagawa SF	5,384	1	0	1	0	0	0
Bald Knob SF	1,695	0	1	1	2	6	0
Beaury SF	4,568	1	6	7	9	77	0
Clouds Creek SF	10793	0	0	0	2	26	0
Donaldson SF	2,331	3	12	15	10	63	0
Edinburgh Castle SF	949	2	4	7	2	37	0
Gilgurry SF	9,531	1	3	4	1	7	0
Kangaroo River SF	11,399	1	0	2	0	0	38.5
Koreelah SF	708	0	1	1	2	8	0
Mount Lindesay SF	3,046	0	3	3	5	10	0
Richmond Range SF	6,340	1	3	4	2	25	0
Unumgar SF	3,563	1	3	5	0	0	0
Yabbra SF	8,417	2	8	10	7	24	0
Wild Cattle Creek SF	9,667	0	0	0	0	0	3.7
	77391	13	44	60	42	283	42.2

3.3 Identifying Eucalyptus dunnii

Eucalyptus dunnii presents particular challenges for survey and mapping because field based identification can be difficult. We initially calibrated our observers using a botanist experienced with the species to demonstrate the primary diagnostic attributes including fruit, buds, shape and colour of juvenile and adult leafs, and bark habit. Comparisons against similar eucalypts including E. *saligna*, *E. grandis* and *E. tereticornis* highlighted primary diagnostic features. Limited identification material can mean that the presence of the species may remain uncertain until a suitable time of year.

Map 4: **Existing vegetation mapping**



3.4 New survey effort

3.4.1 Survey stratification and design

Initially we planned an initial stratified field survey to generate sufficient presence and absence data to develop statistical models describing the distribution of *E. dunnii*. We identified zones within state forests known to support *E. dunnii* by aggregating existing records within a five-kilometre area using GIS. We overlaid a 600-metre grid within the derived polygons and marked points at each grid intersect. At each intersect we aimed to record all tree species present and assess the dominance of *E. dunnii* (if present). We planned to collect data from 150 pre-determined point locations defined by the grid intersects and record the locations of individuals encountered during traverses.

We also designed a second survey effort to capture detailed location and abundance data around known populations. These localised efforts aimed to inform our initial aerial photo interpretation. Stands of *E. dunnii* were located and circumnavigated to mark the outer extent of patches identifiable in the field. Species observations within and outside the defined stand of *E. dunnii* were made at individual points.

Thirdly, we targeted several mapped areas of *E. dunnii* within Clouds Creek and Wild Cattle Creek State Forests on the basis that they had no field based evidence that *E. dunnii* was present.

3.4.2 Survey method

Point based

At each point, the number of trees (if any) of *E. dunnii*, in 10 centimetre diameter classes, were recorded within a 20 metre x 20 metre square centred on the point. If no *E. dunnii* was present, the number of trees was recorded as zero. Also within the sample square, regardless of the presence of *E. dunnii,* all overstorey species were recorded with an estimate of projected foliage cover of each species within the overstorey in accordance with the NSW Native Vegetation Interim Type Standard (Sivertsen 2009). The presence or absence of *E. dunnii* within a 50 metre radius of the point was also recorded.

***E. dunnii* stands**

We identified a discrete stand as a stand in which *E. dunnii* is the dominant overstorey species (> 50 percent projected foliage cover) over an area of at least 0.1 hectare (approximately 30 metres x 30 metres). In cases where other species were almost equally dominant, and there is doubt about whether *E. dunnii* is the single dominant, we recorded the co-dominant species present. We delineated the stand boundary using GPS, with the boundary defined by the crown perimeter of *E. dunnii* trees on the periphery of the stand. Within each delineated stand, estimates were recorded of the projected foliage over of *E. dunnii* in the overstorey, the projected foliage cover of all other overstorey species combined, and the two species other than *E. dunnii* with highest projected foliage.

Incidental records

Observations of *E. dunnii* during traverse and reconnaissance routes were recorded by a hand held GPS or mobile tablet and later entered into the NSW Bionet.

3.5 Aerial photograph interpretation

Aerial photograph interpretation (API) was assessed for its suitability as a method to discriminate *Eucalyptus dunnii* from other eucalypts. We commenced our assessment using a set of new georeferenced field observations (see 2.4.2) in Kangaroo River State Forest that identified individual *E. dunnii* trees and adjoining species. Traverses from known points were extended until no further *E. dunnii* individuals were observed and a point recorded to mark the outer limit. Multiple field points were taken to bound a stand of *E. dunnii*.

An API technician, experienced in interpretation of NSW forest and vegetation types, used recent high resolution (50 centimetre ground sample distance) stereo digital imagery, in a digital 3D GIS environment, to assess whether locations of *E. dunnii* supported an interpretable crown signature in the photo imagery. We used an image stretch function to enhance colour separation using the equalise and dynamic range functions in Stereo Analyst. Image patterns showing whiter-grey saturations associated with fuzzy or shaggy textured crowns were features that separated *E. dunnii* from *E. saligna* and *E. grandis*.

We used these findings to extrapolate patterns across unvisited areas within Kangaroo River, Wild Cattle Creek, Gundar and Bagawa State Forests. We identified our initial areas for mapping based on the identification of habitats likely to support the species, namely areas on or adjoining basalt and on alluvial soils draining these substrates (Benson & Hager 1993). We interpreted matching crown signatures and drew a boundary around the outer limit of *E. dunnii* crowns. Each mapped polygon was assigned a crown cover class to describe the cover of *E. dunnii* within the polygon. Table 5 describes the crown cover classes. The interpreter also assigned a confidence score describing the extent to which the observed and mapped patterns conformed to the reference crown signatures. Table 6 defines the confidence classes applied.

Table 5. Crown cover classes used to assess the abundance of *E. dunnii* within a mapped polygon (McDonald et al, 1990)

Crown Cover Code	Description	Measure
4	crowns touching to slight separation	50-80% cover
3	Crowns clearly separated	20-50% cover
2	Well separated	10-20% cover
1	Very well separated to isolated	0-10% cover

Table 6. Interpreter confidence classes assigned to each mapped polygon

Confidence Class	Description
1	High: visited areas and/or photo patterns are high contrast features that are separable on structural characteristics and require limited interpretation
2	High-Medium: Confident Extrapolation based on field sampling where interpretability of features is high and consistent with patterns confirmed elsewhere through field sampling
3	Medium-Low: Not visited. Similarity with features sampled elsewhere, but species interpretation not always possible or inconsistent resulting in some uncertainties. Environmental niche important indicator of species composition
4	Low Remote or Unvisited area showing photo pattern inconsistent with features sampled elsewhere, low confidence in species interpretation, and represents best call using available classes and known habitat relationships.

We extended the mapping into the Urbenville/Woodenbong region by adopting the crown signatures from Kangaroo River SF as a basis for interpretation. We supported the extrapolation by visiting selected areas of forest dominated by *E. dunnii* in Tooloom National Park, Beaury, Donaldson and Edinburgh Castle State Forests. Table 7 shows the state forests assessed using API based on existing records and the results of our predictive habitat models

Table 7 State forests included in API mapping.

State Forest (SF)	Total Area (ha))
Bagawa SF	5,384
Bald Knob SF	1,695
Beaury SF	4,568
Clouds Creek SF	10,241
Donaldson SF	2,328
Edinburgh Castle SF	949
Gilgurry SF	9,531
Gundar SF	119
Kangaroo River SF	11,399
Koreelah SF	673
Mount Lindesay SF	3,045
Nana Creek SF	1,793
Orara West SF	4,459
Richmond Range SF	6,340
South Toonumbar SF	410
Toonumbar SF	1,528
Unumgar SF	3,563
Wild Cattle Creek SF	9,667
Woodenbong SF	306
Yabbra SF	8,417
Total	86415

3.6 Indicative EEC distribution map

3.6.1 Background

A niche modelling approach (also known as species or habitat distribution modelling) was used to create indicative potential distribution maps for WGMF. This approach attempts to extrapolate the fundamental niche of the TEC outside the locations where it is known to be present (its realised niche), by relating known occurrence and absence to environmental predictors.

Modelling the distribution of a TEC requires the characterisation of environmental conditions that are suitable for the community to exist. The inclusion of the absence data from the plot allocation allows us to constrain the potential distribution model to a narrow set of favourable environmental conditions that are not occupied by other vegetation communities. Nonetheless, without API and associated on-ground validation, it is difficult to determine the extent to which potentially suitable habitat is actually occupied by the TEC.

Ecological niche modelling involves the use of environmental data describing factors that are known to have either a direct (proximal) or indirect (distal) impact on a species or ecological community. Proximal variables directly affect the distribution of the biotic entity, while distal variables are correlated to varying degrees with the causal ones (Austin 2002). Austin and Smith (1989) differentiate between indirect gradients, which have no physiological effects on plants, and direct or resource gradients, which directly influence plant growth or distribution. Direct or resource gradients mainly concern light, temperature, water and nutrients, whereas the main indirect gradients are altitude, topography and geology (Austin & Van Niel 2011). An environmental variable may act both as a resource that provides building blocks for growth processes and as a condition that fulfils the requirements for physiological processes to function effectively.

Diagram 1 provides a basic conceptual framework for how plant communities are likely to respond to their environment. Arrows in the figure show how particular indirect variables interact to generate more direct environmental drivers through biophysical processes. We note plant distributions are also influenced by stochastic processes such as extreme heat or cold, landslip or erosion, high winds, drought, flood and fire. However, in niche modelling, we assume that the composition of vegetation is primarily determined by environment rather than successional status or by time since last disturbance (Franklin 1995). It is also assumed that vegetation is in equilibrium with the environment, or at least a quasi-equilibrium where change is slow relative to the life span of the biota.

<u>Diagram 1</u>: Conceptual model of relationships between resources, direct and indirect environmental gradients and their influence on growth, performance and geographical distribution of plants and vegetation communities in general. Source: Guisan and Zimmermann (2000; Figure 3).

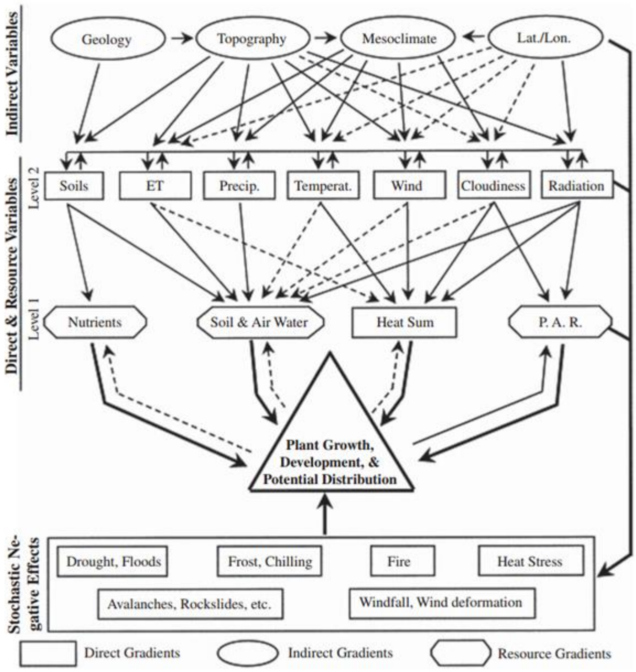
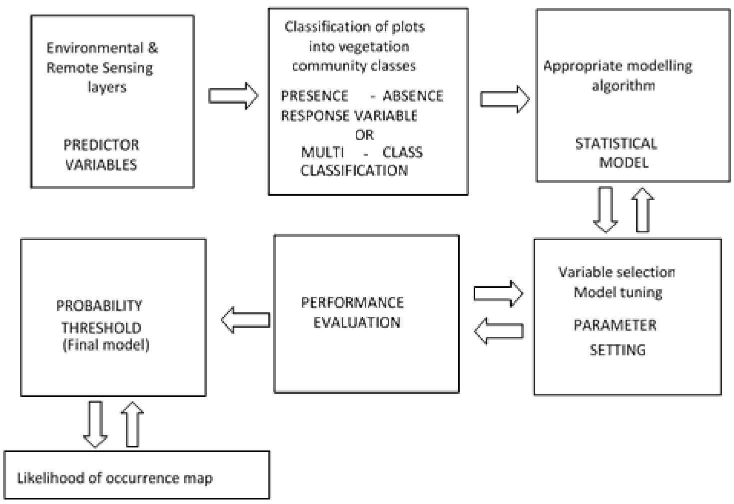


Diagram 2 provides an overview of the step-by-step modelling process, which involves a ‘classification-then-modelling’ approach (Ferrier et al. 2002) with two distinct stages. In the first stage, the biological survey data is subjected to a vegetation classification, and full-floristic vegetation plots are allocated to presence/absence category for the TEC. This classification is run without any reference to the environmental data. In the second stage the TEC entity as defined by the classification are modelled as a function of environmental predictors. The statistical model refers to the choice of (i) a suitable machine-learning algorithm for predicting a presence-absence response variable and its associated theoretical probability distribution, and (ii) the choice of an appropriate variable selection procedure that has the goal of optimising either prediction accuracy or interpretability.

<u>Diagram 2</u>: Process for creating indicative TEC distribution maps



3.6.2 Modelling complex ecological systems

The niche modelling community has made considerable headway in developing machine-learning algorithms to predict the occurrence of species and communities using presence-absence data (Evans & Cushman 2009). The methods model vegetation patterns as continuous measures of site suitability or probability of occupancy. Non-parametric approaches such as Classification and Regression Trees (CART) have gained widespread use in ecological studies (De'ath and Fabricius 2000). However, CART suffers from problems such as over-fitting and difficulty in parameter selection. Solutions to deal with these issues have been proposed that incorporate iterative approaches (Breiman 1996). One such approach, Random Forests (Brieman 2001), has risen to prominence due to its ability to handle large numbers of predictors and find signal in noisy data (Cutler et al. 2007). Another advantage of Random Forests is that, by permutation of independent variables, it provides local and global measures of variable importance.

Random Forests is an algorithm that developed out of CART and bagging approaches. By generating a set of weak-learners based on a bootstrap of the data, the algorithm converges on an optimal solution while avoiding issues related to CARTs and parametric statistics (Cutler et al. 2007). Ensemble-based weak learning hinges on diversity and minimal correlation between learners. Diversity in Random Forest is obtained through a Bootstrap of training, randomly drawing selection of *M* (independent variables) at each node (defined as *m*), and retaining the variable that provides the most information content. To calculate variable importance, improvement in the error is calculated at each node for each randomly selected variable and a ratio is calculated across all nodes in the forest.

The algorithm can be explained by:

1. Iteratively construct *N* Bootstraps (with replacement) of size *n* (36%) sampled from *Z*, where *N* is number of Bootstrap replicates (trees to grow) and *Z* is the population to draw a Bootstrap sample from.
2. Grow a random-forest tree T_b at each node randomly select *m* variables from *M* to permute through each node to find best split by using the Gini entropy index to assess information content and purity. Grow each tree to full extent with no pruning (e.g., no complexity parameter).
3. Using withheld data (OOB, out-of-bag) to validate each random tree T_b (for classification
OOB Error; for regression pseudo R^2 and mean squared error).
4. Output ensemble of random-forest trees

$$\{T_b\}\frac{B}{1}$$

To make a prediction for a new observation x_i:
Regression:

$$\hat{f}_{\mathrm{rf}}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

Classification: Let $\hat{C}_b$ (*x*) be the class prediction of the *B*th random-forests tree then

$$\hat{C}_{rf}^{B}(x) = \text{majorityvote}\left\{\hat{C}_b(x)\right\}\frac{1}{B}$$

Commonly, the optimal *m* is defined for classification problems as sqrt (*M*); and for regression *M*/3, where *M* is a pool of independent variables. It has been demonstrated that Random Forest is robust to noise even given a very large number of independent variables (Breiman 2001a; Hastie, Tibshirani & Friedman 2009).

All modelling was performed in the statistical software package R version 3.3.0

3.6.3 Spatial data and the variable selection process

A set of 175 variables were available for modelling. These include a set of

- 130 continuous environmental variables relating to climate, topography and Euclidean distance to features such as the coastline, permanent water bodies and various stream orders
- 32 variables derived from Landsat and Spot 5 imagery, and
- 13 categorical variables such as great soil group and single dominant lithology type, which were extracted from state-wide corporate GIS layers.

All variables were in the form of gridded Erdas Imagine rasters (*.img), with exactly the same cell size (30 x 30 metre) and extent.

The raster layers were stacked in R using the Raster Package (Hijmans & van Etten 2014). The grid cell values for each of the 175 potential predictor variables were extracted for each site in the allocation file using a customised script in R, and the resulting csv file loaded into R. To improve 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 that identifies whether any variables are forcing other variables to appear multicollinear.

Random Forest models are a good starting point for making inferences about the factors driving the distribution of a plant species or ecological community. However, they 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 a crucial step in the modelling process. We used a variable selection procedure developed by Murphy, Evans and Storfer (2010) which standardises the relative importance values of predictors to a ratio and iteratively subsets variables within a given ratio, running a new model for each subset of variables. Each resulting model is compared with the original model, which is held fixed. Model selection is achieved by optimising model performance based on a minimisation of both "out-of-bag" error and largest "within-class" error for classification. There is also a penalty for the number of variables selected in a model, resulting in a preference for the lowest number of predictors from closely competing models. For each model generated, we checked whether the shape of the fitted functions for predictors made sense based on our knowledge of the types of environments that the TEC is likely to occupy.

We ran preliminary Random Forest models using three types of predictor sets. The first used the full set of continuous environmental variables, with the aim of predicting the potential distribution (realised niche) of the TEC in its broadest sense. The second used a combination of continuous environmental and remote sensing variables. The inclusion of remote sensing variables added information about the spectral characteristics of vegetation at a site and its dynamics through time, giving a better reflection of the actual distribution of the TEC as opposed to potential distribution of the TEC. Categorical variables were not incorporated into the models directly, but the data was occasionally used to compare frequency histograms across presence and absence sites to see if a distinct preference for a particular soil type or fertility class existed. However, given that the number of absence sites greatly outnumbered the presences, there was generally insufficient data to draw conclusions about preferences for one group of soil classes over another.

Through a series of initial trials, we found a third hybrid approach produced the best set of predictors for modelling. Here we used the variable selection process described above to identify a subset of 30 environmental predictors out of the 130 available. We then added the 32 remote sensing variables and reran the same variable selection process, selecting out two subsets, one with 15 and the other with 30 predictors. These numbers were set *a priori* since previous modelling had suggested that a minimum of around 12 predictors (those with the highest relative influence values) was generally needed to get a levelling out of the performance curves (see below). Beyond this stabilisation point, one could double or triple the number of predictors in a model, but this would have little effect on overall performance since the new predictors tended to have a very small influence on the model.

3.6.4 Model performance and TEC-habitat relationships

As a means to assess model performance, we plotted the predicted probability of occurrence (PO) values for all plots allocated to a TEC (in descending order) against the same number of highest ranked absence plots. A good model was defined as having high PO values across the majority of TEC presence sites, with a possible drop sharply at the end for those plots that occupy marginal environmental space (and could potentially be misclassified false positives). If there were no overlap in PO values for the lowest ranked presence sites and the highest ranked absence sites, performing a classification using any number between these two values would result in the correct prediction of 100% of presence and absence sites. In such a case, there was no need to present a confusion matrix describing the percentage of sites correctly classified.

In most cases, environmental variables were found to strongly dominate the set of 15 predictors, although occasionally one or two remote sensing variables were selected. However, in the set of 30 predictors, it was common for a number of the original environmental variables to reduce and be replaced by remote sensing variables. We found that models with 15 predictors generally had very good performance with 100% of sites allocated to the TEC and 100% of absence sites correctly classified. However, we also found that doubling the number of predictors generally resulted in a better model. Although a tighter fitting, finer threaded potential distribution map was produced, it was sometimes unclear as to whether the additional variables picked up important variation not captured in the main set of 15 predictors, or whether they simply account for noise in the dataset.

To understand and evaluate the habitat relationships for WGMF, we used a combination of the scaled variable importance values for predictors and shape of the response functions in partial plots as a measure of the strength and nature of interactions. From this, we assessed whether the models were likely to predict onto escarpment slopes and foothills, as we expected them to.

3.6.5 Spatial interpolation

We used the Random Forest models with 15 and 30 variables to create two alternative probability of occurrence maps covering the upper North Coast study area. From the performance plots described above, we selected a single threshold just below the maximum PO across all absence sites to represent the cut of above which the TEC has the potential to occur, and below which, we assumed the TEC is absent.

3.7 Validation

We tested the accuracy of our API maps by targeting two areas within each of the northern and southern populations. We applied a systematic grid over both our mapped polygons and unmapped areas and randomly chose a selection of points for field surveyors to visit and assess for the presence and dominance of *E. dunnii*. At each point, notes were taken as per Section 3.4.2. Any observations of *E. dunnii* during traverses were also recorded.

4 Results

4.1 New survey effort

4.1.1 Stratified survey

We completed only 21 of our planned 150 sample points. Table 8 presents the results of the stratified survey effort. We abandoned this method as field traverses were very slow and our progress encumbered by dense lantana thickets and viney scrub.

Table 8: Stratified survey effort within each state forest accessed showing number of *E. dunnii* observations recorded.

State Forest	Number of Points Visited	Number of *E. dunnii* records at site	Number of *E. dunnii* records during traverse
Mount Lindesay	9	0	0
Unumgar	4	1	1
Edinburgh Castle	3	1	3
Donaldson	4	1	1
Bald Knob	2	0	0
Total	23	3	5

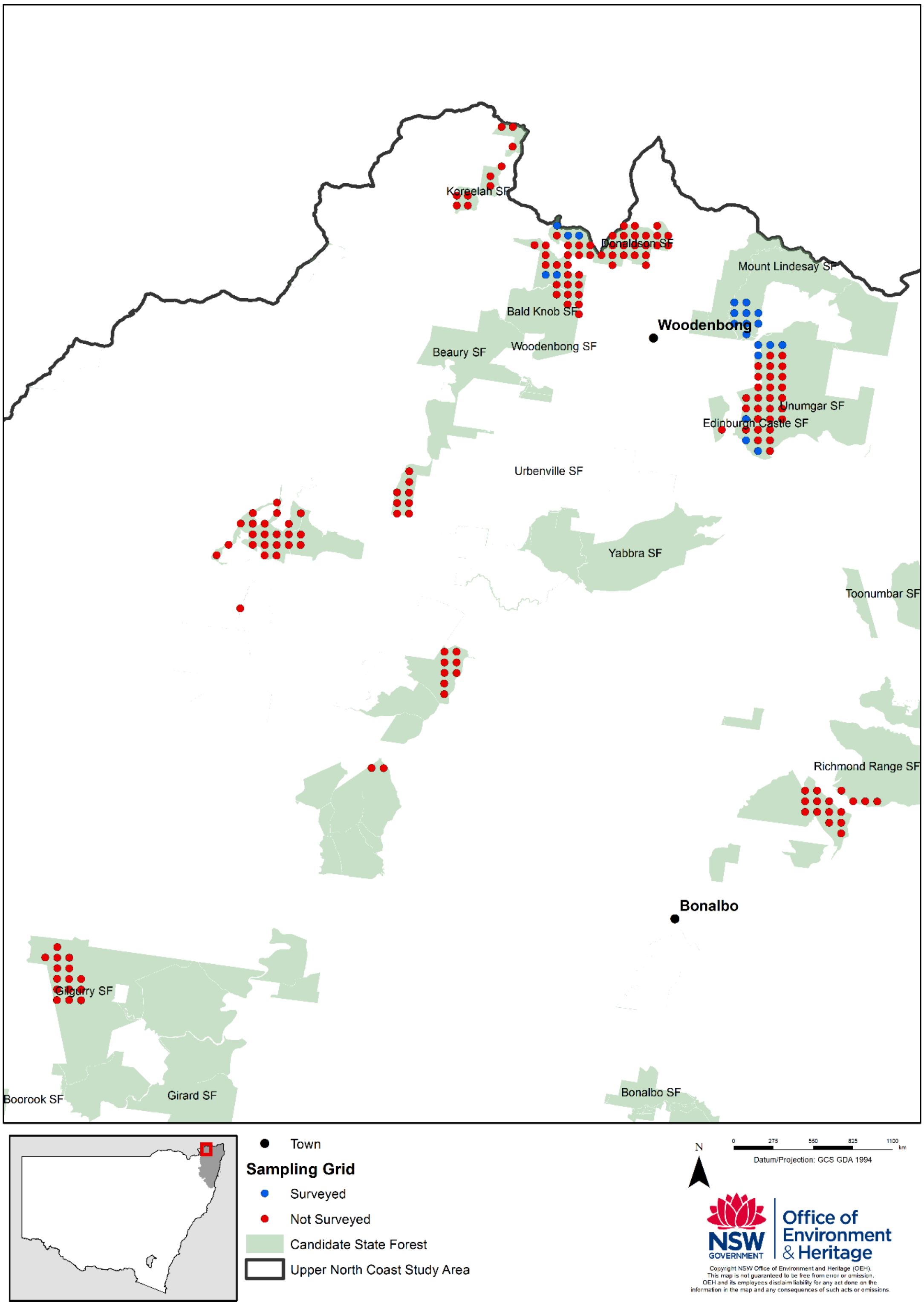
4.1.2 E. dunnii stands

We collected 279 observation points in Kangaroo River State Forest to mark seven patches of *Eucalyptus dunnii* in areas not previously covered by existing mapping. Two smaller patches in the adjoining Bagawa State Forest were defined from seven observation points.

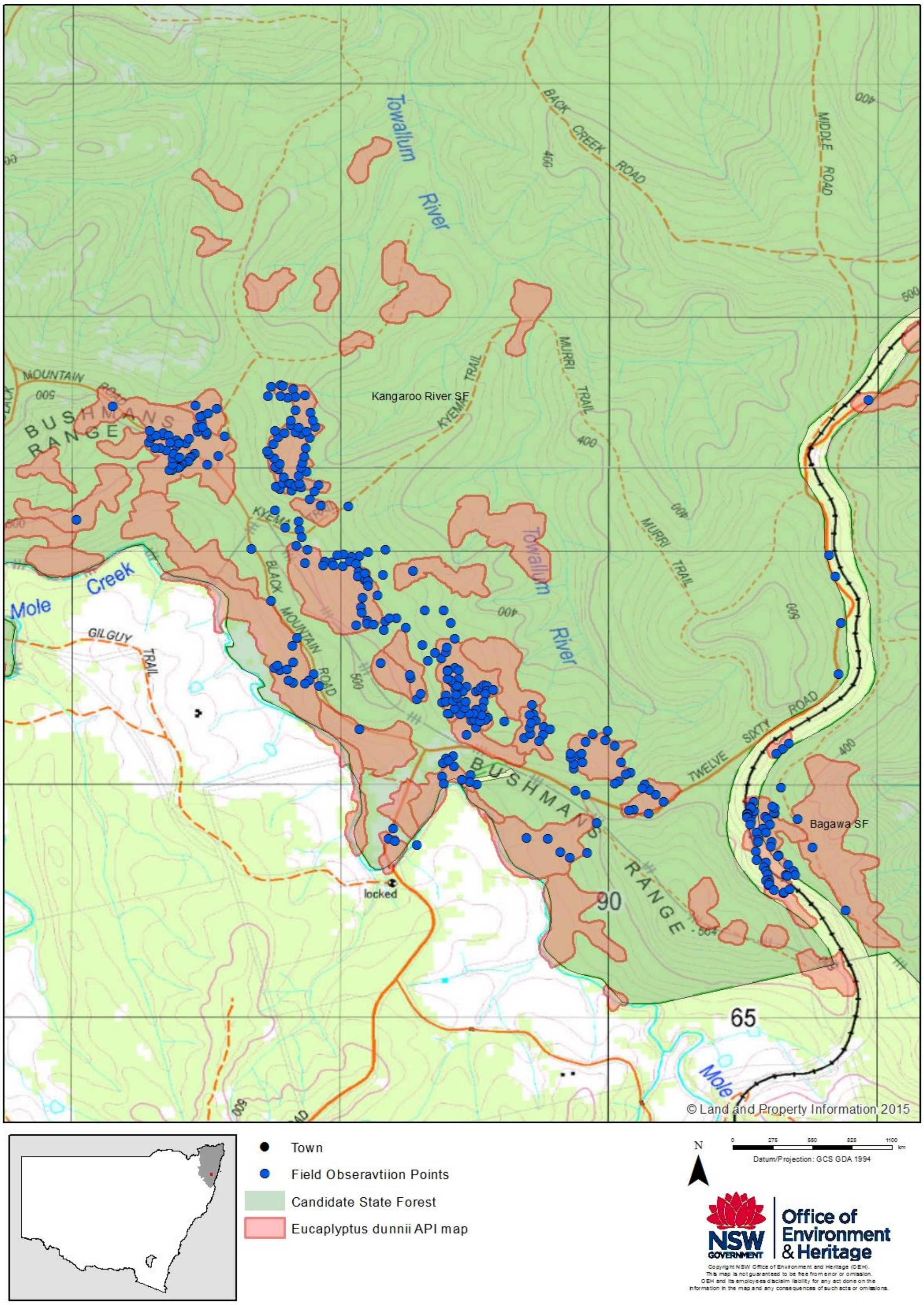
4.1.3 Targeted survey

We traversed 26 hectares of mapped forest type 51 within Clouds Creek State Forest and found no evidence of *E. dunnii*. Stands included *E. saligna* with specimens of *E. dorrigoensis* taken for further identification. Four sites recorded the primary tree species present. No additional evidence was obtained from 19 field observation points completed in the forest during a Koala Habitat Mapping Pilot (NSW Environment Protection Authority 2016).

Map 5: **Visited sites within stratified sampling grid targeting *E. dunnii***



Map 6: **Field observations marking *E. dunnii* stands in Kangaroo River State Forest.**



4.2 Aerial photo interpretation

4.2.1 Summary

We mapped 980 hectares of forest we assessed as dominated or co-dominated by *E. dunnii* across 16 state forests. Table 9 indicates the amount mapped by state forest by confidence levels. Around a third of the mapped area includes polygons that have confirmed the presence of *E. dunnii* during our work or from existing records. However around 50% of our mapping has higher levels of uncertainty in the interpretation of crown signatures used to discriminate *E. dunnii.*

Across both areas, our mapping of *Eucalyptus dunnii* covers over three times the area identified within existing forest type maps for this species.The results of the mapped cover class (Table 10), indicates that most stands are likely to be co-dominant or dominant *E. dunnii*. As we did not attempt to map isolated individuals within larger complexes, the low cover classes contain relatively few mapped polygons.

Table 9: Results of *E. dunnii* mapping within state forests by assigned confidence class.

	Total Area Assessed (Ha)	Total Area Mapped (Ha)	Confidence Class 1 (Ha)	Confidence Class 2 (Ha)	Confidence Class 3 (Ha)	Confidence Class 4 (Ha)
Bagawa SF	5,384	70	15	9	25	21
Bald Knob SF	1,695	13	2	0	8	3
Beaury SF	4,568	215	64	26	49	75
Donaldson SF	2,331	110	35	35	38	2
Edinburgh Castle SF	949	82	63	0	6	12
Gundar SF	119	20	0	2	16	2
Kangaroo River SF	11,399	190	75	57	56	2
Koreelah SF	708	26	10	0	4	12
Mount Lindesay SF	3,046	22	2	8	0	11
Nana Creek SF	1,793	9	0	0	5	4
Orara West SF	4,459	14	0	2	12	0
Richmond Range SF	6,340	18	8	5	0	5
Toonumbar SF	1,528	27	0	0	0	28
Unumgar SF	3,563	14	2	0	0	12
Wild Cattle Creek SF	6,963	18	0	0	18	1
Yabbra SF	8,417	134	24	36	10	65
Grand Total	63,263	980	302	180	247	255

<u>Table 10:</u> Results of *E. dunnii* mapping by mapped Cover Class

Crown Cover Class	Total Area (Ha)	Count of Polygons	Proportion of Area
1 (<10%)	8	4	1%
2 (10-20%)	189	51	19%
3(20-50%)	528	170	54%
4 (50-80%)	255	71	26%
Grand Total	980	296	100%

4.2.2 Northern distribution

Two thirds of the mapped area of *E. dunnii* occurs in forests north of the Bruxner Highway. Beaury, Donaldson and Yabbra State Forests include the largest areas, (Map 7). However, portions of these mapped areas have been assigned lower levels of interpretation confidence. During our field traverses there are a number of eucalypt species that share similar crown signatures including *E. tereticornis* and at lower elevations *E. siderophloia.* Flowering *E. acmenoides* also confused our initial interpretations. Canopy disturbance and stands dominated by regrowth eucalypts similarly reduced interpretation confidence.

Mapping in Gilgurry State Forest, an area with confirmed observations and mapping of *E. dunnii,* was not assessed in our project due to imagery problems.

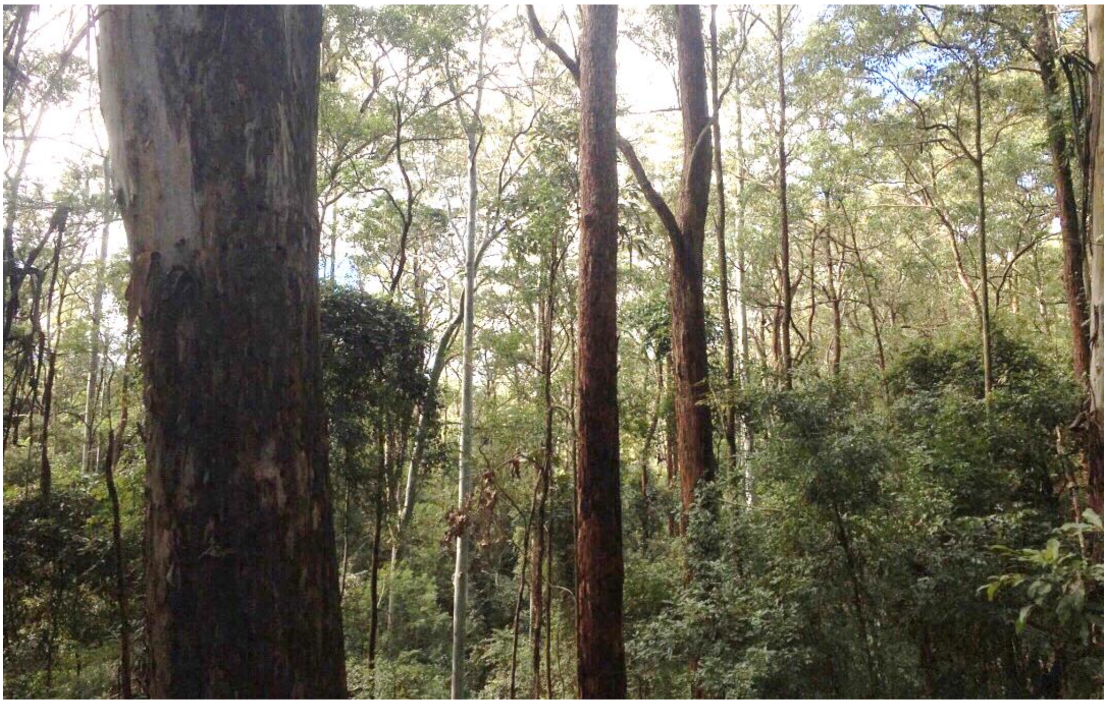
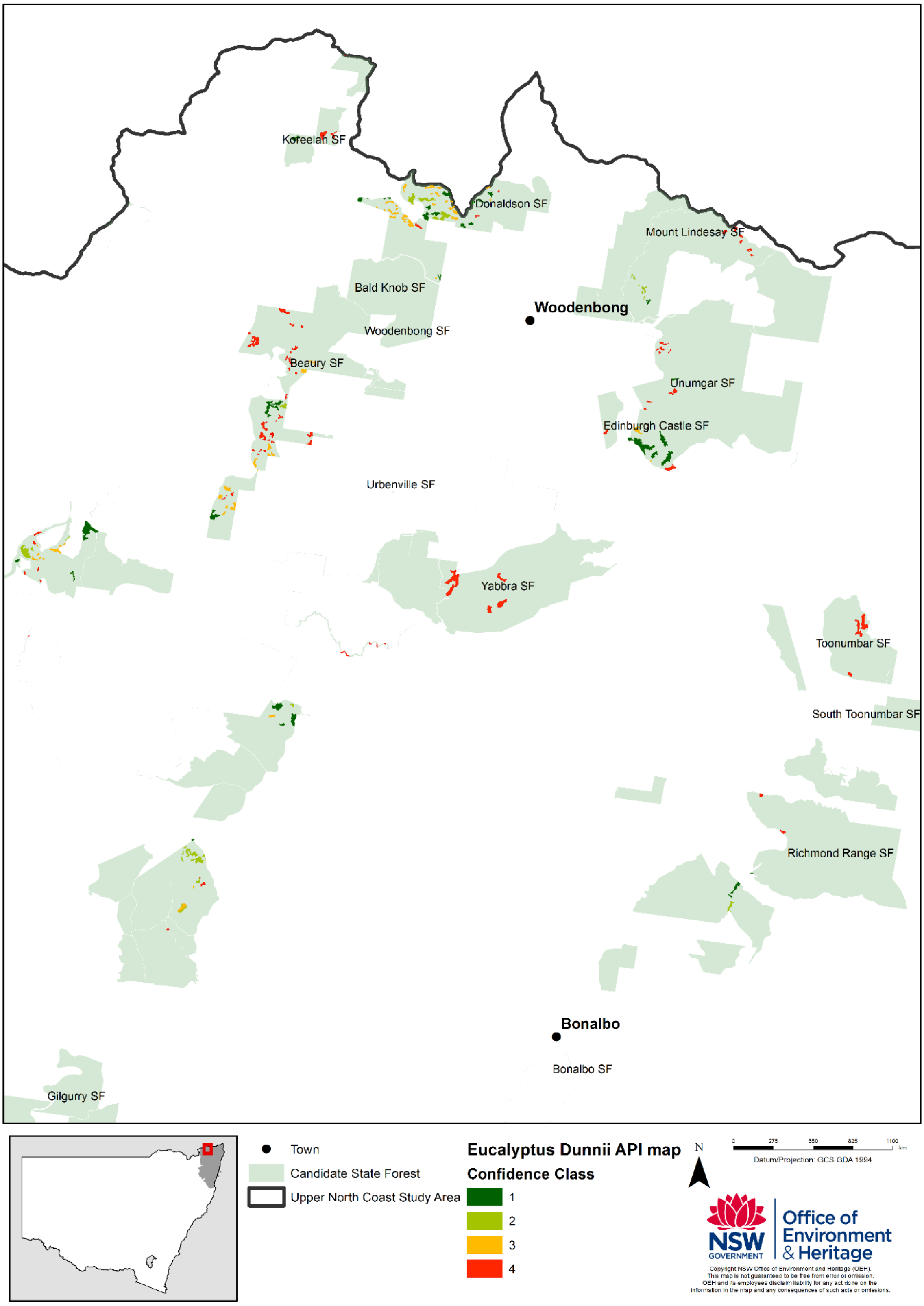


Photo 1: In Beaury State Forest *E. dunnii* sometimes occurs in mixed stands of eucalypts. Here on the edge of Mt Lindsay highway *E. dunnii* (foreground) occurs with *E. microcorys*, *E. saligna* and *E. grandis.*

Photo 2: On the Border trail in Donaldson SF some stands are almost completely dominated by *E. dunnii*

Photo 3: *E. dunnii* can be distinguished by its distinctive bark habitat at certain times of year. This can be helpful separating *E. saligna* and *E. grandis*.

Map 7: **Mapped occurrence of *Eucalyptus dunnii* in the northern area.**

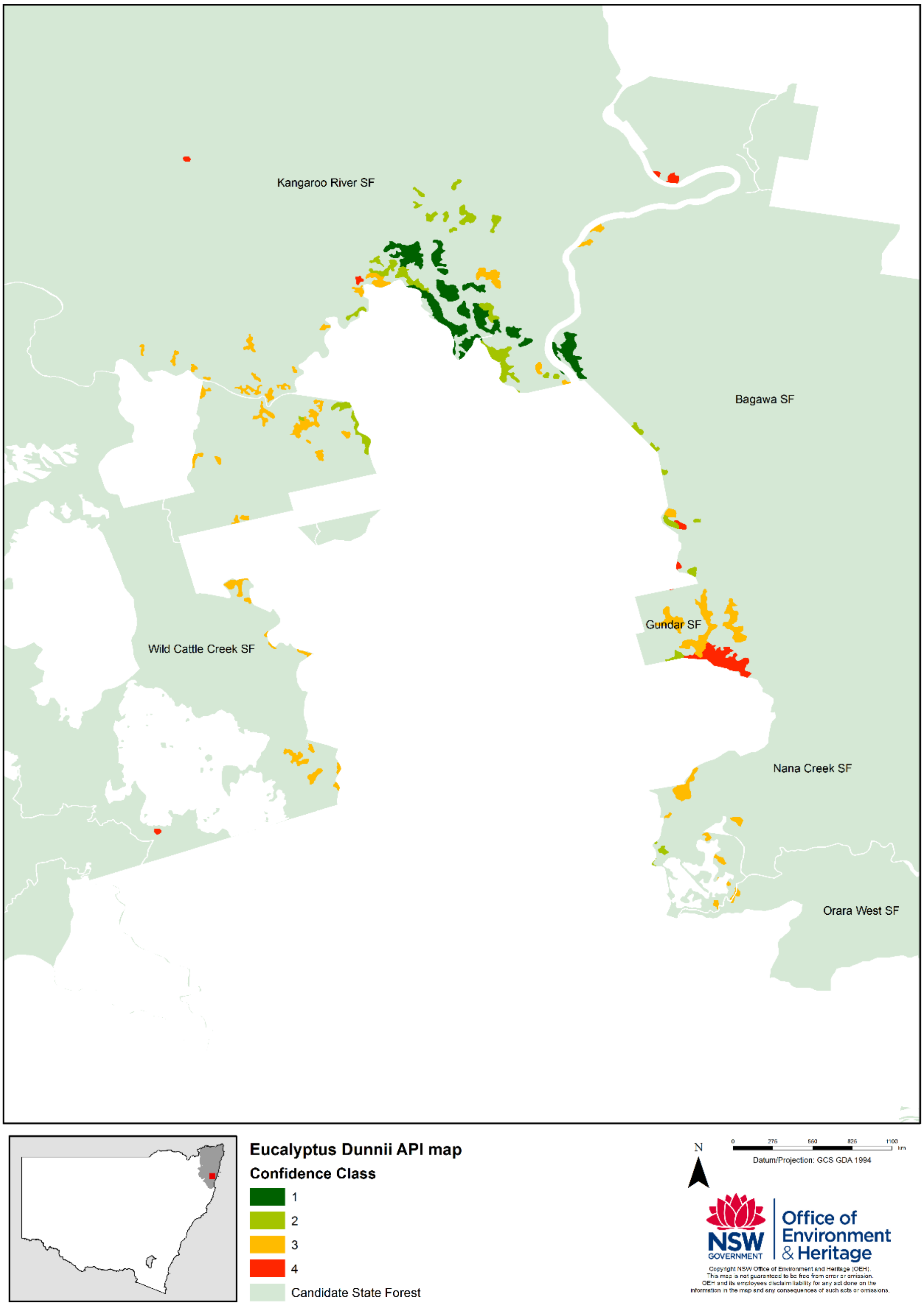


4.2.3 Southern distribution

We mapped 321 hectares within five state forests associated with the southern populations of *E. dunnii* with the largest areas are present within Kangaroo River State Forest, (Map 8). Much of the area within this State Forest has been traversed during intensive field survey. We identified smaller areas within adjoining forests with lower levels of confidence.

We also assessed areas in Clouds Creek State Forest as part of the review of areas with existing mapping. We found no evidence of crown signatures matching *E. dunnii* in this forest.

<u>Map 8:</u> Mapped occurrence of *Eucalyptus dunnii* in the southern area.



4.3 Indicative TEC mapping

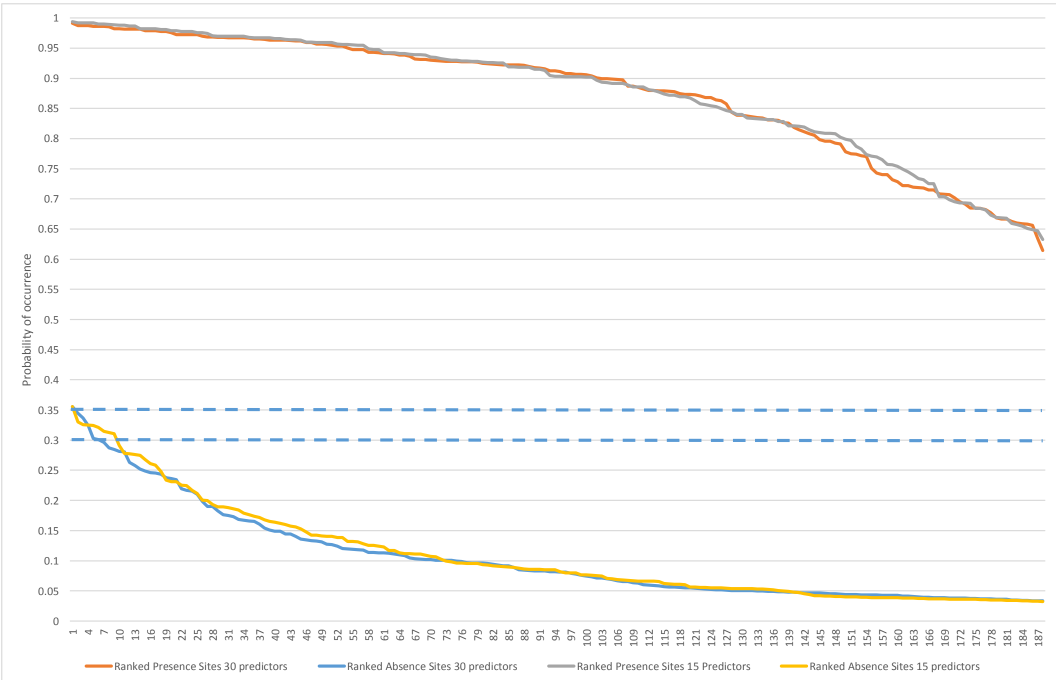
4.3.1 Model performance

Using the site allocation results described above, a Random Forest presence-absence model was used to predict the distribution of WGMF across its range. We developed a model using a subset of 29 of the original 175 predictors, as well as a narrower subset of only 15 predictors.

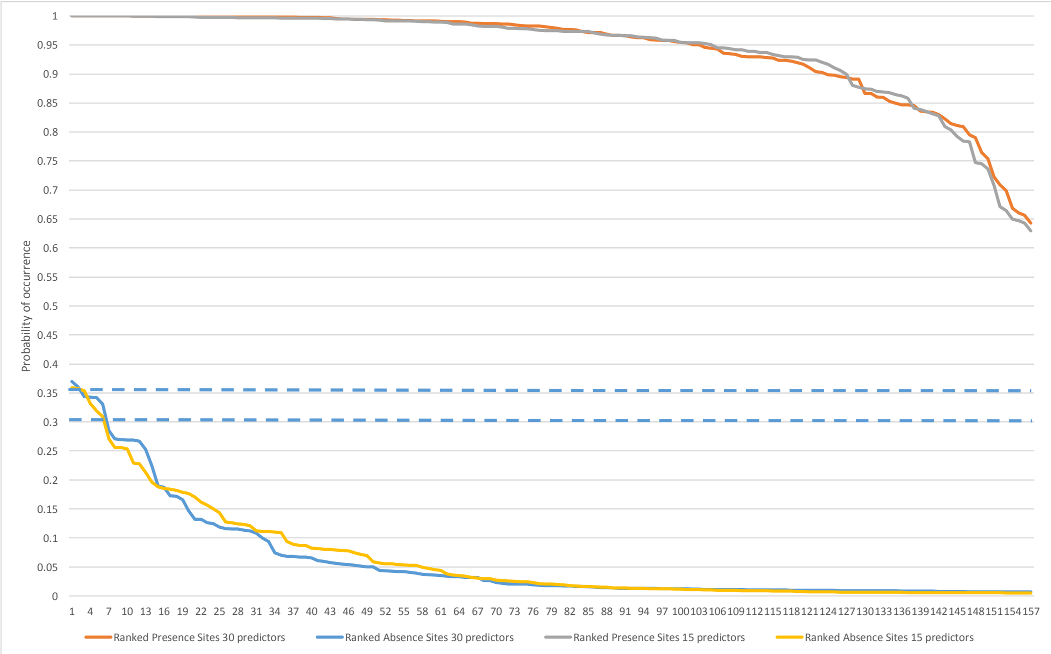
Figure 1 shows plots of the predicted probability of occurrence for sites allocated to WGMF (in order of descending probability) plotted against the same number of highest ranked absence plots. There is no overlap between the lowest probability of occurrence value for a WGMF present site and the highest probability of occurrence for a WGMF absent site. Thus choosing any threshold between these two values results in 100% of all ‘present’ and ‘absent’ sites being correctly classified.

<u>Figure 1</u>: Predicted probability of occurrence (PO) values for sites allocated to each TEC (in order of descending probability) plotted against the PO values for the same number of highest ranked absence plots. The double lines represent models with 15 and 30 predictors. The order of plots are: a) northern population, b) southern population.

A) NTH



B) STH

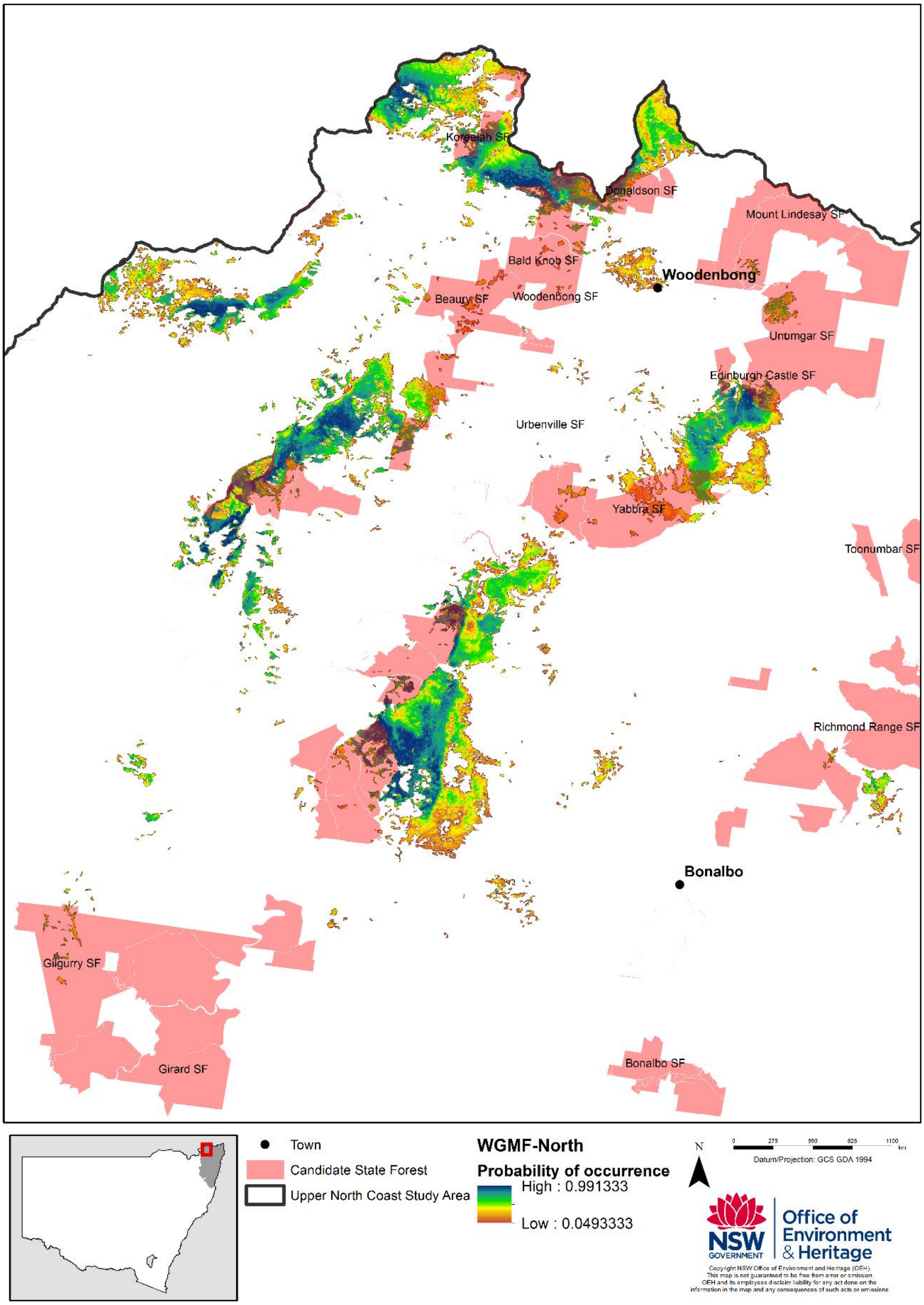


4.3.2 TEC indicative maps

The indicative maps predict the distribution of a TEC based on the probability of occurrence values above a particular threshold. From the modelling, we identified four possible indicative maps for each TEC. This includes two sets of models (each with 15 and 30 predictors), and two thresholds to predict the potential extent of the TEC (0.25 and 0.2). At these thresholds, we accept a very small level of misclassification of absence sites (only 2-4 sites out of more than 5200). This has the effect of expanding out the model just enough to account for spatial inaccuracies that may exist in the data.

All four sets of predicted occurrence maps were examined in ArcGIS using ADS40 imagery as the backdrop, and an assessment made as to which model/threshold best discriminated the underlying habitat features and our understanding of the vegetation patterns. In this case, the model with 29 predictors and the higher of the two thresholds (narrower distribution) produced the models that aligned with our knowledge and these formed the basis for new survey and mapping efforts. Maps 9 and 10 shows the predicted distribution of WGMF within the northern and southern part of the distribution.

Map 9: **Indicative map showing the full extent of the potential distribution of WGMF in the northern part of its range.**



Map 10: **Indicative map showing the full extent of the potential distribution of WGMF in the southern part of its range.**

4.3.3 Environmental relationships

Individual fitted functions for variables in the Random Forest models are useful for determining whether a model matches what we know about the broad distribution and habitat requirements of a TEC. For example, we know from the final determination that WGMF '*typically occurs on the escarpment slopes and foothills of the north-east NSW, most commonly between 400 and 650 metres elevation, where mean annual rainfall exceeds approximately 1000 millimetres and has a summer maximum (DEC 2007). Soils that support the community are relatively fertile and derived from basalt or fine-grained sediments, or colluvium or alluvium influenced by the presence of these substrates upslope or upstream. The community is typically found in gullies and on lower slopes, but has been recorded on upper slopes and basalt ridges (Binns 1995). It occurs less commonly on west-facing slopes than on other aspects*'. Table 10 lists the variables that were selected in models with 15 and 39 predictors. The scaled variable importance values for both models are also provided in Figure 2. These give a measure of the relative contribution each variable has on the overall model, with low standardised variable importance values having relatively little impact on the probability of occurrence values.

For the Northern WGMF model with 30 predictors, a range of climatic variables interact to influence the broad distribution of WGMF across the study area. These include Distance to Coast, Radiation Seasonality, Lowest Period Radiation, Average Rainfall in Spring, and Average Areal Actual Evapotranspiration. At a finer scale, the distribution of the TEC is largely driven by four remote sensing variables that relate to the 5th percentile and mean greenness in summer, and the mean and 95th percentile of dry (no-green) vegetative cover in summer.

For the two Southern models, a range of climatic variables interact to tightly constrain the distribution of WGMF to a relatively small area in Kangaroo River State Forest. These include Highest Period Radiation, Average Areal Actual Evapotranspiration, Average Daily Maximum Temperature in Summer and Distance to Stream Orders 8 and above. Similarly, a broad range of soil profile variables influence the distribution of the TEC at a local level, although soil nitrogen is the only soil profile variable common to both the p30 and p15 models.

The shape of the individual fitted functions for each of the variables are shown in Figure 3. Some of the responses match what we expect for the TEC. For example, with the moist nature of forests is best reflected at a local scale by high greenness indices in summer, while the TECs preference for relatively fertile soils is matched by a strong preference for soils with high soil nitrogen content.

Table 10 List of variables selected in the WGMF Random Forest models with 15 and 30 predictors.

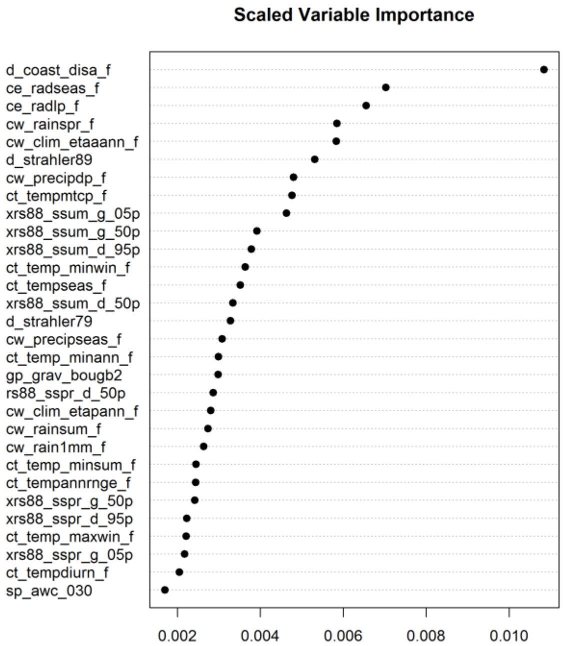
Code	Description	Northern area	Southern area
ce_radhp_f	Highest Period Radiation (bio21)		1*
ce_radlp_f	Lowest Period Radiation (bio22)	1*	
ce_radseas_f	Radiation of Seasonality: Coefficient of Variation (bio23)	1*	
ct_temp_maxsum_f	Average daily max temperature - Summer		1*
ct_temp_maxwin_f	Average daily max temperature - Winter	1	
ct_temp_minann_f	Average daily min temperature - Annual	1	
ct_temp_minsum_f	Average daily min temperature - Summer	1	
ct_temp_minwin_f	Average daily max temperature - Winter	1*	

Code	Description	Northern area	Southern area
ct_tempannrnge_f	Temperature Annual Range: difference between bio5 and bio6 (bio7)	1	1
ct_tempdiurn_f	Mean Diurnal Range (Mean(period max-min)) (bio2)	1	1
ct_tempiso_f	Isothermality 2/7 (bio3)		1*
ct_tempmtcp_f	Min Temperature of Coldest Period (bio6)	1*	
ct_tempseas_f	Temperature Seasonality: Coefficient of Variation (bio4)	1*	1*
cw_clim_etaaann_f	Average areal actual evapotranspiration - Annual	1*	1*
cw_clim_etapann_f	Average areal potential evapotranspiration - Annual	1	
cw_precipann_f	Annual Precipitation (bio12)		1*
cw_precipdp_f	Precipitation of Driest Period (bio14)	1*	
cw_precipseas_f	Precipitation of Seasonality: Coefficient of Variation (bio15)	1	1*
cw_precipwp_f	Precipitation of Wettest Period (bio13)		1*
cw_rain1mm_f	Average Number of days with rainfall greater than 1mm Annual	1	1
cw_rainspr_f	Average Rainfall - Spring	1*	1*
cw_rainsum_f	Average Rainfall - Summer	1	1
d_coast_disa_f	Distance from NSW East Coast (Euclidian)	1*	
d_flooded	Distance (Euclidean) from seasonally flooded water bodies		1*
d_permwater	Distance (Euclidean) from permanent water bodies		1*
d_strahler49	Euclidean distance to 4th order streams and above		1
d_strahler79	Euclidean distance to 7th order streams and above	1	
d_strahler89	Euclidean distance to 8th order streams and above	1*	1*
gp_grav_bougb2	Bouguer gravity - band 2	1*	
lf_rough1000_f	Neighbourhood topographical roughness based on the standard deviation of elevation in a circular 1000 m neighbourhood. Derived from DEM-S		1
sp_awc_030	Available water capacity (15 - 30cm)	1	
sp_bdw_060	Bulk density (30 - 60cm)		1
sp_bdw_100	Bulk density (60 - 100cm)		1
sp_bdw_200	Bulk density (100 - 200cm)		1
sp_cly_005	Clay content (%) (0 - 5cm)		1
sp_nto_005	Total nitrogen (%) (0 - 5cm)		1*
sp_nto_015	Total nitrogen (%) (5 - 15cm)		1*
sp_nto_030	Total nitrogen (%) (15 - 30cm)		1*
sp_snd_100	Sand content (%) (60 - 100cm)		1
sp_snd_200	Sand content (%) (100 - 200cm)		1
sp_soc_015	Soil Organic Carbon (%) (5 - 15cm)		1
sp_soc_030	Soil Organic Carbon (%) (15 - 30cm)		1

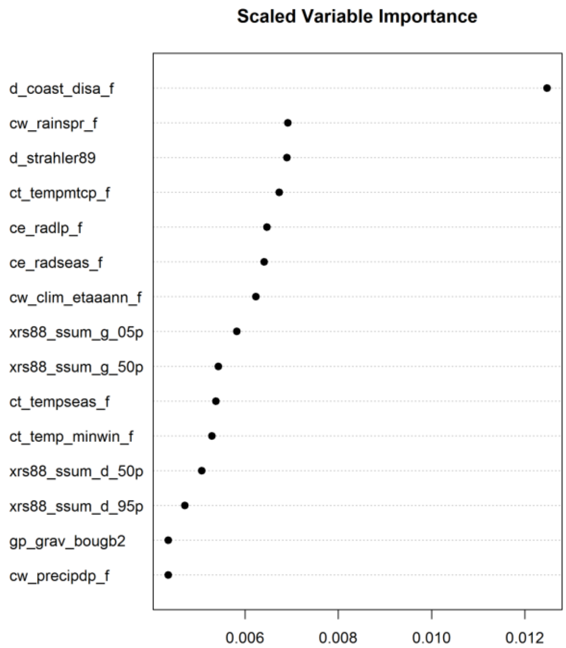
Code	Description	Northern area	Southern area
xrs88_sspr_d_50p	Landsat 25-year seasonal dry (non-green) vegetation in spring (50th percentile)	1	
xrs88_sspr_d_95p	Landsat 25-year seasonal dry (non-green) vegetation in spring (95th percentile)	1	
xrs88_sspr_g_05p	Landsat 25-year seasonal greenness in spring (5th percentile)	1	1
xrs88_sspr_g_50p	Landsat 25-year seasonal greenness in spring (50th percentile)	1	
xrs88_ssum_d_50p	Landsat 25-year seasonal dry (non-green) vegetation in summer (50th percentile)	1*	
xrs88_ssum_d_95p	Landsat 25-year seasonal dry (non-green) vegetation in summer (95th percentile)	1*	
xrs88_ssum_g_05p	Landsat 25-year seasonal greenness in summer (5th percentile)	1*	
xrs88_ssum_g_50p	Landsat 25-year seasonal greenness in summer (50th percentile)	1*	

Figure 2: Scaled variable importance values in relation to models with 30 and 15 predictors. a) northern population, b) southern population.

a1)

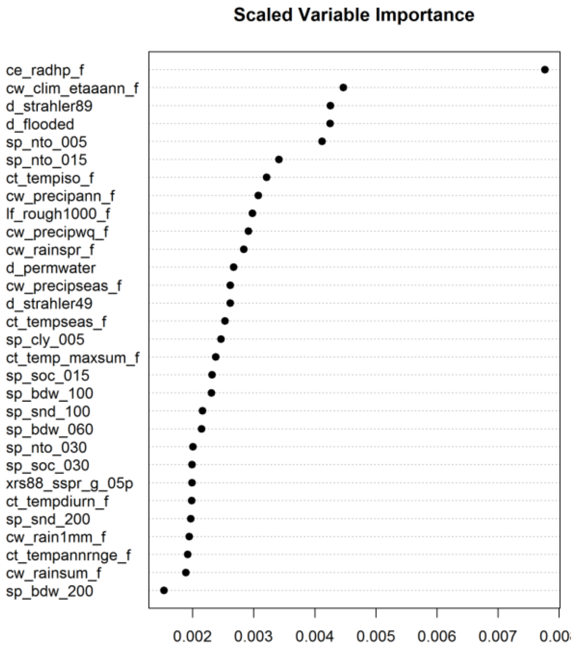


a2)



b1)

b2)


Scaled Variable Importance
ce_radhp_f
cw_clim_etaaann_f
d_strahler89
d_flooded
sp_nto_005
sp_nto_015
ct_tempiso_f
cw_precipann_f
lf_rough1000_f
cw_precipwq_f
cw_rainspr_f
d_permwater
cw_precipseas_f
d_strahler49
ct_tempseas_f
sp_cly_005
ct_temp_maxsum_f
sp_soc_015
sp_bdw_100
sp_snd_100
sp_bdw_060
sp_nto_030
sp_soc_030
xrs88_sspr_g_05p
ct_tempdiurn_f
sp_snd_200
cw_rain1mm_f
ct_tempannrnge_f
cw_rainsum_f
sp_bdw_200
0.002
0.003
0.004
0.005
0.006
0.007

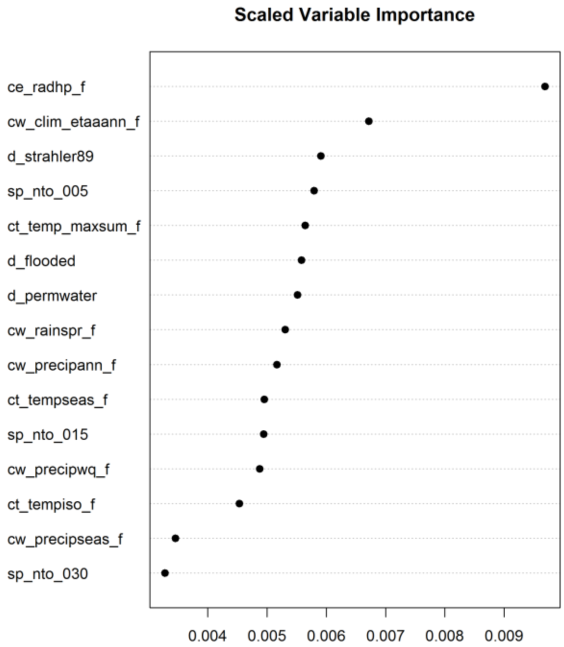
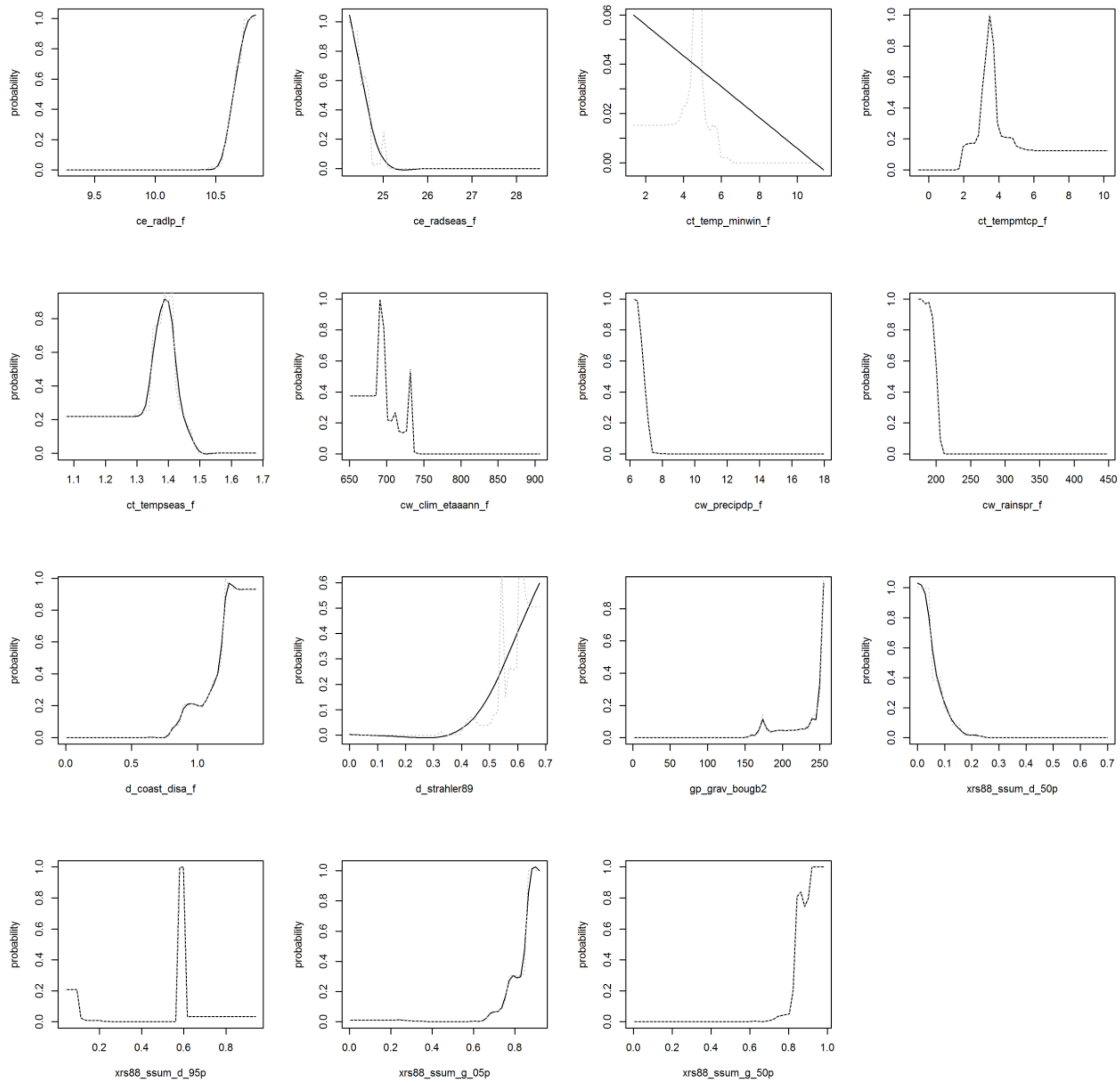
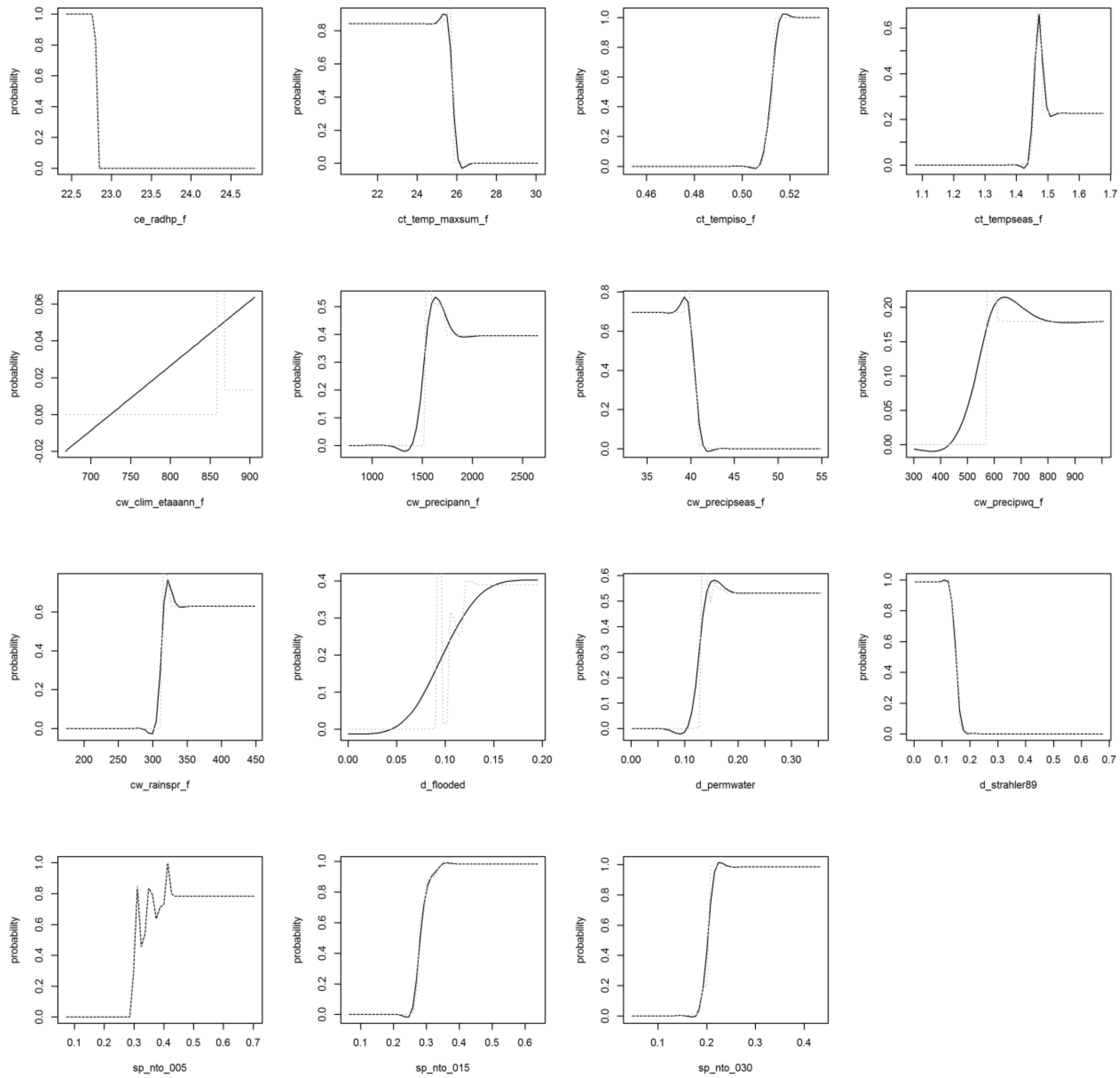

Scaled Variable Importance
ce_radhp_f
cw_clim_etaaann_f
d_strahler89
sp_nto_005
ct_temp_maxsum_f
d_flooded
d_permwater
cw_rainspr_f
cw_precipann_f
ct_tempseas_f
sp_nto_015
cw_precipwq_f
ct_tempiso_f
cw_precipseas_f
sp_nto_030
0.004
0.005
0.006
0.007
0.008
0.009

Figure 3: Shape of individual fitted functions in relation to models with 15 predictors. a) northern population, b) southern population.

a)



b)



4.4 Validation

4.4.1 Northern area

Edinburgh Castle State Forest

We visited the Brumby Plains Road area of Edinburgh Castle and assessed the presence of *E. dunnii* within mapped and unmapped areas. We collected 24 observation points from six mapped polygons covering 75 hectares. Four of these polygons had at least one *E. dunnii* observation from the NSW Wildlife Atlas enclosed within. Two polygons overlapped existing forest type mapping, two partially overlapped and two had no previous mapping.

Map 11 and Table 11 shows the results of sites and traverses. Overall, we recorded *E. dunnii* present within our mapped polygons at 75% of sites visited however at only half of those sites was *E. dunnii* assessed as dominant. Individual polygons recorded mixed scores indicating presence and dominance, presence only and absence suggesting that polygons comprise a mixed cover of *E. dunnii*. There were too few sites to make comparisons against mapped cover classes.

Fewer sites were visited outside mapped areas. Isolated trees and small patches occurred outside mapped areas at three of the eight sites completed.

Table 11 Validation results and sample points in Edinburgh Castle State Forest

Zone	Number Sites	Proportion of Sites%
Within Mapped Polygon		
Present	9	37.5
Dominant	9	37.5
Present or Dominant	18	75
Absent	6	25
Subtotal	24	100
Outside Mapped Polygon		
Present	3	37.5
Dominant	0	0
Present or Dominant	3	37.5
Absent	5	62.5
Subtotal	8	100

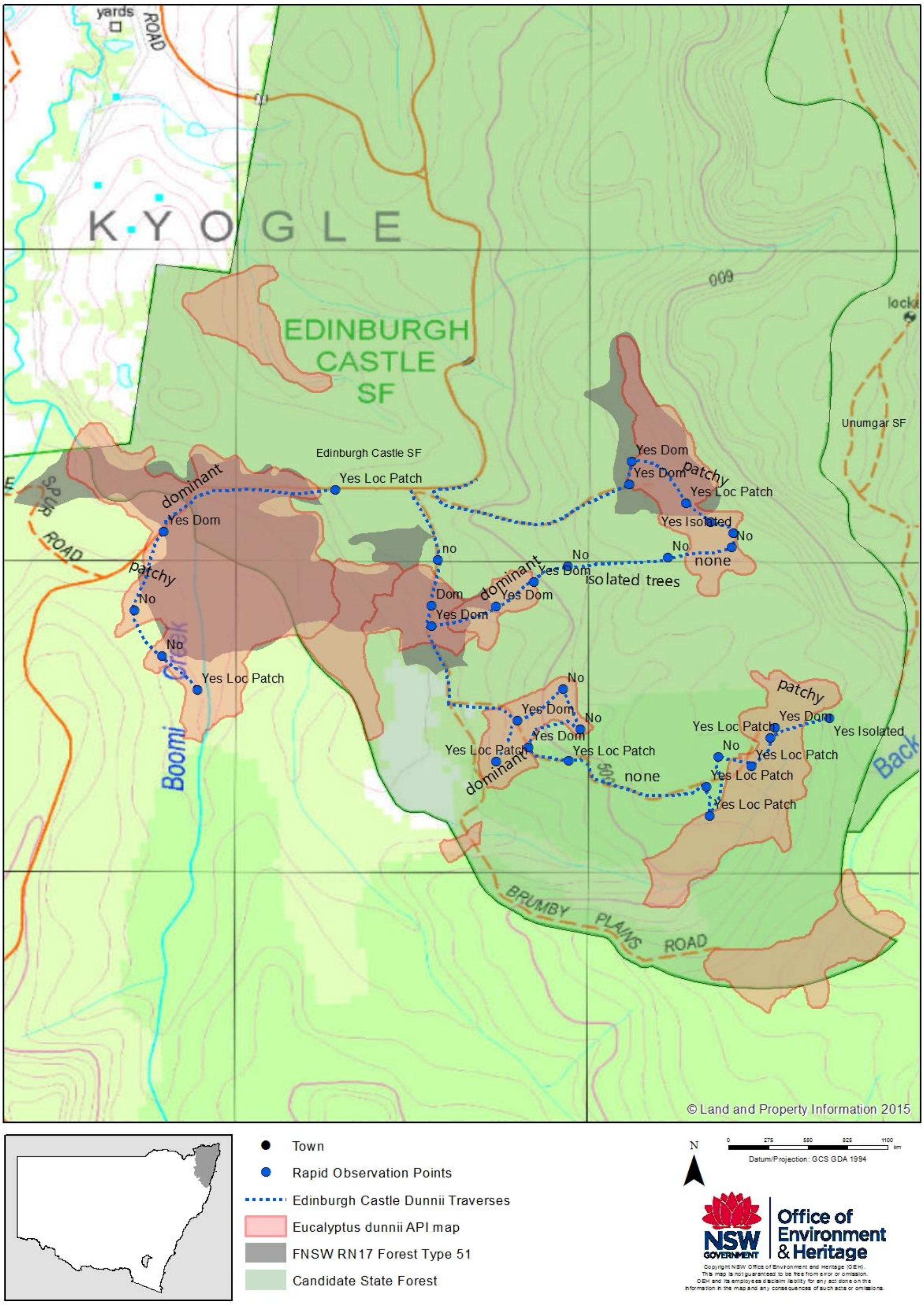
Donaldson State Forest

We visited six sites in the Border Trail area, five of which were located outside mapped polygons and one within. The latter was mapped as *E. dunnii* within existing forest type mapping and covered six hectares. We did not record *E. dunnii* outside our mapped areas and found the species dominant within part of the mapped polygon.

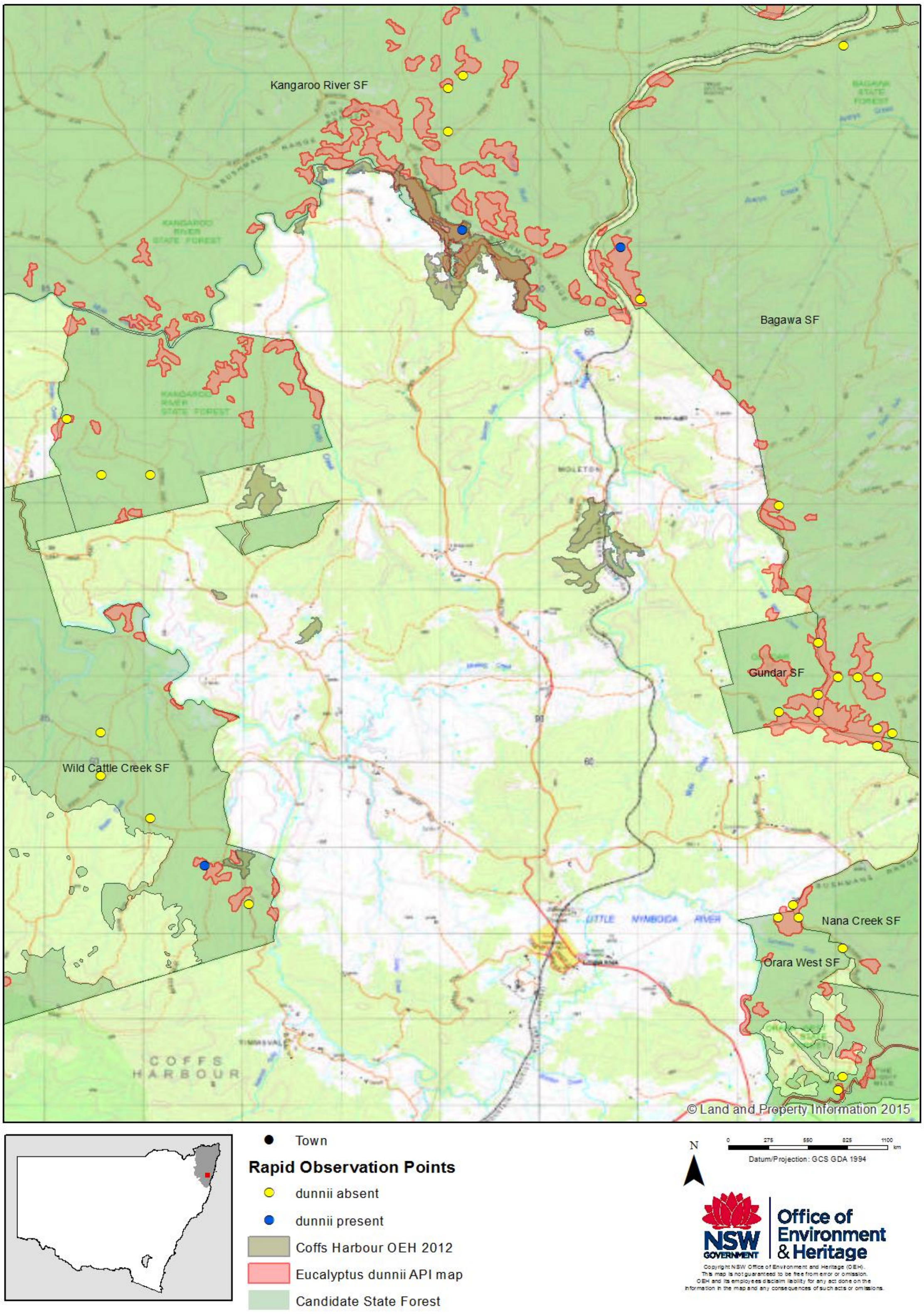
Beaury State Forest

We visited seven sites in the Kangaroo Creek trail area, three within mapped polygons and four outside. Both mapped polygons (covering 34 hectares) were also included within forest type mapping and included existing observations. We found *E. dunnii* dominant in all mapped polygons and no evidence outside mapped areas.

Map 11: **Validation traverses for mapped polygons in Edinburgh Castle State Forest.**



Map 12: **Validation points located within Kangaroo River, Bagawa, Gundar, Nana Creek, Orara West and Wild Cattle Creek State Forests.**



4.4.2 Southern area

We visited the Lowanna district and assessed the presence and abundance of *E. dunnii* in an area with limited previous mapping or observation data. A total of 20 sites sampling seven mapped polygons was completed and a further 6 sites outside mapped areas. We also sampled four additional polygons in Kangaroo River State Forest in an area previously intensively sampled by our survey.

In the Lowanna district, the results were poor with one site supporting *E. dunnii* and absent at 15 sites. These sites sampled polygons attributed with lower interpretation confidence levels however, no *E. dunnii* was found during either traverses or travel to and from sample areas. In Kangaroo River State Forest, there were fewer sites within mapped polygons although these returned positive results at three out of four sites. Collectively in the area, no *E. dunnii* was recorded outside of mapped polygons during validation surveys.

Table 12 Validation results and sample points in Lowanna District in Bagawa, Kangaroo River State Forest

Zone	Number Sites	Proportion of Sites%
Within Mapped Polygon		
Present	4	16
Dominant	2	8
Present or Dominant	6	24
Absent	19	76
Subtotal	25	100
Outside Mapped Polygon		
Present	0	0
Dominant	0	0
Present or Dominant	0	0
Absent	9	0
Subtotal	9	100

5 Discussion

5.1 Summary of survey and mapping

The results from our provisional validation produced mixed results. This introduces significant uncertainty for the use of the maps for operational applications. Generally, it appears that both our API and predictive models overestimate the extent of *E. dunnii* present in state forest and are likely to bound areas that are completely or in part dominated or co-dominated by other eucalypts. Our mapping and survey also indicates that existing forest type mapping significantly underestimates the extent of *E. dunnii* and we conclude that these maps alone are not suitable for operational purposes. However as the existing forest type mapping was used as a basis for field investigations (Benson & Hager 1993) many forest type polygons contain independent *E. dunnii* observations. This provides some certainty that these polygons are likely to contain *E. dunnii* but there is less certainty that the species is dominant or that the mapped boundaries represent the full extent in the locality.

Our API mapping indicates that there are interpretable crown signatures associated with *E. dunnii* but that mapping needs to be supported by higher levels of field reconnaissance to build greater confidence in extrapolations to unvisited areas.

We recommend that both our API maps and forest maps be used as a basis for highlighting state forests requiring field based assessment methods until further mapping work is completed.

5.2 Summary of interpretation

5.2.1 Cited vegetation communities and determination species assemblage list

The application of TEC Reference Panel principles to the floristic attributes of White Gum Moist Forest TEC in the north coast region was simplified by the reliance on *E. dunnii* as the primary diagnostic attribute. This is consistent with statements in the final determination relating to characteristic species and the use of the eucalypt to define the area of occupancy for the threat assessment. Notwithstanding this, some uncertainty remains, because a TEC is defined as an assemblage of species. In the determination for WGMF, it is uncertain, whether the ecological community is defined by the species assemblage or by *E. dunnii* itself. The extent to which floristic assemblages referable to the determination list, and which are not dominated by *E. dunnii* are included as TEC is untested. Such an interpretation is likely to significantly extend the range of the community and conflict with the stated threat assessment. We were unable to resolve this uncertainty for this project.

5.2.2 Distribution and habitat descriptors

The final determination includes a set of environmental descriptors that assist in locating White Gum Moist Forest on the North Coast. We found general agreement with the elevation thresholds (400 to 650 metres above sea level) described in the determination. However, there are locations where *E. dunnii* occurs around 750 metres above sea level, mostly around Beaury State Forest and Tooloom State Forest.

5.3 TEC Panel review and assessment

5.3.1 Summary of discussions

The results of the community analysis and map products were subject to a review process by the TEC panel. Table 13 presents the summary of the findings.

Table 13: Summary of issues and Panel review of WGMF

Determination	TEC Panel Principles	Our Project	TEC Panel Review
Occurs in "….North Coast Bioregion"	Accept Bioregional Qualifiers	Adopted	Agreed
Typically occurs on the escarpment slopes and foothills of the north east of NSW most commonly between 400-650m in elevation and where mean annual rainfall exceeds approximately 1000mm.	Assess habitat descriptors and whether these constrain or define the limits of the TEC which otherwise may have a broader distribution	Indicative only. Modelled areas and API methods applied at higher elevations to cover known areas exceeding 750m asl	Agreed
Soils that support the community are relatively fertile and derived from basalt or fine-grained sediments, or colluvium or alluvium influenced by the presence of these substrates upstream. The community is typically found in gullies and on lower slopes, but has been recorded on upper slopes and basalt ridges.		Indicative only	Noted
White Gum Moist Forest includes 'Dunn's White Gum' (Forest Type 51) habitat of Eucalyptus dunnii is described by Benson and Hager (1993), 'Eucalyptus dunnii' (Floristic Group 73) of NPWS (1995), 'Eucalyptus dunnii' Community (URBov8) of Binns (1995) and 'Dunn's White Gum Community' (Forest Ecosystem 45 of NPWS (1999).	Assess references to existing vegetation classification sources in the determination. The panel will note whether the existing classifications are "included within" are "part of" or "component of" the determination.	Indicative, noted that all references cited were overstorey classifications based on the dominance of E. dunnii	Noted
Characterised by the list of 86 plant species	Be guided by the species lists presented in the determination	We used E. dunnii as the surrogate for the species assemblage	Agreed
In NSW is currently known from the local government areas of Clarence Valley, Coffs Harbour, Kyogle and Tenterfield, but may occur elsewhere within the bioregion. In addition, suitable habitat for the community is predicted to occur within the LGAs of Bellingen, Glen Innes-Severn and Tenterfield.	consider the precise wording of location descriptors and administrative boundaries that identify any LGAs by name, as to whether the entity "occurs within" or is "recorded or known from" or has qualifiers that indicate it "may be known from elsewhere in bioregion";	Not constrained to stated LGAs	Agreed

Determination	TEC Panel Principles	Our Project	TEC Panel Review
A map of forest ecosystems in north-eastern NSW (NPWS 1999), shows less than 1000 ha of 'Dunn's White Gum Community' (Ecosystem 45) throughout the range of Eucalyptus dunnii in NSW, suggesting that less than 1% of modelled suitable habitat is occupied by the community (DEC 2007). Based on available mapping and site records, and using a grid scale of 4 km2 (as recommended by IUCN 2006, White Gum Moist Forest is estimated to occupy an area of about 600 km2.	ensure that interpretations of distribution are consistent with the threat assessment, including threatening processes, that are documented in the determination;	Consistent with use of E. dunnii to assess total distribution and area of occupancy	Agreed.

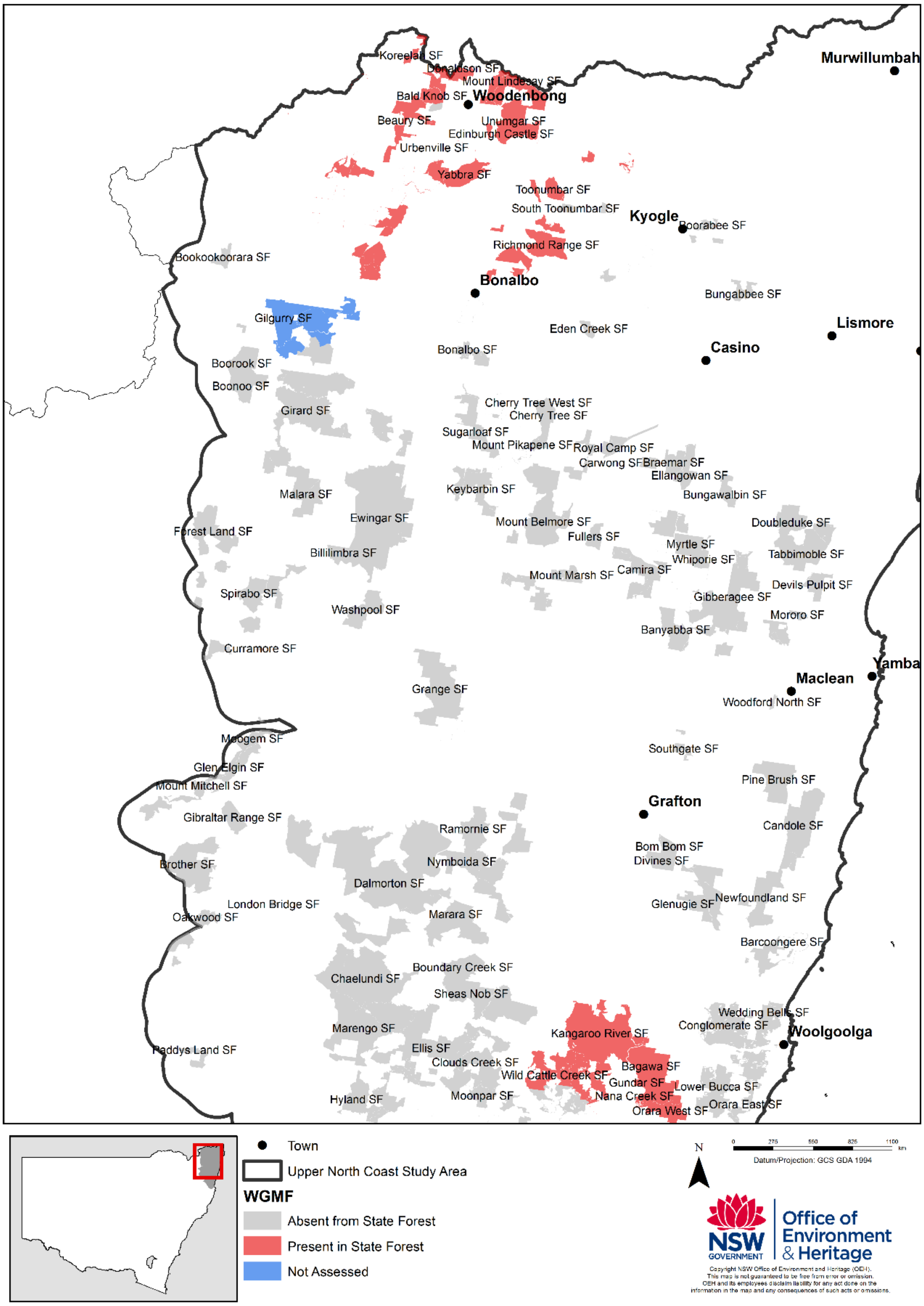
5.4 Final state forest-TEC occurrence matrix

Table 14 lists state forests known or likely to include White Gum Moist Forest TEC within the north coast bioregion. This is based on new and existing field data and mapping. We exclude Clouds Creek State Forest following field validation of mapped polygons and include Gilgurry State Forest, which was not assessed during our project but supports both mapping and existing observations of *E. dunnii.*

Table 14 State forests known to include observations or mapped areas of White Gum Moist Forest TEC.

State Forest	Total State Forest Area (ha)
Bagawa SF	5,384
Bald Knob SF	1,695
Beaury SF	4,568
Donaldson SF	2,328
Edinburgh Castle SF	949
Gilgurry SF	9,531
Gundar SF	119
Kangaroo River SF	11,399
Koreelah SF	673
Mount Lindesay SF	3,045
Nana Creek SF	1,793
Orara West SF	4,459
Richmond Range SF	6,340
South Toonumbar SF	410
Toonumbar SF	1,528
Unumgar SF	3,563
Wild Cattle Creek SF	9,667
Woodenbong SF	306
Yabbra SF	8,417
Total	76174

<u>Map 13:</u> **State forests with mapped occurrences of *Eucalyptus dunnii***



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Appendix A: Field key for identification of White Gum Moist Forest in the NSW North Coast Bioregion

This key assumes the vegetation to be assessed is in NSW North Coast Bioregion. White Gum Moist Forest TEC (WGMF) by definition does not occur outside this Bioregion.

While the determination for WGMF provides a list of characteristic species (68), the primary diagnostic attribute of this TEC is the dominance of *Eucalyptus dunnii* in the over storey, either in pure stands, or with other species. *Eucalyptus dunnii* is taken to be an indicator for the assemblage within the WGMF Indicative Map area.

Assessment should be done in 20m x 20m plots or areas of similar size. The more plots assessed, the more reliable the result. This key is based on distinguishing WGMF from other vegetation communities including other TECs, although vegetation identified as WGMF by this key may also, or alternatively depending on degree of floristic overlap, belong to other TECs such as Grey Gum Grey Box Wet Sclerophyll Forest.

1. Is *Eucalyptus dunnii* present?

   If yes, the vegetation may be WGMF

   If no, the vegetation is not WGMF

2. Is *Eucalyptus dunnii* dominant (≥50% projected foliage cover*)?
   If yes, the vegetation is WGMF
   If no, the vegetation is not WGMF

Note: *E dunnii* can be challenging to identify. Primary diagnostic attributes to distinguish E dunnii from other eucalypt species (E. *saligna*, *E. grandis* and *E. tereticornis*) include fruit, buds, shape and colour of juvenile and adult leafs, and bark habit. Limited access to identification material can mean that the presence of the species may remain uncertain until a suitable time of year.

* crown cover may be a more effective measure of dominance in areas where E dunnii foliage is affected by dieback.