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Koala survey of the Mid North Coast assessment area

Department of Climate Change, Energy, the Environment and Water

Acknowledgement of Country

Department of Climate Change, Energy, the Environment and Water acknowledges the Traditional Custodians of the lands where we work and live.

We pay our respects to Elders past, present and emerging.

This resource may contain images or names of deceased persons in photographs or historical content.

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Cover photo: Koala (*Phascolarctos cinereus*) in forest red gum (*Eucalyptus tereticornis*). John Turbill/DCCEEW

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Summary

In 2023, the NSW Government committed to establishing a Great Koala National Park on the Mid North Coast. The 'assessment area' is the 176,000 ha of state forest that is being considered for inclusion in the proposed Great Koala National Park. The assessment area does not include existing national park estate.

To provide high-quality data on the koala (*Phascolarctos cinereus*) populations in the assessment area, the Science and Insights' Koala Science Team within the NSW Department of Climate Change, Energy, the Environment and Water (the department) developed a survey design for the assessment area. Koala surveys commenced in 2024, with assistance from the department's National Parks and Wildlife Service, and the Forestry Corporation of NSW.

The objectives of this survey were to:

1. determine the geographic distribution and abundance of koalas within the assessment area
2. ascertain underlying relationships between koalas and environmental parameters.

The Koala Science Team surveyed 169 sites using drones across the 'study area' during the period of 2 April to 12 July 2024. The study area encompasses both state forest and national parks, that is, the assessment area plus the area of national park that was surveyed. Of these 169 sites, 120 (71%) were on state forest and 49 (29%) were on national park. The survey effort undertaken to count koalas in the study area was significant and involved more than 4,000 km of drone flight, at night, by a team of 26 drone pilots.

Overall, findings show substantial spatial variation in the abundance and distribution of koalas in the assessment area.

Summary of findings

- The estimated population of koalas in the assessment area is 10,311 to 14,541 koalas (95% confidence interval), with a mean estimate of 12,111 koalas.
- Koalas were detected throughout the assessment area, with at least one koala detected at 63% of sites.
- A total 212 koalas were detected during the surveys across 75 sites in the assessment area, with koala detections ranging from 0 to 12 per site.
- The central-east section of the assessment area had substantially higher koala densities compared to other parts of the assessment area. The northern assessment area was mostly associated with low, or no, koalas detected at sites.
- Positive relationships were found between koala abundance and vegetation health, depth of soil profile and preferred tree species, highlighting the significance of habitat quality to koala abundance.

- A negative relationship was found between koala abundance and areas most severely impacted by the 2019–20 fires.

Introduction

NSW Government commitment

Koalas (*Phascolarctos cinereus*) were listed as an endangered species in New South Wales in 2022, and the combined populations of New South Wales, Queensland and the Australian Capital Territory were listed as endangered by the Australian Government in 2022. The 2020 inquiry into NSW koala populations and habitat concluded that, without action, koalas in New South Wales could be extinct by 2050 (NSW Parliament 2020). They face increasing and cumulative threats from habitat loss, fragmentation and climate change leading to more intense and frequent heatwaves, drought and bushfires. These landscape-scale threats are exacerbated by the impacts of local threats, such as vehicle strike, dog attack and disease (NSW Chief Scientist and Engineer 2016).

It is accepted that koala populations will need large areas of connected and preferably high-quality habitat to persist in the wild into the future. The NSW Government has committed to establishing a Great Koala National Park on the Mid North Coast. The area of state forest to be assessed for inclusion in the Great Koala National Park is approximately 176,000 ha (Figure 1), is referred to as the 'assessment area', and does not include flora reserves or plantations.

Of the 10 strongholds for koalas identified by the *NSW koala strategy: towards doubling the number of koalas in New South Wales by 2050* (DPE 2022), 3 occur within or adjacent to the assessment area. The koala strategy prioritises strategic action in stronghold areas to reduce major threats and improve available habitat.

Purpose

The purpose of this report is to provide detail on the survey findings which are intended to support NSW Government decision-making in relation to the assessment area.

The report provides a current map of koala sightings and predicted population abundance in the assessment area, together with an overall koala population estimate for the assessment area. This data was gathered at an ecologically significant scale utilising cutting-edge aerial drone technology specifically designed for koala surveys. This approach is now considered one of the best methods to accurately count koalas (Beranek et al. 2024). Rigorous modelling was then undertaken to understand key ecological and environmental influences associated with koala abundance across the assessment area.

Objectives

In 2023, the department's Koala Science Team developed a survey design for the study area (that is, the assessment area plus the area of national park that was included), to inform spatial prioritisation decisions regarding the assessment area. The survey commenced in 2024.

The objectives of this survey were to:

1. determine the distribution, abundance/density and occupancy of koalas within the assessment area
2. identify underlying relationships between koalas and relevant environmental parameters.

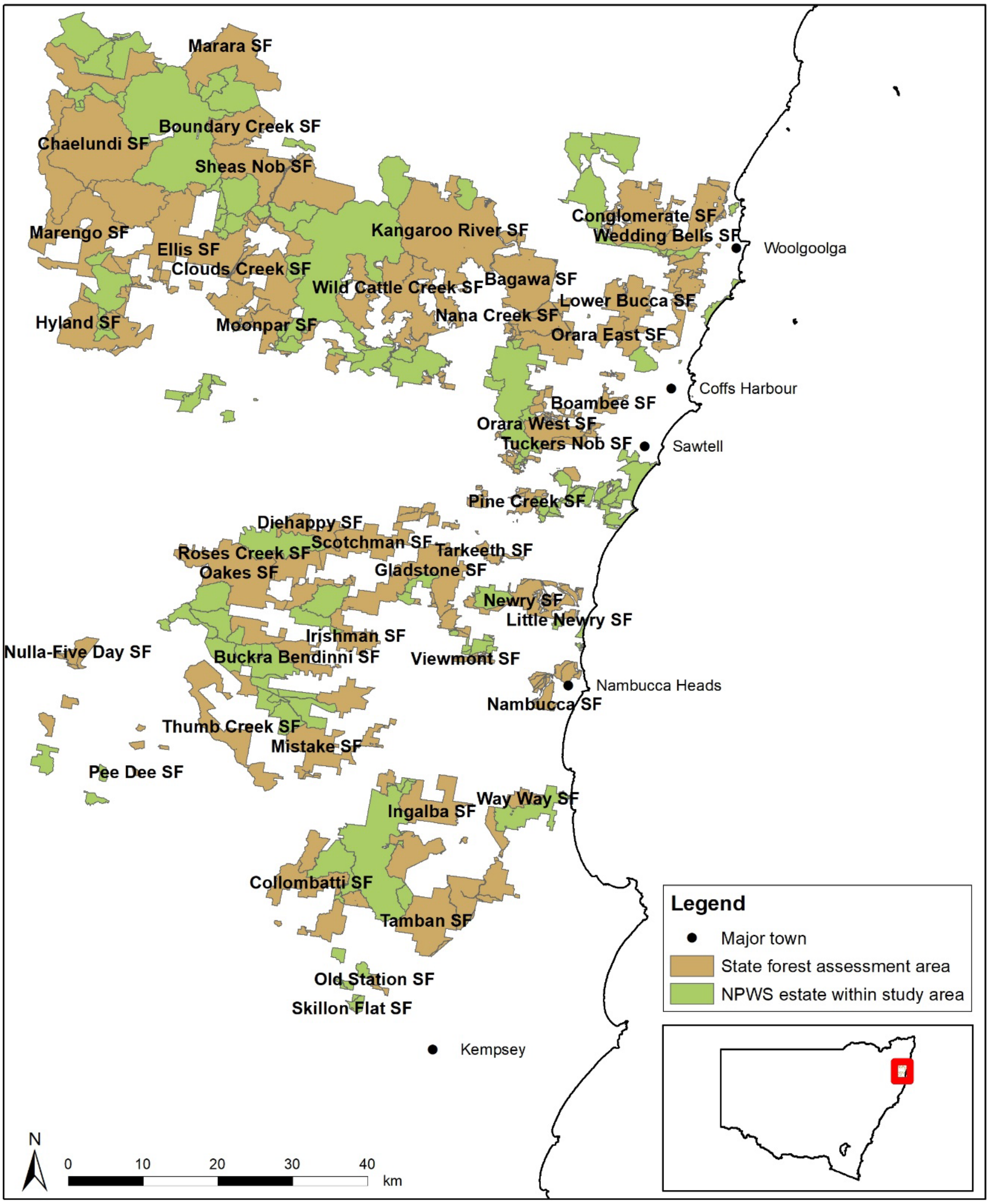


Figure 1 **Map of the assessment area and study area (note: plantations and flora reserves are excluded from the assessment area)**

Summary of survey results

Sites

- **Study area**: 169 sites (each 56 ha in size) were chosen through a stratified randomisation process and were surveyed using drones across both state forest and national park during the period of 2 April to 12 July 2024. For detailed information about the survey design and methods see Appendix A. Of these sites, 120 (71%) were on state forest, within the assessment area, and 49 (29%) were on national park estate, outside the assessment area (Figure 2). For detailed survey results see Appendix B.

Koala detections

- **Assessment area (176,000 ha state forest):** Koalas were detected broadly across the assessment area, with at least one koala recorded at 75 of 120 sites. This represents a 'naive' site occupancy of 63% (that is, the proportion of sites where a koala was detected). A total of 212 unique koalas were detected during the surveys, with the number of koala detections ranging from 0 to 12 per site. The greatest number of koalas was detected at sites in Boambee State Forest (SF), Bagawa SF, Pine Creek SF and Orara West SF (Figure 2).
- **Study area:** Koalas were detected throughout the study area, with at least one koala detected at 104 of 169 sites (Table 1). Overall, 373 unique koala detections were reported from the study area. The greatest number of koalas was detected at sites in the national park estate, in Cascade State Conservation Area (SCA), Cascade National Park (NP), Bongil Bongil NP and Nymboi-Binderay NP (Figure 2).

Table 1 Summary of unique koala detections across tenures (state forest and national park)

Metrics	Unique koala detections
Combined state forest and national park metrics (n = 169 surveyed)	
Number of sites with detections	104
Percentage of sites with detections	62%
Total number of detections	373
State forest summary metrics (n = 120 surveyed)	
Number of sites with detections	75
Percentage of sites with detections	63%
Total number of detections	212
Highest number detected at a site	12
Naive koala density/ha*	0.031
National park summary metrics (n = 49 surveyed)	
Number of sites with detections	29
Percentage of sites with detections	59%
Total number of detections	161
Highest number detected at a site	24
Naive koala density/ha*	0.059

* Please note naive density estimates (that is, the raw mean of the density of koalas per hectare) for each tenure are not directly comparable and should be interpreted as standalone estimates within tenure.

Distribution and abundance of koalas across the assessment area

Observed patterns of koala distribution

Koalas were observed at 75 of 120 sites in the assessment area, yielding a naive site occupancy of 63% (Figure 2). However, koalas were not distributed uniformly across the assessment area, with 3 key patterns emerging:

1. Koalas are broadly recorded across the assessment area.
2. The central-east section of the assessment area had the highest concentration of occupied sites (for example, Boambee SF, Bagawa SF, Pine Creek SF and Orara West SF), reflecting favourable habitat conditions.
3. The majority of sites where koalas were not recorded – 'koala-absent sites' (37% of all sites in the assessment area) – were clustered in the northernmost and north-western regions of the assessment area (for example, Wedding Bells SF, Conglomerate SF, Marara SF, Boundary Creek SF, Marengo SF and Hyland SF). The remaining koala-absent sites were scattered sparsely throughout the southern assessment area.

It is important to note that koala-absent sites may not indicate a permanent absence of koalas, but rather that none were detected during the drone surveys. The high presence of numerous clustered koala-absent sites, in the northernmost and north-western regions of the assessment area, suggests low koala occupancy in those areas.

Observed patterns of koala detections

A total of 212 unique or non-repeated detections of koalas were observed during surveys across the 75 occupied sites in the assessment area, with the number of koalas per site ranging from 0 to 12 (Figure 2 and Appendix B). The mean number of koala detections per site was estimated at 1.74 ± 1.5 to 1.98 (95% credible interval, CI) koalas per 56-ha site (212 koalas across 120 sites) or 0.031 ± 0.024 to 0.038 (95% CI) koalas per hectare (212 koalas across 6,750 ha of the surveyed assessment area).

The number of koalas detected within sites showed substantial spatial variation across the assessment area, with 3 key patterns emerging.

1. Higher koala detections were more common in the central-east section of the assessment area compared to other regions. This area included those sites surveyed in Boambee SF, Bagawa SF, Pine Creek SF and Orara West SF.
2. Lower or no koala detections were observed at sites in the northern parts of the assessment area. In particular, the north-eastern (Wedding Bells SF, Conglomerate SF) and north-western (Marara SF, Boundary Creek SF, Marengo SF and Hyland SF) regions of the assessment area had a higher proportion of koala-absent sites.

3. Moderate numbers of koala detections were observed elsewhere across the assessment area.

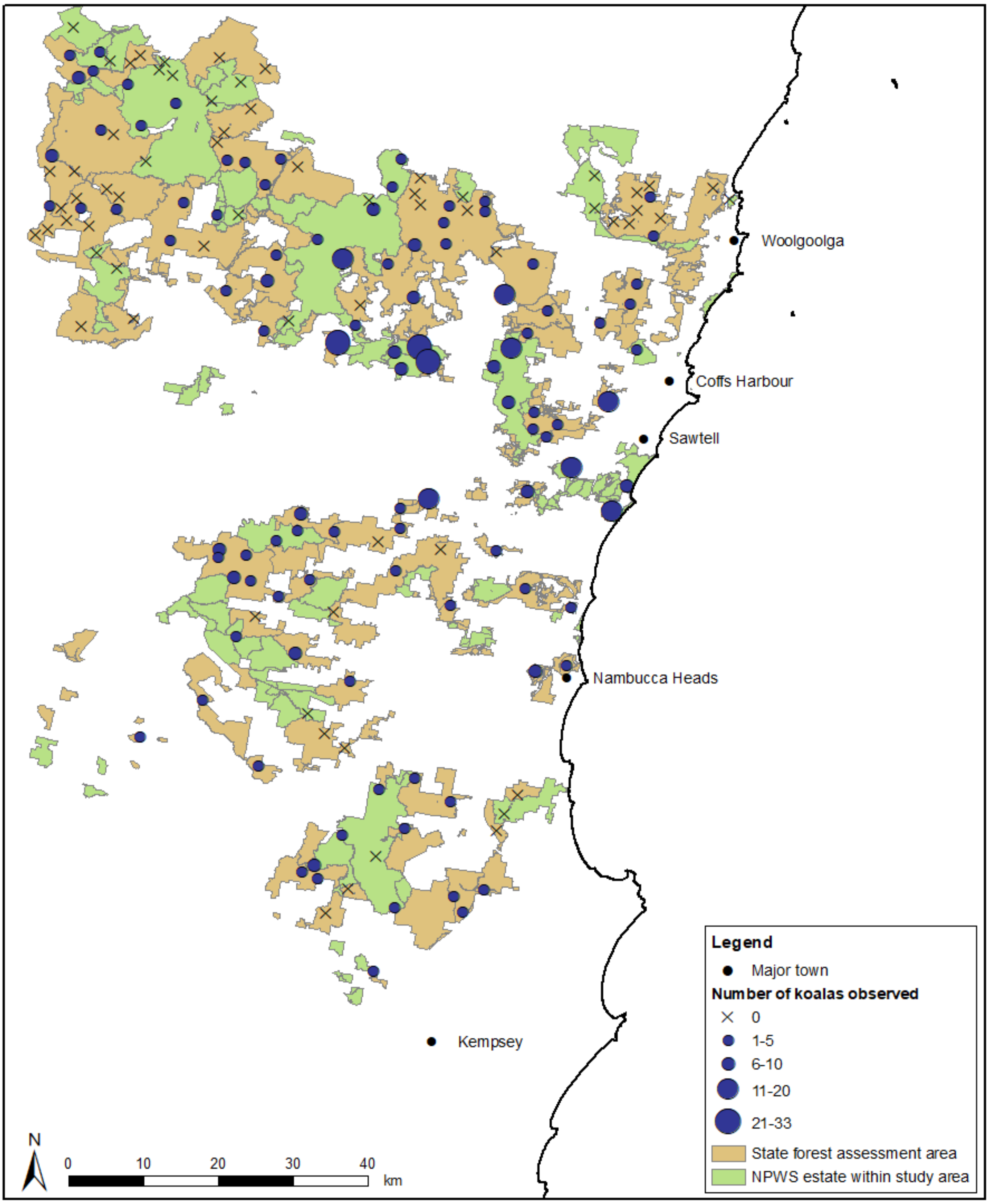


Figure 2 **Number of unique koalas observed in each 56-ha survey site in the assessment area and within the study area**

Predicted patterns of koala abundance

To predict patterns of koala abundance across the entire assessment area, beyond the 120 surveyed sites, it is crucial to identify the most important ecological and environmental factors (that is, covariates) that best explain variation in the koala counts observed at the survey sites. This allows the prediction/interpolation of koala abundance from the survey sites to the whole assessment area based on similar ecological and environmental characteristics which are strongly correlated with the observed koala abundances. Appendix C lists and explains the candidate covariates that were assessed for use in the modelling.

After a robust process of covariate assessment and elimination to ensure accurate model fit, 4 of the 23 covariates assessed were identified to best predict koala abundance across the assessment area (refer to Appendix D). Three variables had positive linear, and one had negative non-linear, relationships with koala abundance (Figure 3 to Figure 8).

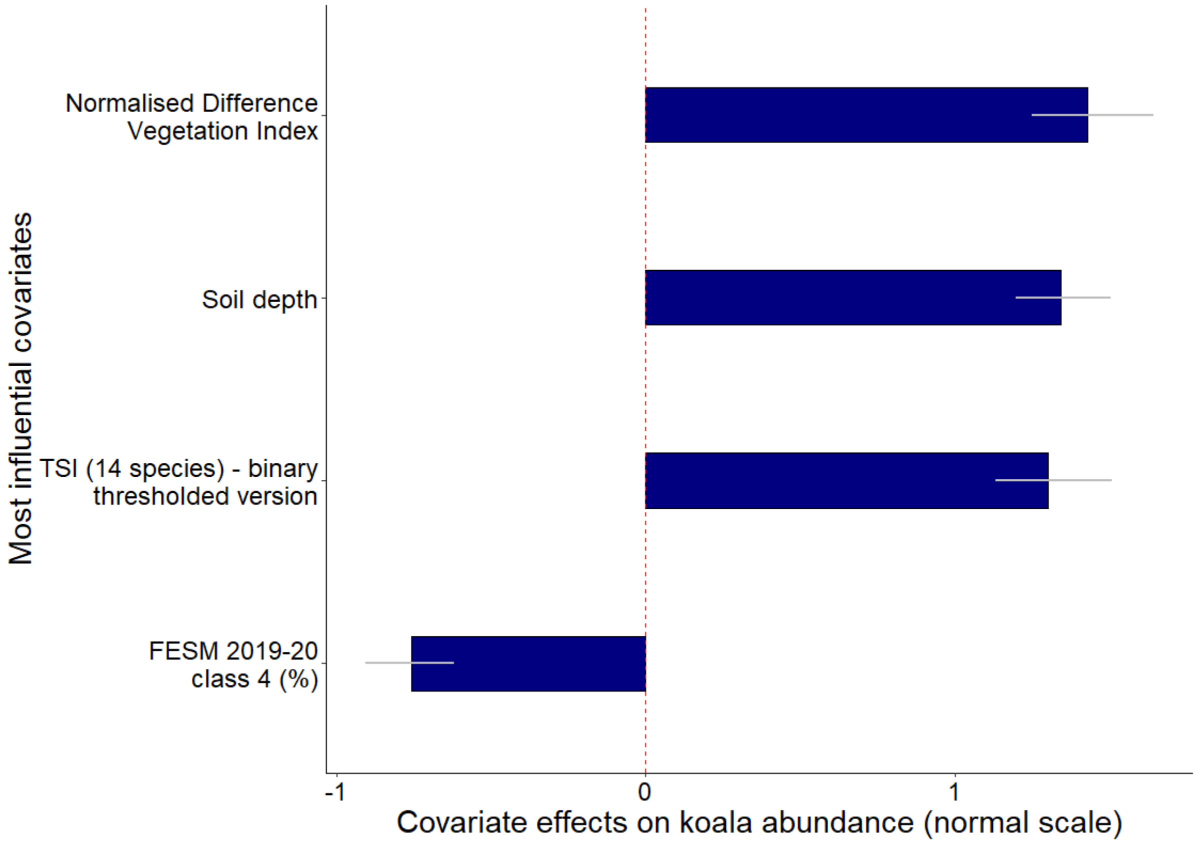
In order of the positive covariate's importance, the following were selected for the final models:

1. Normalized Difference Vegetation Index Q3 (covariate 'rs_ndvi_q3'), a measure of vegetation health and growth in each quarter of the calendar year, in this case the third quarter (July to September, Spring)
2. Soil depth (covariate 'sp_des0220'), which is the depth of soil (A and B horizons) down to 2 m
3. Tree Species Index (TSI) (14 species) – binary thresholded version (covariate 'TSI_14sppb'), which represents locations where there is a greater than 50% chance of at least one of the 14 most important koala feed trees in the assessment area occurring.

These 3 variables highlight the importance of vegetation health, soil quality and preferred eucalypt tree species to positively influence koala population abundance.

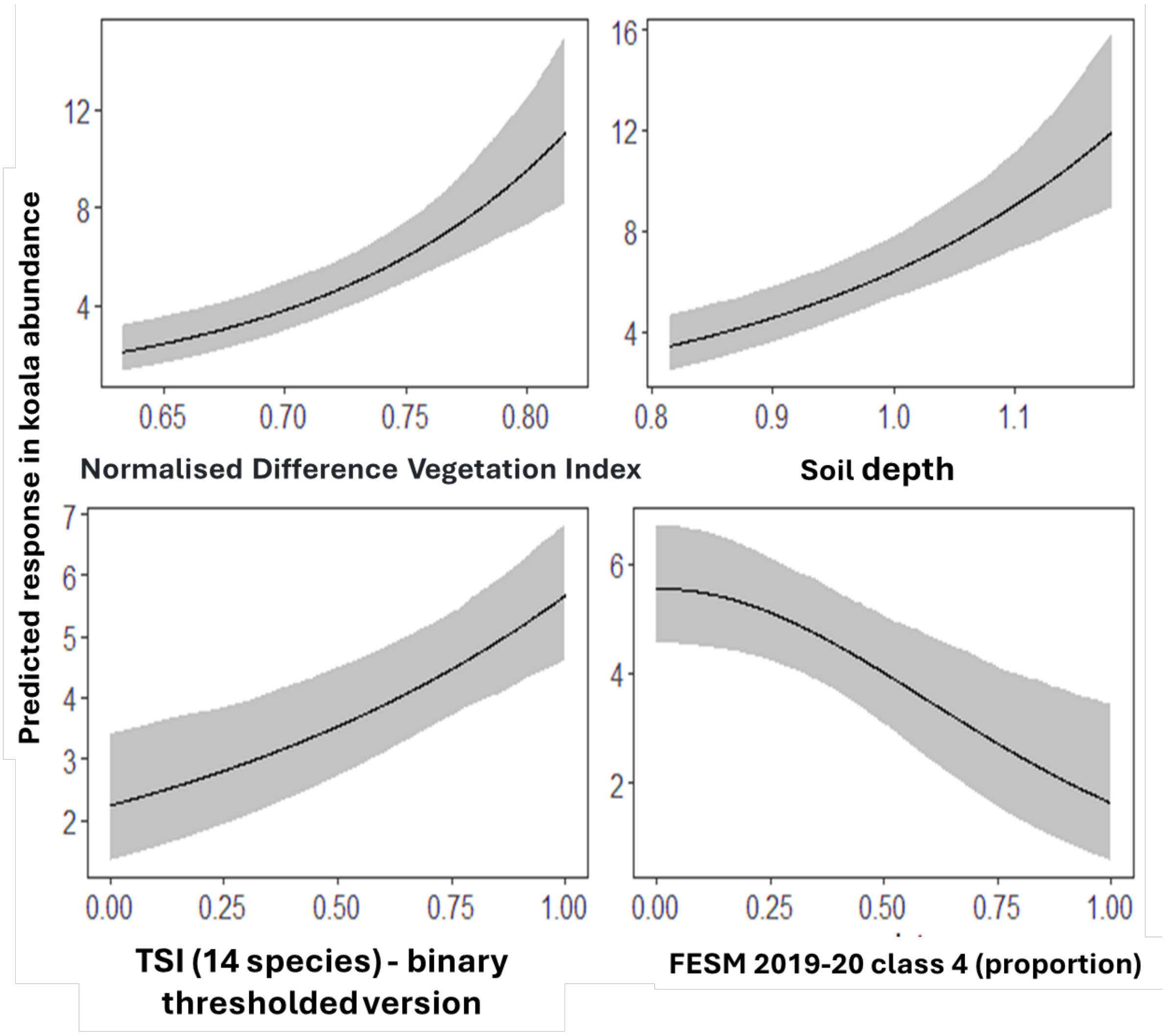
Conversely, the FESM 2019–20 class 4 variable was associated with a negative impact on koala abundance. This variable is Fire Extent and Severity Mapping representing class 4, extreme severity, fires in 2019–20 (covariate 'fesm_4b'). Recent and severe fire history implies how extreme disturbance could, directly through mortality and indirectly through loss of habitat, decrease local koala populations due to mortality, reduced fecundity and migration.

These 4 variables were used to predict koala abundance across the entire assessment area (Figure 9). The predicted pattern of koala abundance mirrored the observed data (Figure 2) against the distribution of these covariates (Figure 9). Importantly, predictions of koala abundance also identified potential areas of high and low koala abundance or habitat suitability. The central-east section of the assessment area was again highlighted as the area with the highest predicted koala abundance. Moreover, the model extended beyond observed data to identify further areas of high koala abundance or habitat suitability, especially along the coast from north of Woolgoolga to the south-eastern part of the assessment area. Like the observed pattern, the model predicted and extended areas of lowest koala abundance or habitat suitability around the northern and north-western areas of the assessment area. Additionally, the model predicted that small, isolated state forests in the south-west of the assessment area would have low koala abundance and habitat suitability. Elsewhere, the model predicted that koalas were in low to medium abundance throughout the assessment area.



Notes: TSI = Tree Species Index; FESM = Fire Extent and Severity Mapping.

Figure 3 **Effect sizes (blue boxes) and 95% credible intervals (grey lines) of the 4 variables that best explain koala abundance in the assessment area**



Notes: TSI = Tree Species Index; FESM = Fire Extent and Severity Mapping.

Figure 4 The 4 covariates that best explained and predicted koala abundance across the assessment area

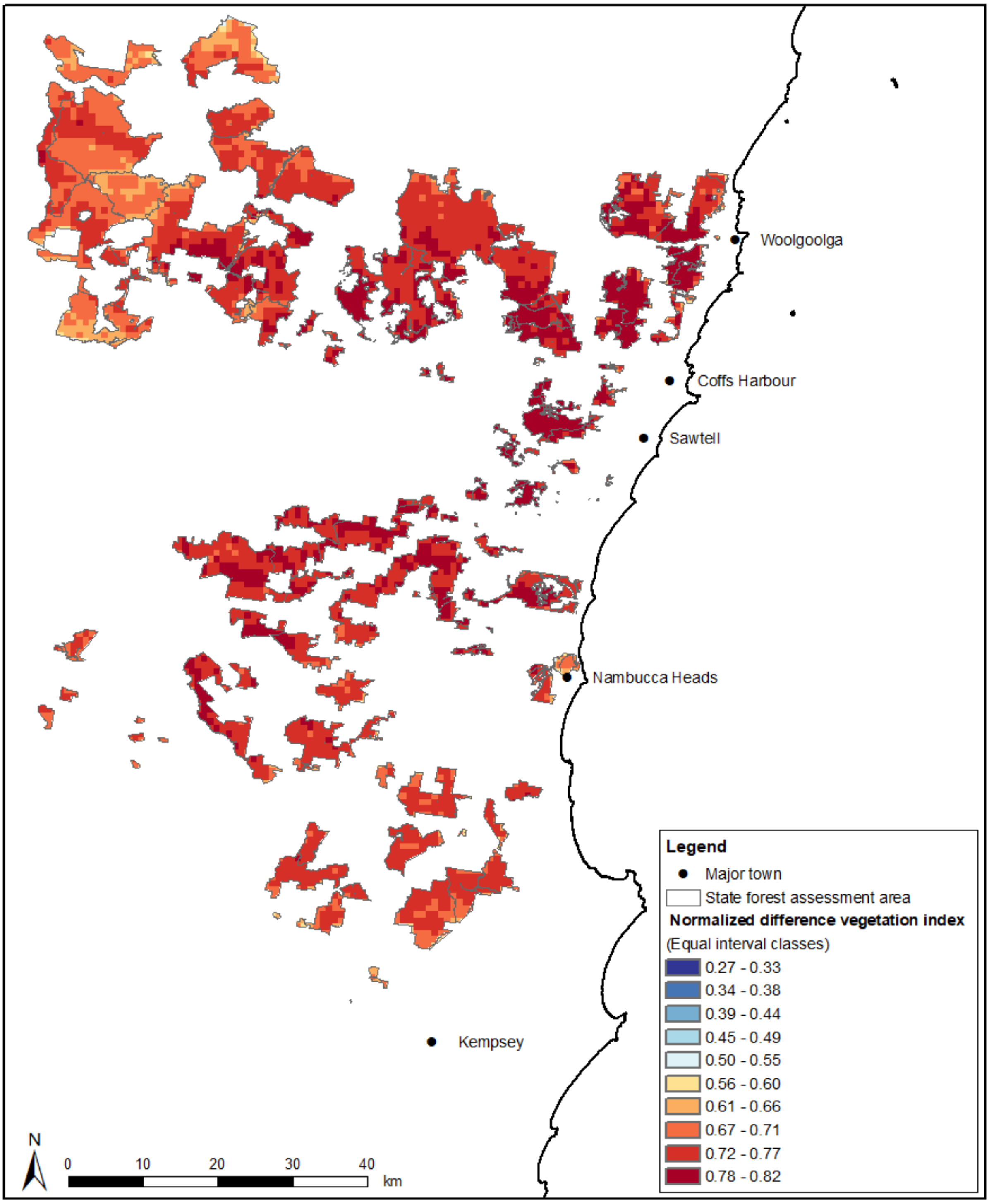


Figure 5 **The spatial distribution of Normalised Difference Vegetation Index third quarter, one of the 4 covariates identified to most influence koala abundance across the assessment area**

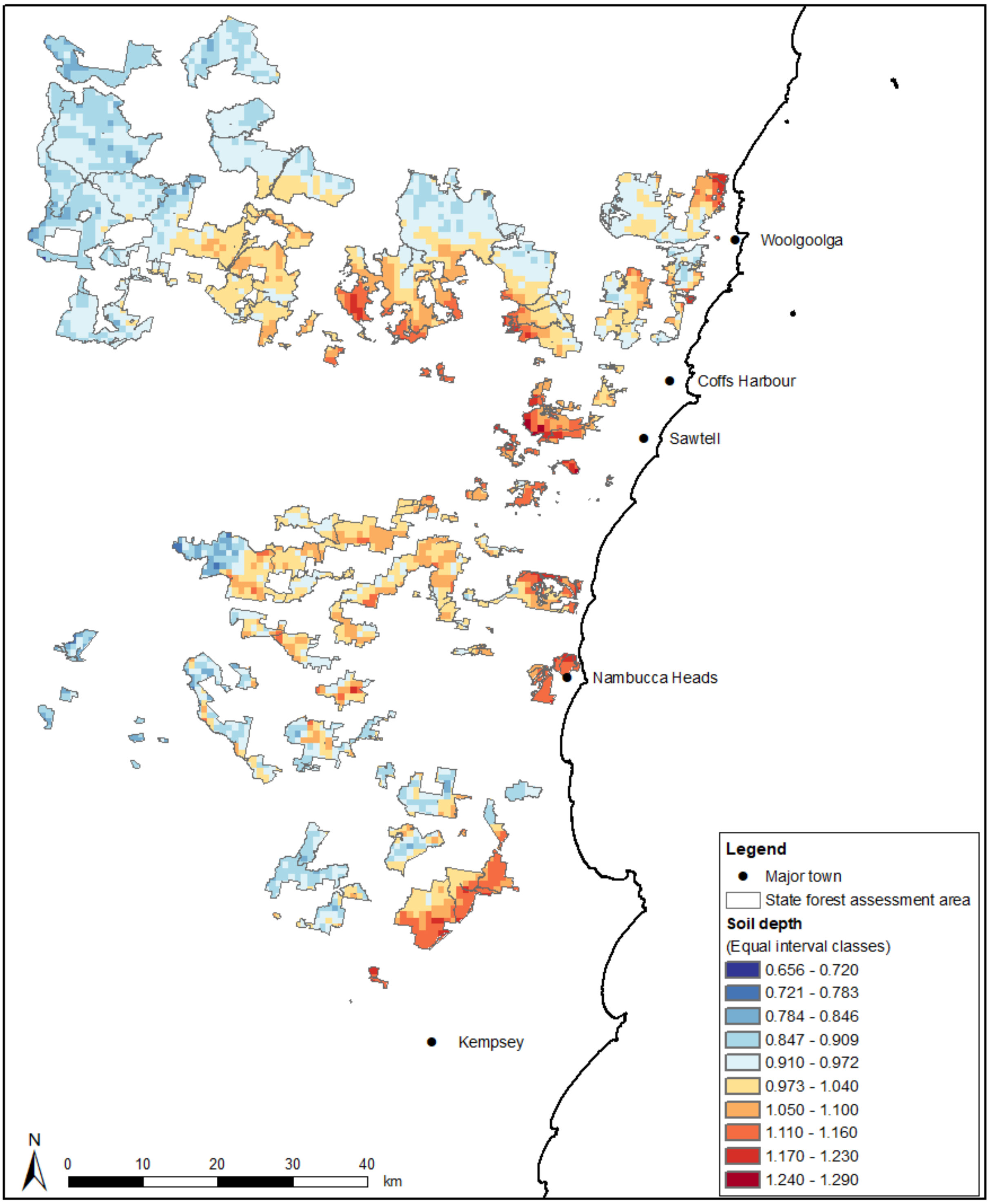


Figure 6 **The spatial distribution of the soil depth covariate, one of the 4 covariates identified to most influence koala abundance across the assessment area**

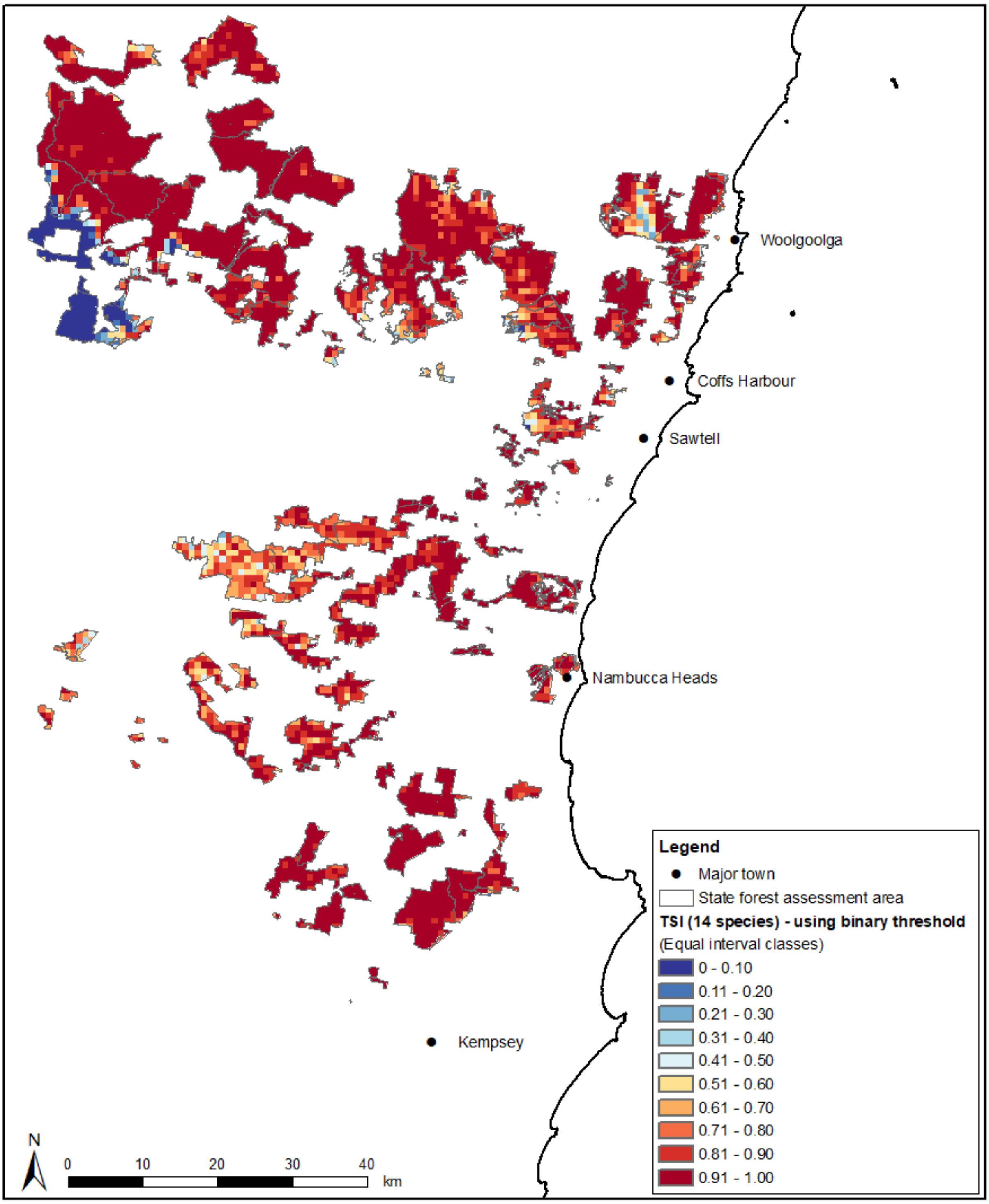


Figure 7 **The spatial distribution of the Tree Species Index (14 species) binary thresholded version covariate, one of the 4 covariates identified to most influence koala abundance across the assessment area**

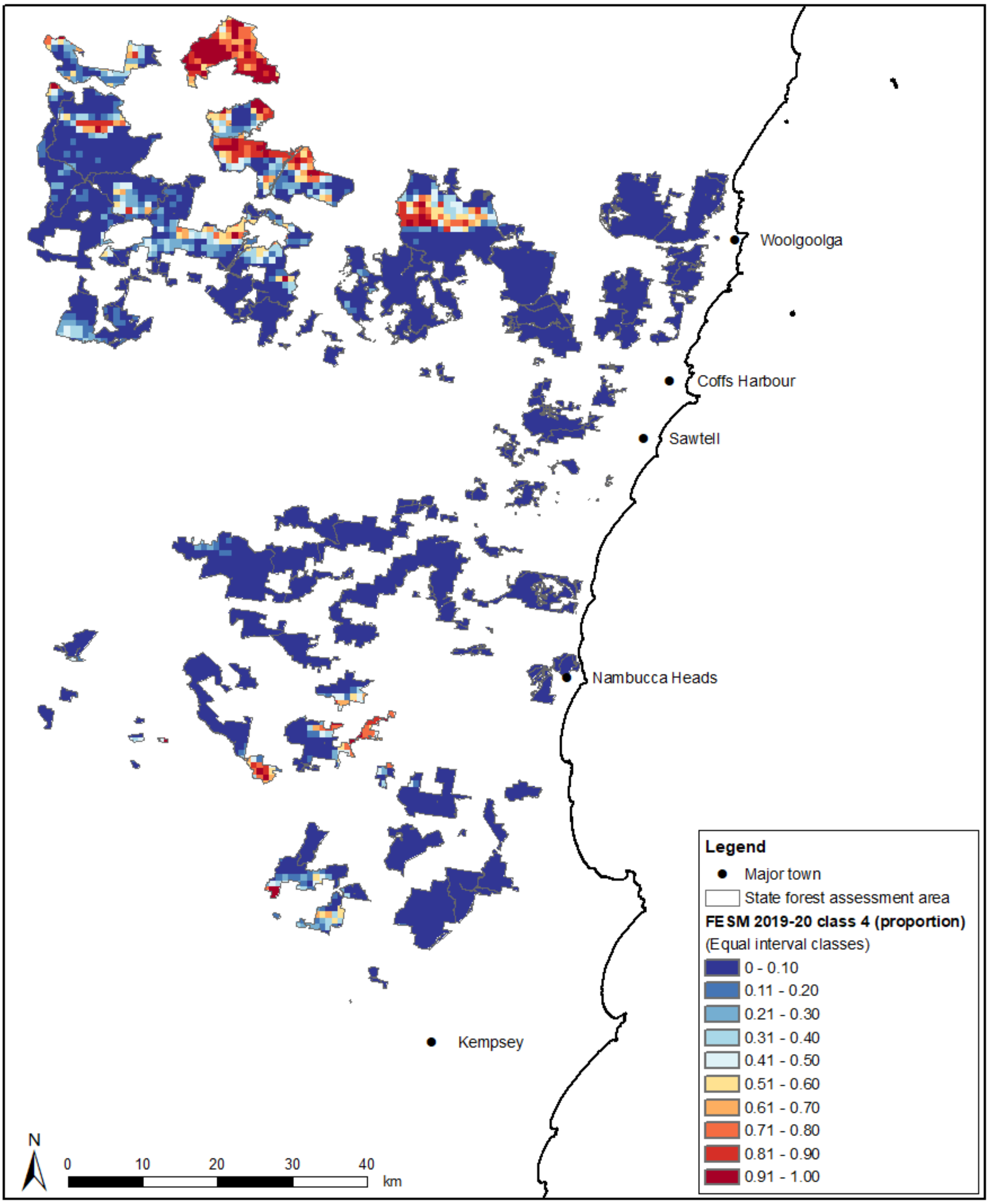


Figure 8 **The spatial distribution of the Fire Extent and Severity Mapping 2019–20 class 4 (proportion) covariate, one of the 4 covariates identified to most influence koala abundance across the assessment area**

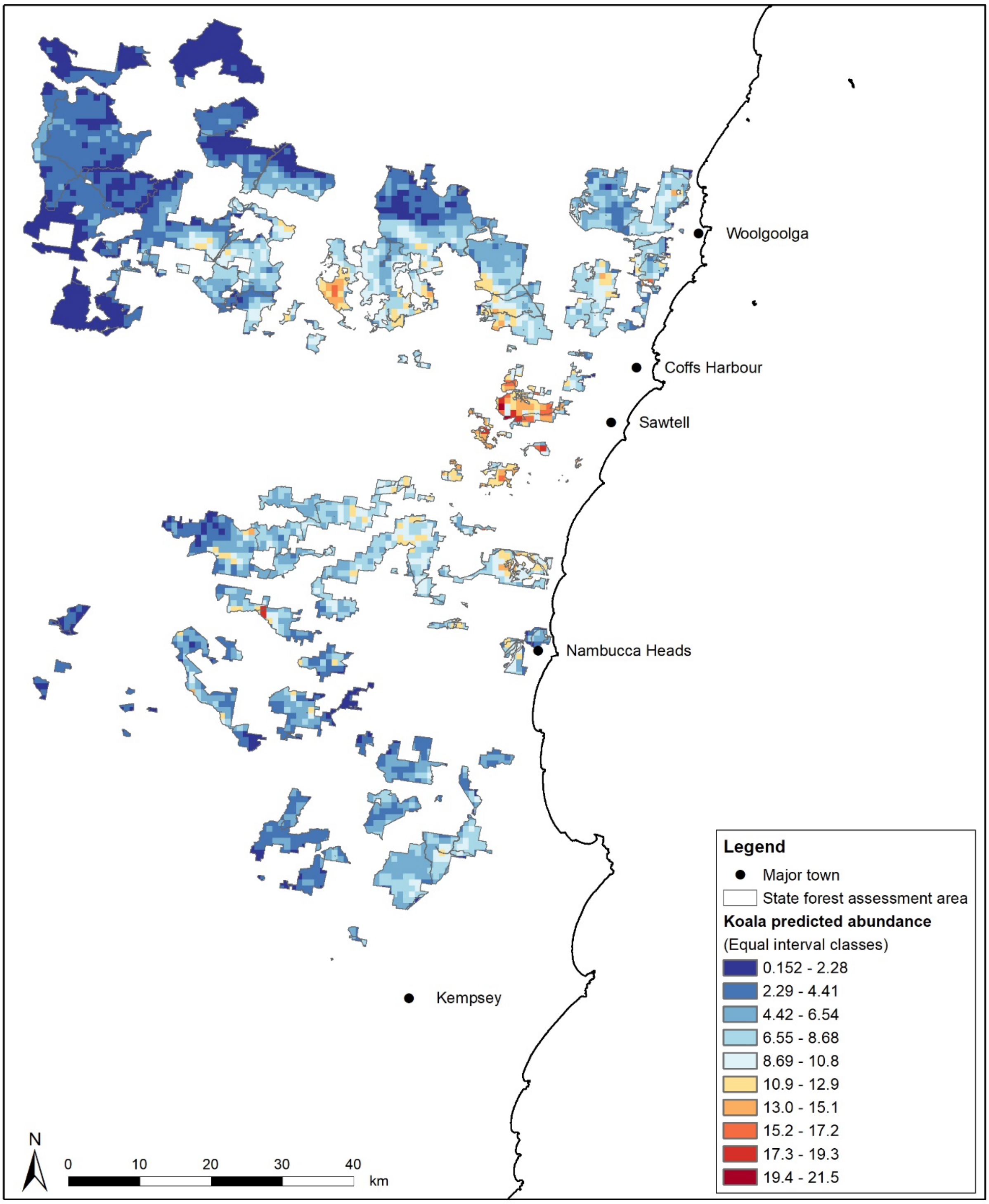


Figure 9 **Predicted koala abundance (number of individuals per 56-ha grid cell) in the assessment area**

Total estimated koala abundance across the assessment area

Repeated or independent double-observer koala counts were obtained at 120 state forest survey sites, representing about 3.8% survey coverage of the assessment area (176,000 ha). A total of 212 unique koalas (from 291 koala detections) were counted at the 120 survey sites. On the first drone survey 173 koalas were counted, and on the second survey 118 were counted, including 79 koalas that were resighted (that is, observed on the first survey). The resighting probability for koalas in the second survey represented nearly half (p = 0.46) of those observed in the first survey, suggesting the importance of repeat surveys to estimate koala abundance.

Mean naive density estimates (see point 3 in Table 2) were corrected for imperfect detection by using the koala resighting probability specific to each model (as explained in Appendix D). Using these corrected density estimates, 3 different abundance modelling approaches were used to produce 3 independent estimates of koala density. These 3 predicted estimates, alongside the naive density estimate, were averaged to produce a single consensus estimate (point 4 in Table 2). Lastly, this consensus density estimate was then multiplied by the total area (176,000 ha) of the assessment area to produce a total population estimate of 10,311 to 14,541 koalas (point 6 in Table 2 and Appendix D).

Table 2 Producing a total population estimate of koalas in the assessment area

Steps	Calculations
1. Number of unique koalas	173 + 118 − 79 = 212 (first survey + second survey − resightings)
2. Sites × hectares	120 × 56.25 ha = 6,750 ha of survey area (3.8% of 176,000 ha)
3. Mean naive density	0.031 ± 0.024 to 0.038 (95% CI) koalas/ha
4. Consensus density estimate	0.069 ± 0.059 to 0.083 (95% CI) koalas/ha
5. Density extrapolation to entire assessment area	0.069 ± 0.056 to 0.083 (95% CI) koalas/ha x 176,000 ha
6. Total population estimate	**10,311** (lower range) to **12,111** (mean) to **14,541** (upper range)

Observations of koalas on national park

Sites were also surveyed on national parks adjacent to the assessment area; and 161 unique koalas were detected across the 49 sites. The site occupancy of 59%, representing 29 of 49 sites, is similar to the 63% occupancy observed at state forest sites. The mean koala density was estimated at 3.30 ± 2.79 to 3.81 (95% CI) koalas per 56-hectare site (161 koalas across 49 sites) or 0.059 ± 0.05 to 0.068 (95% CI) koalas per hectare (161 koalas across 2,744 ha [= 49 × 56] hectares]) of the surveyed national park area. The modelled koala density on national park (using the consensus model) was 0.151 ± 0.120 to 0.197 (95% CI). Most koalas were primarily found at sites west of Coffs Harbour and along the coast south of Sawtell. The highest numbers of koalas counted on national park were sites located in Cascade SCA, Cascade NP, Bongil Bongil NP, Bindarri NP and Nymboi-Binderay NP (Figure 2).

Discussion

The department's Koala Science Team developed a survey design in 2023 to reliably count koalas within the assessment area. In 2024, this survey commenced using cutting-edge thermal drone technology, making it among the largest drone-based survey effort for koalas conducted to date across a continuous landscape in Australia. These intensive efforts have allowed for an accurate depiction of the distribution and abundance of koalas within the assessment area. Importantly, key areas of high and low koala population abundance are correlated to 4 key ecologically relevant factors, including those previously shown to influence koala population parameters (such as occupancy) in this region (Law et al. 2024a).

Distribution and relative abundance of koalas

The observed and predicted koala abundance results showed a strong alignment with identified key regions within the assessment area associated with high and low koala population abundance. Notably, the modelling highlighted 4 covariates whose spatial distributions are strongly associated with the observed and predicted differences in koala abundance across the assessment area. To fully understand how these factors influence koala population abundance, it is crucial to consider them collectively rather than in isolation (James and McCulloch 1990). It is also important to note that many of the initial candidate covariates (Appendix C), all of which had some influence over koala abundance, were removed due to high correlation with one another (Appendix D) (Graham 2003).

Survey results and predictions both identified the central-east section of the assessment area as the area with the highest observed and predicted koala abundance. This 'core area of high koala abundance' was associated with the highest values in 2 of the 3 most important positive covariates, that is, Normalized Difference Vegetation Index Q3 and soil depth (refer Figure 5 and Figure 6).

Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index Q3 (NDVI Q3) covariate had the strongest positive influence on koala abundance across the assessment area. This covariate indicates vegetation health and growth during the third quarter of the calendar year (July to September).

Healthy, photosynthetically active vegetation reflects more near-infrared light and absorbs more red light, resulting in higher NDVI values. Conversely, stressed or unhealthy vegetation, which reflects less near-infrared light, produces lower NDVI values. Areas with higher NDVI could benefit koala abundance through several processes.

Higher NDVI Q3 values across the assessment area (at a time of year when water is most limiting) would favour nutritional quality, as higher rates of NDVI and corresponding photosynthesis are linked with higher leaf nitrogen content, a major nutritional constraint for koala survival and reproductive capacity (Moore et al. 2004). Indeed, multiple studies support the importance of spatial variation in NDVI to similarly influence animal population abundance (Pettorelli et al. 2011). Several koala-specific publications have also identified NDVI as being positively correlated to koala abundance and occupancy at different spatial scales (Kotzur et al. 2024; Law et al. 2024a).

Soil depth

Soil depth was identified, based on its effect size, as the second most important covariate to positively influence koala abundance. Increased soil depths were most associated with the central-east section of the assessment area. Soil depth is expected to indirectly influence koala abundance due to its well-recognised effects on soil properties that would affect vegetation quality, including the health of eucalypts, through influencing foliage nutrient quality and water content (Attiwill and Adams 1996; Cunningham and Read 2003). Deep soils typically can retain more water, providing a consistent supply to eucalyptus trees, especially during dry periods. Additionally, deeper soil promotes eucalypt root expansion which promotes stability and the capacity to access greater volumes of soil water and nutrients (Stalenberg et al. 2014). Thus, soil depth could also, in part, explain the positive influence of NDVI because it would be responsible for providing nutrients and waters that are essential for photosynthesis, leaf production, and overall eucalypt health and good koala habitat quality (Stalenberg et al. 2014). Shallow soils, on the other hand, may restrict root growth, limiting access to water and nutrients, which can lead to lower NDVI values.

Tree Species Index

The Tree Species Index, developed specifically for this study, provides an estimation of the probability of finding at least one of the 14 most regionally important koala food tree species in the assessment area.

The 14-species Tree Species Index – binary thresholded version was the third most important influence on koala abundance. It represents areas where there is a greater than 50% chance that at least one of the 14 most important koala feed trees in the assessment area occurs. This index captures information on koala habitat suitability, based on the distribution of preferred food and shelter trees within the assessment area (Callaghan et al. 2011; McAlpine et al. 2008). However, unlike both NDVI and soil depth, TSI does not show a distinct spatial pattern closely associated with areas of highest and lowest koala abundance. Instead, high TSI values were widespread across the assessment area, including in areas with no or low koala abundance. The one exception is that very low TSI values were strongly associated with an area of multiple survey sites in the north-western assessment area where koalas were not detected.

The association between TSI and koala abundance suggests it may serve as a general predictor of koala habitat occupancy (that is, any sites with koala abundance greater than 0) more so than predicting finer-scale variation in site abundance (that is, the index cannot identify koala abundance ‘hotspots’). This is consistent with the strong positive relationship between TSI and koala presence predicted at regional, statewide and national scales in Australia (Callaghan et al. 2011; CSIRO 2023; McAlpine et al. 2023; DCCEEW 2019).

Fire Extent and Severity Mapping

Fire Extent and Severity Mapping class 4, representing the most severe locations of 2019–20 fire activity, was negatively associated with koala abundance (DPIE 2021). While half of all assessment area sites were exposed to the 2019–20 fire-related activity, this most severe category of fire-related disturbance (extreme severity) was spatially concentrated in specific areas within the north-western region and 2 smaller areas in the south and south-west of the assessment area. Here FESM class 4 was associated with 'colder spots' of low koala abundance. In these areas koalas were not detected or were in low abundance at many sites.

Importantly, the effect of FESM class 4 was non-linear, indicating that koala abundance decreased as the proportion of FESM class 4 activity increased. On average, koala abundance was predicted to decline by more than 60% from sites with no fire activity to those most severely impacted by FESM class 4. Similarly, Law et al. (2022a) estimated that koala density declined from 0.04 to 0.016 koalas/ha (that is, 60%) shortly after a severe fire in Bellangry SF.

That the most severe FESM class (extreme severity, class 4) is associated with decreased koala abundance is supported by similar findings from other koala studies in the region. For example, Law et al. (2022a) found that severe fire impacts on koala occupancy were also localised across the landscape. This finding supports the assessment area results in this report, which also indicated that impacts on koala abundance are restricted to those areas of severe impact.

Importantly, 4 to 5 years after the 2019–20 fires, koalas remain absent from many survey sites subjected to high severity fire. This suggests that the time needed for localised koala colonisation into severely burnt habitats may be longer compared to studies that demonstrate rapid colonisation of koala into areas exposed to less intense fire (Law et al. 2022a).

It is also noted that while the other less severe FESM classes and fire history covariates have less predictive influence than FESM class 4 on koala abundance, all had negative associations (Appendix C). All fire-related covariates (that is, FESM classes and fire frequency) clearly show that recent and historical fire-related activity is strongly associated with lower koala abundance in the assessment area (Appendix D). Similar patterns of historical and recent fire history suggest that part of the assessment area may be more fire prone and may provide areas of poor koala habitat suitability even if associated with other measures of favourable habitat quality (for example, preferred tree species).

Total koala abundance in the assessment area

A koala population of 10,311 to 14,541 is estimated for the assessment area. A caveat for any 'total abundance estimate' is to first assess the accuracy of the initial density estimate through comparison with other estimates of koala density elsewhere. The raw (naive) and consensus density estimates (~0.03 and ~ 0.068 koalas/ha, respectively) for the assessment area fall within the range of estimates seen in the NSW koala population, varying in density from 0.01 to 0.5 koalas/ha (Crowther et al. 2021; Law et al. 2021; Law et al. 2022a; Phillips 2018) (Appendix E).

Strengths and limitations of the survey design

The survey was explicitly designed to sample broadly and statistically randomly across the assessment area to estimate the influence of a broad range of covariates expected to influence koala abundance at this scale. This design is excellent for identifying 'hot' and 'cold' spots of koala abundance across the assessment area.

This design does not support a detailed investigation of koala abundance within state forests per se. Such an analysis would require a different survey design, one that stratifies surveys based on the size of each state forest and ensures sufficient replication within even the smallest forests. This would be necessary to obtain robust local estimates of koala abundance and variance.

For similar reasons, the current survey design is inadequate for assessing the effects of timber harvesting on koala abundance. This objective would require a different, more complex stratification approach, capturing replication across forest compartments with varied histories of harvest. These variations in harvest method, frequency and timber extraction over time complicate analysis. Additionally, due to the spatial structuring of koala populations across the assessment area, it would be challenging to find meaningful control sites in previously harvested areas, potentially introducing sampling bias.

Strengths and limitations of the consensus abundance estimate

It is also recognised that an unweighted consensus estimation approach was applied to estimate the total koala abundance in the assessment area. This unweighted consensus estimate, which includes the naive (which is akin to the minimum known-to-be-alive estimate) alongside 3 other predicted estimates (that deal with different degrees of uncertainty and variation in koala count data) applies the precautionary principle (Persson 2016; Lauck et al. 2020). This approach is considered justifiable because it provides a highly conservative estimate of total koala abundance in the assessment area.

Alternatively, a weighted consensus approach (Dormann et al. 2013) of which there are many variations, or indeed using only a single best model (the multinomial model which accounts for detectability and habitat heterogeneity) would increase this overall total koala population estimate in the assessment area. The lower, unweighted consensus estimate used reflects sufficient koalas are present in the assessment area to maintain viable koala populations. Ultimately, conservative estimates reduce the risk of overestimating species population abundance and ensure protection measures are adequate to maintain viable populations amid data limitations or environmental uncertainties (for example, Araujo et al. 2007; Wintle et al. 2011; Williams et al. 2005).

Conclusions

This report provides key information on koala distribution and abundance over a significant extent of the assessment area. Table 3 summarises key observations that are useful to inform decisions relating to the assessment area. Identification of key areas and ecological influences associated with koala abundance and distribution are clearly described to assist in decision-making through spatial prioritisation.

Table 3 Key observations on koala abundance in the assessment area

Key observations	Details
1. Numerous koalas occupy the assessment area	Between 10,311 and 14,541 koalas are estimated to inhabit the assessment area. Koalas are broadly distributed but show significant variation in abundance throughout the assessment area.
2. Ecologically plausible koala densities	The densities of koalas observed and estimated within the assessment area are consistent (that is, sit within range) with estimates observed elsewhere in New South Wales.
3. Identified drivers of koala abundance	Koala abundance responds to 4 ecologically plausible influences linked to habitat quality and fire severity across the assessment area.
4. Koala high abundance 'hot spots' are associated with good habitat	Hot spots of high koala abundance are associated with high-quality habitat, characterised by good vegetation health, deep soil, and preferred tree species.
5. Tree Suitability Index (TSI) is a coarse-scale predictor of koala abundance	TSI is linked to higher koala abundance but is better seen as a broad predictor of habitat suitability.
6. Koala low abundance, or 'colder spots', are associated with the 2019–20 fires	Koala abundance remains lower in areas most affected by the 2019–20 fires.
7. Fire-prone areas are a potential ongoing risk for koalas	Areas of historical and recent fire-related disturbances strongly overlap, implying ongoing risk to koala populations, especially with more frequent and severe fires predicted under climate change.

Appendix A: Koala survey design and methods

Area of study

The assessment area included 176,000 ha of state forest on the NSW Mid North Coast. A 1-km buffer was applied to the larger provisional study area when stratifying sites. The model predictions could then be clipped to either the final assessment area boundary, the study area or national park estate. The final assessment area boundary is used in this report.

Survey design

Stratifying sites

Three covariates were used to stratify prospective survey sites. These were:

1. A 30 × 30 m 3-class Tree Species Index (TSI). This represents the collective predicted distribution of 14 individual tree species, which together are predicted to influence the distribution and/or abundance of koalas (Table 4, Figure 10). The index is an estimate of the probability of finding at least one of the 14 species present in each 30 × 30 m grid cell across the assessment area. The 14 species are listed in Table 4 and comprise 6 rank 1 species (the most preferred food tree species used by koala in the local area) and 8 rank 2 species (less preferred food or important shelter trees in the local area). The 14-species TSI was converted to a simple, 3-class stratification layer (high, medium and low TSI). Note there were no obvious natural breaks upon which to threshold the TSI. This means the high end of the low class and low end of the moderate class are closely related, as are the high end of the medium and low end of the high. A higher abundance of koalas is predicted in either the high, or the high/moderate classes, compared to the low.
2. A 30 × 30 m 2-category 2019–20 Fire Extent and Severity Mapping (FESM) layer (DPIE 2021). The 2 categories were a) fires with canopy scorch (FESM moderate, high and extreme fire severity classes combined), and b) low severity (understory only affected) and unburnt combined. Fire in the landscape in 2019–20 was a substantial disturbance. High severity fires are predicted to decrease koala abundance while koalas may survive lower severity fires (Figure 11).
3. A 30 × 30 m 2-category landform classification. The layer is based on a 16-class broad landform classification that ranges from less productive ridgetops and upper slopes with high rainfall runoff expected (classes 15 and 16), through to more productive wetter soil areas, drainage depressions and alluvial plains (classes 1 and 2). The 2-category layer uses classes 1 to 9 to indicate wetter, more productive positions and classes 10 to 16 as drier, less-productive positions. Overall, more-productive areas are predicted to positively affect the abundance of koalas (Figure 12).

Table 4 List of 14 tree species included in the study area Tree Species Index

Tree species	Common name	No. BioNet records in study area	Rank
Eucalyptus grandis	Flooded gum, rose gum	264	1
Eucalyptus microcorys	Tallowwood	1,001	1
Eucalyptus propinqua	Grey gum, small-fruited grey gum	381	1
Eucalyptus robusta	Swamp mahogany	87	1
Eucalyptus saligna	Sydney blue gum	408	1
Eucalyptus tereticornis	Forest red gum	135	1
Eucalyptus signata	Scribbly gum	46	2
Eucalyptus biturbinata	Grey gum	108	2
Eucalyptus blakelyi	Blakely's red gum	17	2
Eucalyptus quadrangulata	White-topped box, coast white box	17	2
Eucalyptus rummeryi	Steel box, Rummery's box, brown box	64	2
Eucalyptus globoidea	White stringybark	17	2
Eucalyptus moluccana	Grey box, gum-topped box	36	2
Eucalyptus resinifera	Red mahogany, red messmate	98	2

Source: The list is based on local koala tree use preference information provided by J Turbill (DCCEEW) and M Fisher (3D Ecology Mapping).

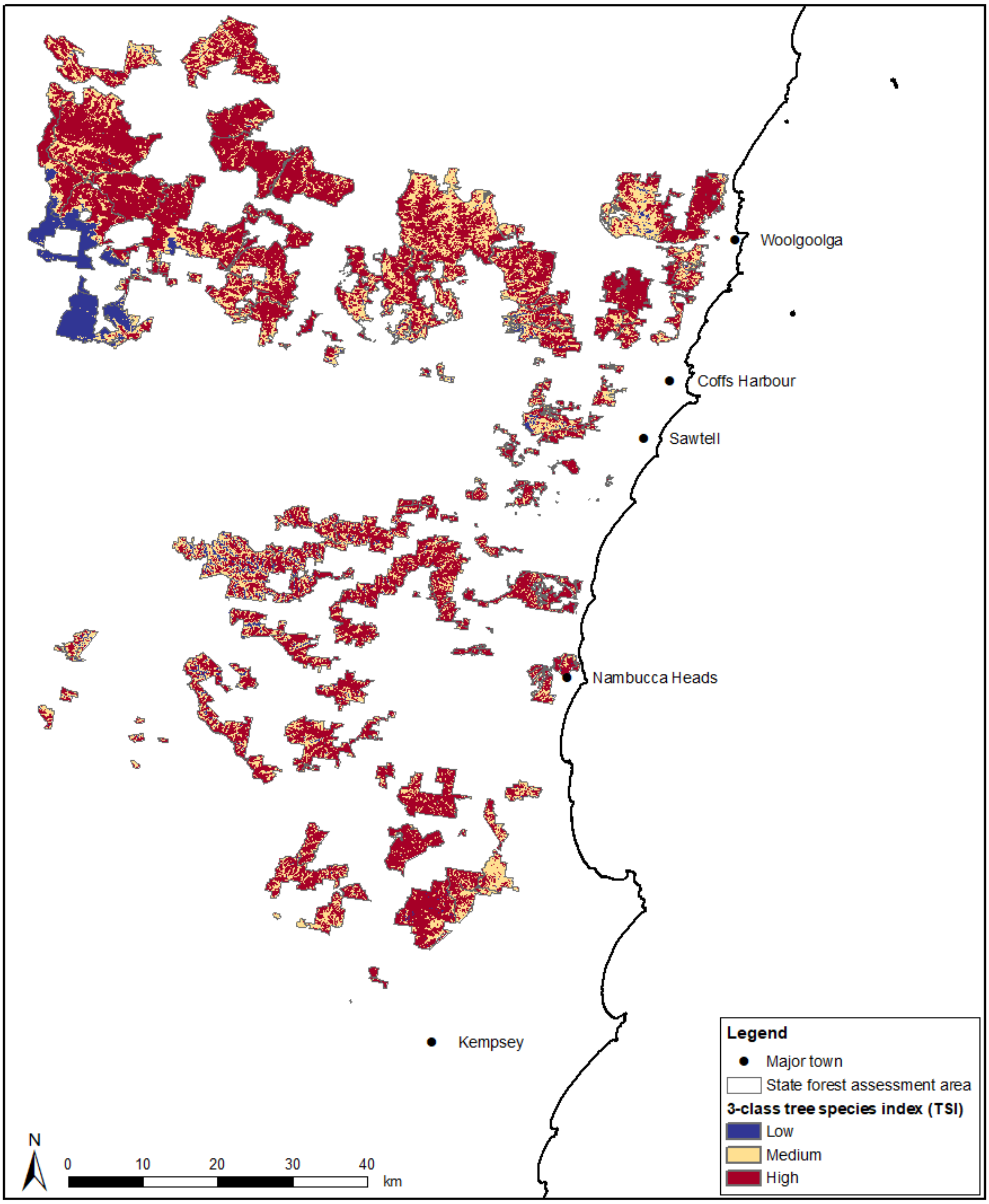


Figure 10 **The first parameter used to stratify prospective survey sites: a 14-species koala Tree Species Index (TSI) showing 3 classes of probability of finding TSI species**

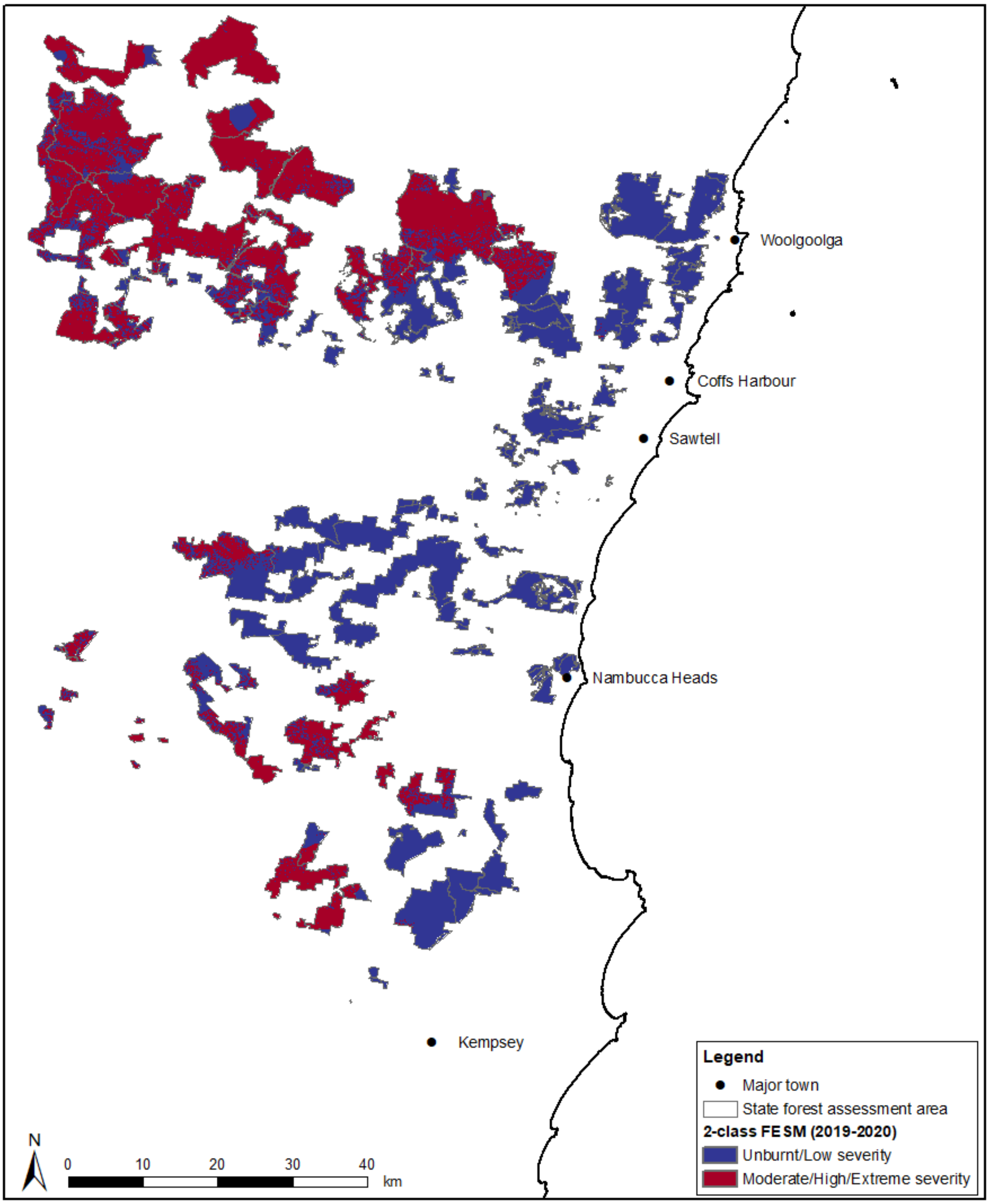


Figure 11 **The second parameter used to stratify prospective survey sites: Fire Extent and Severity Mapping (FESM) for 2019–20 with severity classes combined into 2 categories**

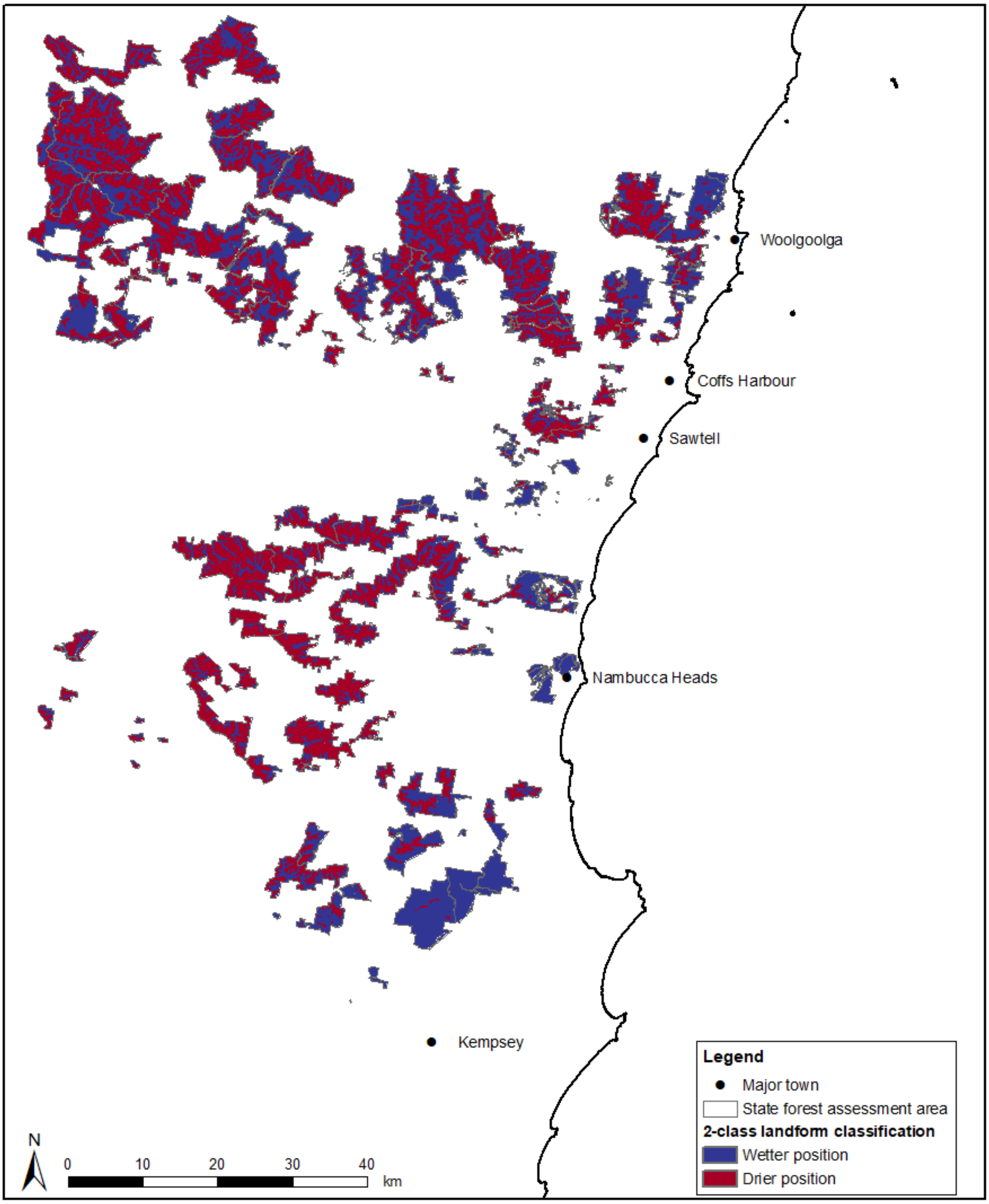


Figure 12 **The third parameter used to stratify prospective survey sites: 2 broad landform classifications showing wetter and drier position**

Sampling design

The final stratification for the assessment area contained 12 stratification units (Figure 13). This includes all combinations of the TSI (3 classes), FESM (2 categories) and landform (2 categories). Other environmental parameters, including more complex fire metrics were considered in post-survey analyses.

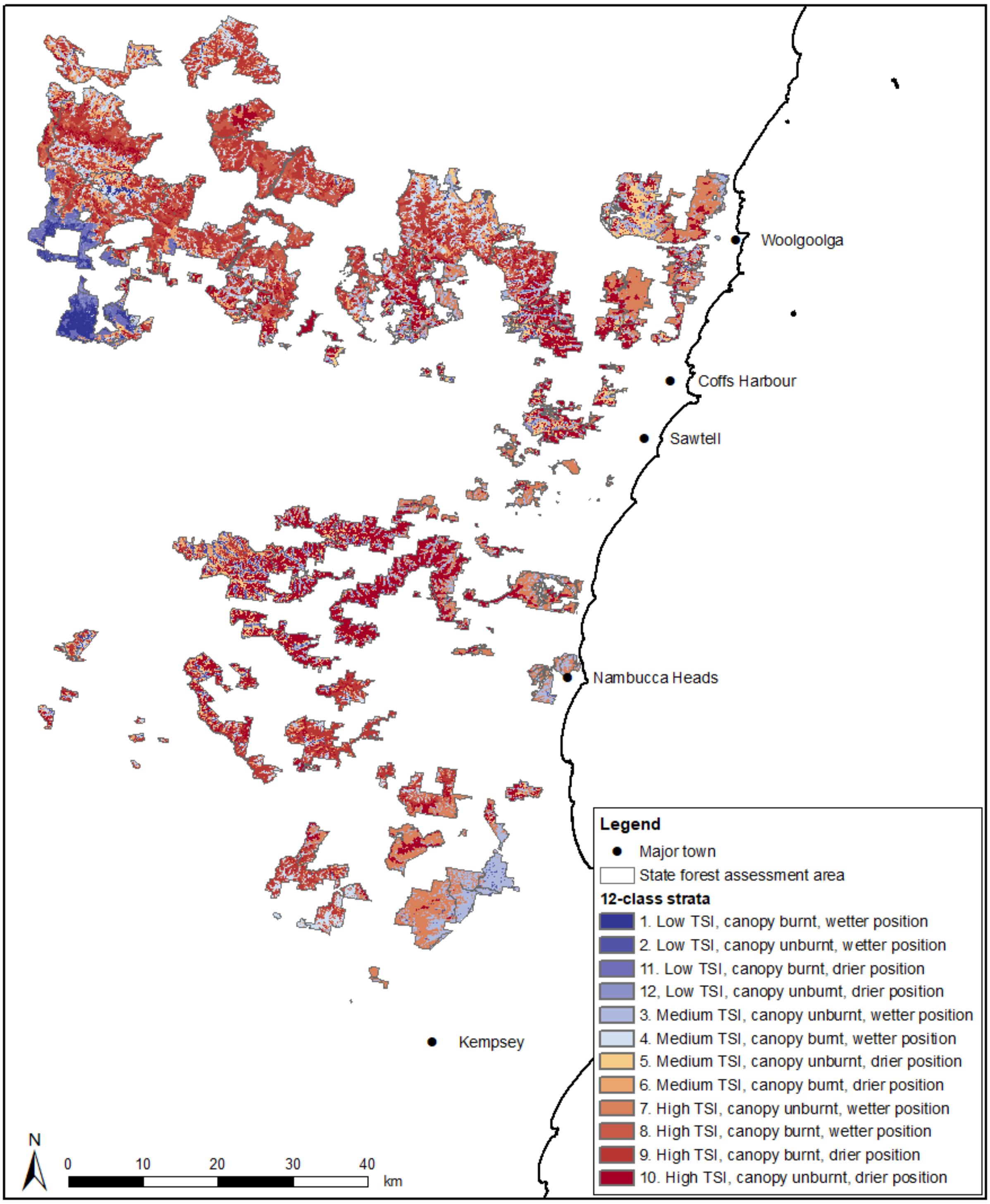


Figure 13 **Sampling design: the product of these parameters provides 12 stratification units across the assessment area**

Site selection

There were 11 to 23 planned sites selected for each stratum, based on their area, to ensure a balanced design and adequate statistical replication. The total number of planned sites was 206 of which 169 were completed (120 state forest sites in the assessment area and 49 national park sites in the study area). The 37 remaining sites were unable to be surveyed due to access issues or because they were in areas excluded from the assessment area, such as plantations or flora reserves (4 sites). This design ensured adequate environmental replication and relatively uniform geographic coverage across the region (Figure 14).

A spatially balanced site selection process was used to choose the survey locations within each stratum. This followed the same site selection process used for the koala baseline and koala monitoring programs. This allowed for the optimised placement of a fixed number of sites over a given area. The process drew on a statewide pool of over 2 million sites that are ordered in such a way that one can select a bounding area of any size and the set of sites within that area will have a spatially balanced order assigned to them. By selecting the first site, then the second and so forth in order, the sites would always be dispersed in an efficient, spatially optimised fashion regardless of the number of sites chosen. See the site ID ordering in Figure 14.

The final site selection was weighted toward state forest (71% of sites were on state forest). Given that each drone site was 56 ha in size, it was common for a site to straddle multiple strata. The strata assigned to each site was that which covered the majority of 30 × 30 m grid cells that made up the site.

Moving sites

During fieldwork, a small number of sites (n = 9) were moved small distances (<2 km) due to unresolvable access issues, ensuring the site still sampled the target strata. Movements consisted of rotating grid squares and/or moving the grid square to a nearby suitable area. The final location selected was based on maximising the amount of the target strata in the new site in an accessible location closest to the original site. Other factors considered were maximising the distance between the moved site and existing sites while preserving the tenure (that is, national park sites were moved to national park tenure and state forest sites moved to state forest tenure); and including (at the broad scale) similar vegetation cover and landforms found at the original site. Where these movement criteria could not be met, the site was deemed non-viable and not surveyed. If a site was moved, covariates were recalculated to the new site location to ensure covariate accuracy.

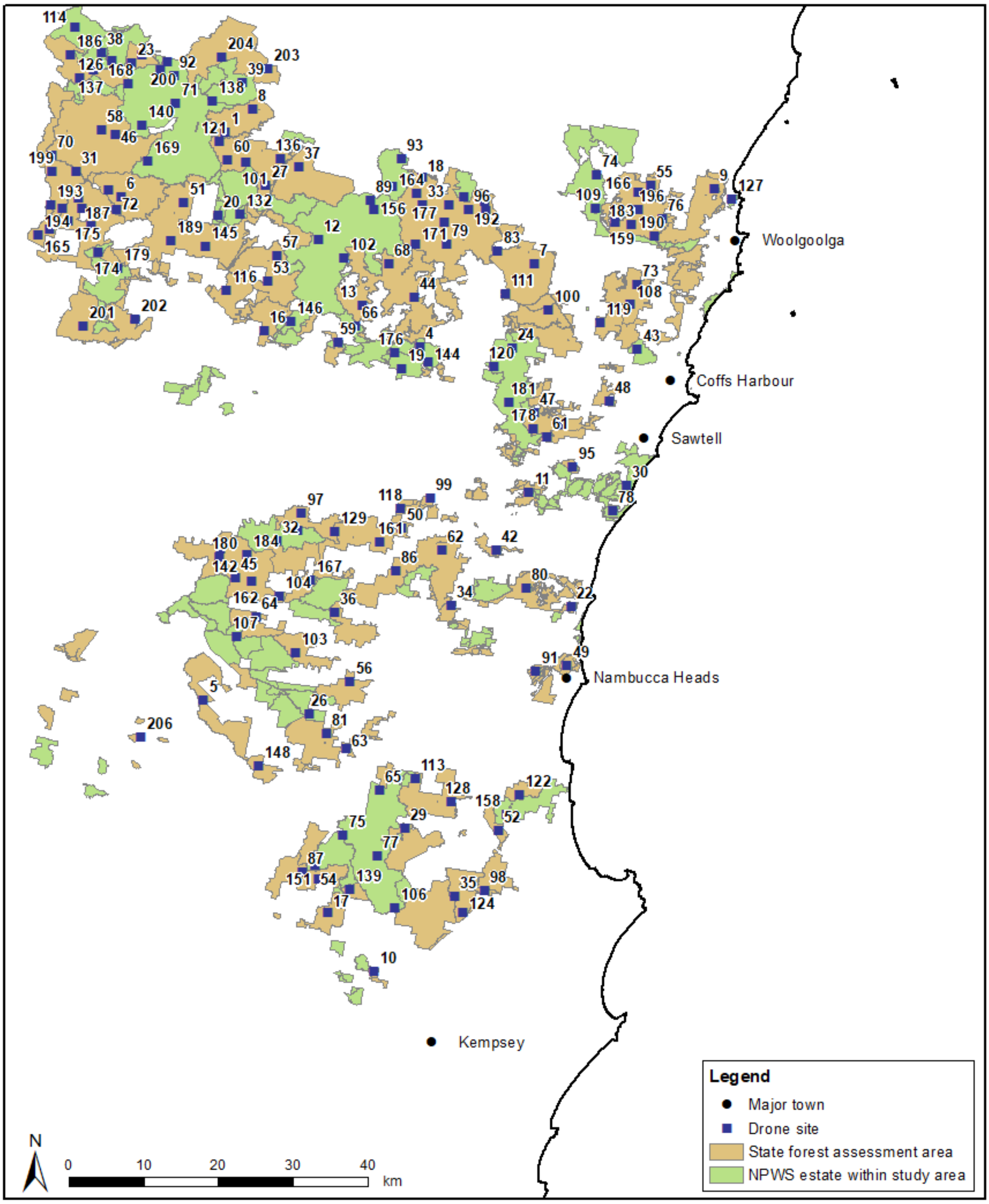


Figure 14 **Location of the 169 completed koala survey sites in the study area**

Survey methods

Sites

Surveys were conducted over 750 × 750 m (~56 ha) sites. The chosen plot size of 56.25 ha was selected to ensure a balance between minimising opportunities for site closure violations in analyses and maximising spatial coverage of survey effort. This is because:

- Site closure assumptions are more likely to be violated when the survey plot is smaller than the home range size of the target species.
- When the site closure assumption is violated, detection probabilities can be underestimated, biasing abundance estimates.
- A plot size of 56 ha exceeds the size of koala home range estimates for many locations throughout the state (unpublished DCCEEW data).

Drone surveys

Drones are considered one of the best and more cost-effective methods of assessing the relative abundance of koalas in New South Wales (Howell et al. 2021; Beranek et al. 2024). Quadcopter drones equipped with a 12 MP wide camera, 48 MP zoom camera, 640 × 512 px 30 fps thermal camera, and one of 2 spotlights were used. Drones followed an automated 'lawn mower' or 'snake scan' flight pattern (parallel linear line-transects with approximately 60 m swathe width) with a 10% overlap to ensure complete coverage of the entire 56-ha site. The entire survey's thermal and colour video imagery was recorded.

Thermal detections of koalas were validated in real time by briefly turning on the spotlight and switching to the colour zoom camera. When koalas were detected, pilots took a picture (thermal and zoom) and recorded it in the Survey123 app. If the detection was a koala, the pilot would manoeuvre the drone directly above the koala, set the gimbal angle pitch to 90 degrees, take another photo at this location, then record the latitude and longitude of the detection (that is, 'drop a pin label' or geotagging) on the drone controller. The pin was labelled with a unique ID identifying the site where the koala was detected and the sequential number of koalas at the site (for example, 80B_1).

Each site was surveyed twice using an independent double-observer approach to increase the sensitivity and precision of abundance or density estimates. Two repeated drone surveys were undertaken on the same night at each site by 2 different pilots (to account for observer bias). Following a random draw to assign pilots to each half of the site, one drone pilot flew on half of the site while the second drone pilot simultaneously flew the other half of the site. Once finished flying, pilots would swap, and each fly the other half of the site. To ensure the independence of surveys, drone pilots were sufficiently separated to ensure they could not view each other's controllers, and they were instructed not to discuss detections nor view the other pilot's drone during the entirety of the survey. This approach, in combination with the geotagging, allowed for accounting of shared koala detections made by each observer.

Ensuring systematic and effective drone survey effort

Environmental conditions, such as temperature, fog and rain, can affect the effectiveness of drone sensors and the accuracy of wildlife detections by human observers. Surveys were conducted systematically under good survey conditions using the following 2 parameters to increase detections:

- air temperature below 16 C
- starting 3 hours after sunset (approx. 9 pm).

If the forecasted temperature did not drop below 16 C all night, drone pilots started the survey at 3 am (or the coldest period of the night).

These conditions were comparable to those of Beranek et al. (2024) where surveys were conducted at night (8 pm to 3 am) to coincide with temperatures below 18 C (range 6 to 18 C).

No surveys were conducted during rain or fog that was sufficient to impair normal survey effort.

Koala data extracted from surveys

This assessment used independent double-observer drone surveys, which resulted in 2 surveys for each site on the same night with a temporal separation. The rules that were applied to determine whether each koala detection was a unique koala, or the same koala counted by both observers are explained below.

Koala count decision rules

Decision tree for counting koalas using an independent double-observer method.

Scenario:

- If a koala is found at the same location (latitude and longitude) in the first and second surveys, it is the same koala.
- If a koala is not found at the same place on the second survey, but is within ≤50 m of the koala seen in the first survey, it is assumed that this is the same koala. This 50-m rule arises from koalas being predominantly nocturnal, moving between one to 5 trees per night within their home range. GPS telemetry studies in mid-coast NSW indicate an average nightly movement of ~200 m (Law et al. 2024b). These behavioural attributes indicate that koalas typically undertake small inter-tree movements under 50 m interspersed by much longer feeding bouts.
- If a koala is not found at the same place in the second survey and is more than 50 m from a koala seen in the first survey, it is a different koala and counts towards the number of unique koalas.

For this report, a single figure of koala detections per site is provided based on the number of 'unique' koalas detected, as described in the decision tree and illustrated in Figure 15.

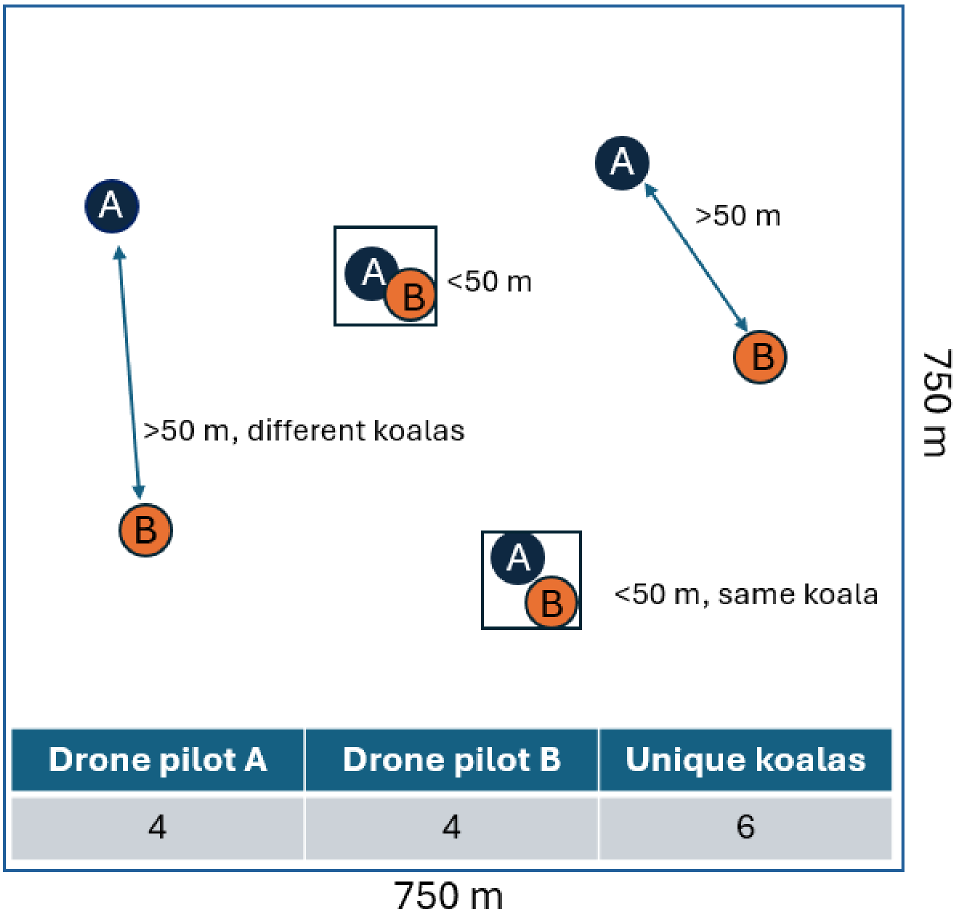


Figure 15 **Illustration of an independent double-observer survey of koalas conducted by 2 drone pilots (pilot A and pilot B) within a 750 × 750 m survey site. The figure represents how the pilots reported individual koala observations and determined whether they observed the same (joint) or 'unique' koalas**

Survey timeline

Drone surveys commenced in April 2024 when night-time temperatures were cool enough to differentiate between arboreal mammals and their surroundings (such as hot rocks, trunks, foliage, hollows). Completed field survey data was made available by 31 July 2024.

A total of 26 drone pilots surveyed the assessment area sites. To complete the surveys in the allotted time, 2 to 6 teams (each comprising 2 personnel, 2 drones and a vehicle) were deployed each week. Teams worked concurrently in the field, alternating each week. Planning and approvals were required before these surveys could proceed, including developing flight plans, aviation compliance and risk management documents and approvals for each drone survey with 2 weeks notice, as well as ground truthing the survey sites to assess suitable access for drone surveys.

Appendix B: Summary of koala survey results

Table 5 shows the strata and final counts of sites surveyed (169) across each strata in the study area.

Table 5 **Strata and number of sites surveyed and sites planned**

Dominant strata	Sites surveyed	Sites planned
1. Low TSI, Canopy Burnt, Wetter Position	9	12
2. Low TSI, Canopy Unburnt, Wetter Position	12	13
3. Medium TSI, Canopy Unburnt, Wetter Position	7	13
4. Medium TSI, Canopy Burnt, Wetter Position	17	20
5. Medium TSI, Canopy Unburnt, Drier Position	14	19
6. Medium TSI, Canopy Burnt, Drier Position	14	15
7. High TSI, Canopy Unburnt, Wetter Position	16	17
8. High TSI, Canopy Burnt, Wetter Position	16	19
9. High TSI, Canopy Burnt, Drier Position	27	28
10. High TSI, Canopy Unburnt, Drier Position	19	25
11. Low TSI, Canopy Burnt, Drier Position	10	10
12. Low TSI, Canopy Unburnt, Drier Position	8	15
Total	**169**	**206**

Table 6 shows the total number of sites surveyed and planned on various tenures across the study area.

Table 6 **Number of sites surveyed and planned on various tenures**

Tenure	Sites surveyed	Sites planned
NPWS estate: national park	30	36
NPWS estate: nature reserve	13	18
NPWS estate: state conservation area	6	10
State forest	120	142
Total	**169**	**206**

Table 7 shows the number of sites surveyed in state forest and NPWS estate across the study area.

Table 7 Number of sites surveyed in each state forest or NPWS reserve

Reserve	No. of sites	Reserve	No. of sites
Baalijin NR	2	Marara SF	2
Bagawa SF	3	Marengo SF	9
Bindarri NP	3	Mistake SF	3
Boambee SF	1	Moonpar SF	1
Bongil Bongil NP	2	Mount Hyland NR	2
Boundary Creek SF	2	Nambucca SF	2
Buckra Bendinni SF	1	Nana Creek SF	1
Byrnes Scrub NR	1	Newry SF	1
Cascade NP	4	Ngambaa NR	5
Cascade SCA	1	Nulla-Five Day SF	1
Chaelundi NP	10	Nymboi-Binderay NP	7
Chaelundi SCA	1	Nymboi-Binderay SCA	1
Chaelundi SF	12	Oakes SF	7
Clouds Creek SF	4	Old Station SF	1
Collombatti SF	4	Orara East SF	1
Conglomerate SF	8	Orara West SF	4
Diehappy SF	1	Pine Creek SF	2
Dunggir NP	1	Scotchman SF	5
Ellis SF	3	Sheas Nob SF	5
Garby NR	1	Sherwood NR	2
Gladstone SF	3	Tamban SF	3
Gumbaynggirr NP	1	Tarkeeth SF	1
Guy Fawkes River SCA	3	Thumb Creek SF	2
Hyland SF	2	Tuckers Nob SF	1
Ingalba SF	3	Ulidarra NP	1
Irishman SF	2	Way Way SF	2
Kangaroo River SF	10	Wedding Bells SF	1
Little Newry SF	1	Wild Cattle Creek SF	3
Lower Bucca SF	2	Yarriabini NP	1
Total			**169**

SF = state forest; NP = national park; SCA = state conservation area; NR = nature reserve.

Table 8 Summary of koala detections across state forests and NPWS estate

Forest/reserve name	No. sites surveyed	No. koalas detected
State forests		
Bagawa SF	3	12
Boambee SF	1	11
Boundary Creek SF	2	0
Buckra Bendinni SF	1	5
Chaelundi SF	12	20
Clouds Creek SF	4	8
Collombatti SF	4	3
Conglomerate SF	8	3
Diehappy SF	1	5
Ellis SF	3	5
Gladstone SF	3	3
Hyland SF	2	0
Ingalba SF	3	7
Irishman SF	2	2
Kangaroo River SF	10	10
Little Newry SF	1	3
Lower Bucca SF	2	4
Marara SF	2	0
Marengo SF	9	2
Mistake SF	3	1
Moonpar SF	1	2
Nambucca SF	2	9
Nana Creek SF	1	1
Newry SF	1	2
Nulla-five Day SF	1	1
Oakes SF	7	20
Old Station SF	1	3
Orara East SF	1	2
Orara West SF	4	9
Pine Creek SF	2	17

Forest/reserve name	No. sites surveyed	No. koalas detected
Scotchman SF	5	15
Sheas Nob SF	5	6
Tamban SF	3	6
Tarkeeth SF	1	2
Thumb Creek SF	2	4
Tuckers Nob SF	1	1
Way Way SF	2	0
Wedding Bells SF	1	0
Wild Cattle Creek SF	3	8
Subtotal state forests:	**120**	**212**
National park estate		
Baalijin NR	2	3
Bindarri NP	3	20
Bongil Bongil NP	2	15
Byrnes Scrub NR	1	0
Cascade NP	4	58
Cascade SCA	1	17
Chaelundi NP	10	4
Chaelundi SCA	1	1
Dunggir NP	1	0
Garby NR	1	0
Gumbaynggirr NP	1	3
Guy Fawkes River SCA	3	2
Mount Hyland NR	2	0
Ngambaa NR	5	10
Nymboi-Binderay NP	7	24
Nymboi-Binderay SCA	1	3
Sherwood NR	2	0
Ulidarra NP	1	1
Yarriabini NP	1	0
Subtotal national park estate:	**49**	**161**
Total:	**169**	**373**

SF = state forest; NP = national park; SCA = state conservation area; NR = nature reserve.

Appendix C: Candidate covariates assessed

Overview

Two distinct and extensive covariate categories, and lists of candidate covariates within each category, were compiled to be considered in the koala abundance modelling across the assessment area: koala detection covariates and koala abundance covariates. This approach reflected that hierarchical models used to assess koala abundance require covariates that can both account for imperfect detection (for example, variation in survey effort and weather conditions) and model relationships between ecologically and environmentally plausible covariates influencing variation in koala abundance.

Koala detection covariates

Several studies report various detection covariates as being relevant to aerial drone surveys of koalas. For example, dense canopy cover can obscure koalas from drone cameras leading to lower detection probabilities. Conversely, cooler ambient temperatures enhance the contrast between koalas and their surroundings in thermal images, thus improving detection. The altitude and speed of the drone also needs to be optimised to balance image resolution and coverage area, thus improving detectability, while minimising disturbance. Koala behaviour is another important factor; koalas that are exposed or moving are easier to detect compared to those resting in dense foliage.

Identifying detection-related covariates is, therefore, crucial for improving the accuracy and reliability of koala population estimates obtained from aerial drone surveys. Understanding and accounting for these factors helps to address the issue of imperfect detection, thereby providing more accurate estimates of koala populations. For the assessment area surveys, a set of survey-specific covariates were selected to correct for imperfect detection, due to variations in drone survey conditions (such as temperature at survey, date of survey, canopy density and height) and observer bias (pilot) (Table 9).

Table 9 Detection covariates considered to help account for imperfect detection of koalas observed using drone surveys in the assessment area

Covariate title	Description	Source of information
Date of flight (Survey_Date)	Date of take-off	Recorded during survey
Time after sunset (Survey_Time)	Time the survey commenced	Recorded during survey
Temperature of flight (Survey_Temp)	Temperature taken at flight altitude 65 m AGL (above ground level), mean value for each site	Air data
Wind on flight (Start_Wind65m)	Wind taken at flight altitude 65 m AGL	Air data
Forest height (Survey_Canheight)	Mean height of forest canopy at take-off, measure canopy height AGL in metres	Survey123, recorded during the survey
Survey order (Survey_Order)	Pilot A and Pilot B	Survey123, recorded during survey
Pilot observer (Pilot)	Name of pilot (3 initials)	Filename of video data on Google drive

Koala abundance covariates

Koala populations respond to multiple ecological and environmental processes that dictate variation in their abundance and distribution at different spatial scales. At the relatively large spatial scale of the assessment area (176,000 ha), alongside a pronounced elevational gradient (1 to 1,332 m above sea level), a broad range of ecological and environmental processes could be expected to influence the capacity of koalas to survive, reproduce and move across the landscape. Through these interactions, considerable variation in local koala abundance measured at the site scale of the survey might be observed.

A broad range of covariates have been used across many studies to assess occupancy, distribution and to a lesser extent abundance across the distribution of the koala. Typically, these covariates are selected to reflect underlying ecological mechanisms and environmental factors that are expected to influence the koala abundance ecosystem. For this study, 5 categories of key influences were used to guide the selection of covariates expected to influence koala occupancy or abundance. These were:

- vegetation type and quality – Normalized Difference Vegetation Index (NDVI), leaf moisture content, and tree species composition, particularly focusing on preferred eucalypt species

- climate variables – temperature, rainfall and extreme weather events (for example, drought or heatwaves)
- topography – elevation, slope and aspect, as they influence microclimates and vegetation
- soils – soil depth, soil organic carbon and soil clay content, which are important for eucalypt species, nutrient availability and leaf moisture
- fire history – frequency, intensity (severity), and recentness of fires, which can affect habitat suitability.

Timber harvesting frequency covariates were not considered because the current survey design is inadequate for assessing the effects of timber harvesting on koala abundance. This objective would require a different, more complex stratification approach, capturing replication across forest compartments with varied histories of harvest. These variations in harvest method, frequency and timber extraction over time complicate analysis. Additionally, due to the spatial structuring of koala populations across the assessment area, it would be challenging to find meaningful control sites in previously harvested areas, potentially introducing sampling bias.

A total of 23 koala-relevant ecological and environmental candidate covariates (detailed in Tables 10 and 11) were considered in the initial models, and these were reduced down to 4 final covariates that best predicted koala abundance based on model ranking criteria (see Appendix D). Table 10 provides a plain English description of the covariates and references other studies that have used similar covariates. Table 10 also highlights (grey shading) the 4 final covariates. Table 11 provides technical detail about each of the covariates. Note that the ‘Covariate’ and ‘Name’ columns are the same in both tables for ease of comparison.

Table 10 List of 23 covariate options for modelling koala abundance/density in the assessment area

No.	Covariate	Name	Plain English explanation	Why is it important?
1	sp_des0200	Soil depth	Modelled product that predicts the depth of soil (A and B horizons) down to 2 m. Part of the Soil and Landscape Grid of Australia. SLGA attribute maps are in raster format at a resolution of 3 arc sec (~90 × 90 m pixels).	Soil depth was considered in the models as it is important for plants (including eucalypts, a key food resource of koalas (Moore et al. 2004) and because deeper rooting means more soil for trees to exploit nutrients and water. Research shows that eucalypt leaf moisture content influences tree feed preferences of koalas (Moore et al. 2004).
2	sp_soc0100	Soil organic carbon	Modelled product that predicts the soil organic carbon fraction in the soil. Source data includes digital soil attribute maps, and their upper and lower confidence limits, representing the soil attribute at 6 depths: 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm and 100–200 cm. The product covers proportionally combined depths from 0 to 100 cm. The maps are in raster format at a resolution of 3 arc sec (~90 × 90 m pixels).	Soil organic matter (SOM) is the portion of organic residues in soil in various stages of decay. The presence of SOM contributes significantly to soil health. Due to its chemical and physical properties, SOM retains large amounts of water and nutrients, which help maintain and increase soil biodiversity, improve water and nutrient availability, and reduce erosion and leaching. Soil organic carbon is the measurable component of SOM and was included in the models as it has been proven to be a strong predictor of koala density in other studies (Ashman et al. 2020).
3	sp_cly0100	Soil clay content	Modelled product that predicts the percentage clay content in soil. Source data includes 6 digital soil attribute maps, and their upper and lower confidence limits, representing the soil attribute at 6 depths:	Soil clay content influences soil water retention, nutrient availability and soil structure. As such it is a crucial factor influencing the composition of tree species,

No.	Covariate	Name	Plain English explanation	Why is it important?
			0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm and 100–200 cm. The product covers proportionally combined depths from 0 to 100 cm. The maps are in raster format at a resolution of 3 arc sec (~90 × 90 m pixels).	including eucalypts, a key food resource of koalas (Moore et al. 2004) and plant communities, which in turn can significantly impact koala habitat suitability.
4	rs_ndvi_q3	Normalized Difference Vegetation Index	Normalized Difference Vegetation Index (NDVI) is a remote sensing index, ranging from −1 to +1. It is a measure of vegetation health. Negative values (−1) show sparse vegetation and positive values (+1) show healthy and dense vegetation. Covariate captures the long-term average NDVI derived from cloud-free Landsat 5 TOA collection in Google Earth Engine. Average values taken for Quarter 3 (spring) between 1984 and 2012. The covariate is in raster format at a resolution of 1 arc sec (~30 × 30 m pixels).	NDVI is a frequently used index of vegetation health. Healthier vegetation results in higher NDVI and is predicted to support more koalas as shown in other relevant research (Moore et al. 2004).
5	rs_fmstd	Foliar moisture standard deviation	Foliar moisture content is a key indicator of vegetation health and influences individual plant resilience to weather, climatic variability, and disturbances such as insects, disease, and fire (Lad et al. 2023). Foliar moisture is predicted from a random forest model that uses a radiative transfer model emulator. Standard deviation through the timeseries. The covariate is in raster format at a resolution of 1 arc sec (~30 × 30 m pixels).	Foliar moisture was used in the models because relevant research has shown that eucalypt leaf moisture content influences tree feed preferences of koalas (Moore et al. 2004).

No.	Covariate	Name	Plain English explanation	Why is it important?
6	rs_fmmean	Foliar moisture mean	Foliar moisture content is a key indicator of vegetation health and influences individual plant resilience to weather, climatic variability, and disturbances such as insects, disease, and fire (Lad et al. 2023). Foliar moisture is predicted from a random forest model that uses a radiative transfer model emulator. Mean through the timeseries. The covariate is in raster format at a resolution of 1 arc sec (~30 × 30 m pixels).	As above
7	rs_fm05	Foliar moisture 5th percentage	Foliar moisture content is a key indicator of vegetation health and influences individual plant resilience to weather, climatic variability, and disturbances such as insects, disease, and fire (Lad et al. 2023). Foliar moisture is predicted from a random forest model that uses a radiative transfer model emulator. Fifth percentile through the timeseries. The covariate is in raster format at a resolution of 1 arc sec (~30 × 30 m pixels).	As above
8	fire_freq	Number times burnt	The covariate, number of times burnt, represents the number of times that any given point within the study area has been intersected by a burnt area polygon in the fire history (raster and vector). The covariate indicates number of times burnt for each 30 × 30 m pixel, as recorded in the fire history layer. Values range from 0 to 14. FireTools Cloud is a web-based GIS processing environment developed by the NSW Bushfire Risk Management Research Hub. The covariate is in raster	Cumulative fire history helps to explain the forest structure and composition and can also help to identify areas that are burnt more often and are therefore potentially less suitable habitat for koalas. This covariate was included in the modelling as it was seen to provide the most useful information to understand cumulative fire history in the assessment area.

No.	Covariate	Name	Plain English explanation	Why is it important?
			format at a resolution of 1 arc sec (~30 × 30 m pixels) developed over the last 100 years. The long chronology of this covariate uses fire severity data sourced from multiple methods including satellite, aerial and on-ground mapping for earlier fires (National Parks and Wildlife Service, Forestry Corporation of NSW, Rural Fire Service). More recent technologies can better quantify multiple attributes of fire severity, however, the qualitative description of the severity of earlier major fires was often well described, particularly by mapping fire extent (that is, an attribute also highly correlated with overall fire severity).	
9	fesm_34b	FESM 2019–20 classes 3 and 4 (%)	Fire Extent and Severity Mapping version 3 (FESM v3) was developed during and after the megafires in 2019–20. Created from a binary raster where 0 is unburnt or burnt at low or moderate severity, and 1 = high or extreme severity. The layer represents the percentage of cells in FESM classes 3 and 4 in 2019–20.	This representation of the 2019–20 FESM data included the classes of fire severity from high to extreme severity. This layer was used in the models to see whether there was a negative relationship between high and extreme fire severity and koala abundance.
10	fesm_maxse	FESM 2016 to 2023	FESM v3 was developed between 2016 and 2023. This representation of the 2016 to 2023 FESM data includes the 5 classes of fire severity from not burnt to extreme severity. Maximum severity (per pixel) between 2016 and 2023. 0 = not burnt, 1 = burnt low intensity, 2 = moderate, 3 = high and 4 = extreme. Uses annual FESM products from 2016 to 2023.	A range of FESM layers were used in the model to explore the influence of different levels of fire severity on koala abundance. Fire is known to affect koala occupancy depending upon the severity and extent. Research shows the effects of fire on koalas using FESM depends on the severity of the fire (Law et al. 2018). For example, low-severity fire did not influence koala occupancy or bellow rate (Law

No.	Covariate	Name	Plain English explanation	Why is it important?
				et al. 2024a). However, a substantial impact of high severity fire was confirmed during the 2019–20 megafires. The severe impacts were localised across the landscape (Law et al. 2022a).
11	fesm_24b	FESM 2019–20 classes 2 to 4 (%)	FESM v3 was developed during and after the megafires in 2019–20. Created from a binary layer where 0 is unburnt or burnt at low severity and 1 = moderate, high or extreme severity for the 2019–20 fire year. The layer represents the percentage of cells in FESM classes 2 to 4 in 2019–20.	This representation of the 2019–20 FESM data included the classes of fire severity from moderate to extreme severity. As koalas are known to persist with low to moderate severity fires (Law et al. 2024a), this layer was used to see whether there was a negative relationship between moderate to extreme fire severity and koala abundance.
12	fesm_14b	FESM 2019–20 classes 1 to 4 (%)	FESM v3 was developed during and after the megafires in 2019–20. Created from a binary layer where 0 is unburnt, and 1 = burnt at low, moderate, high or extreme severity. The layer represents the percentage of cells in FESM classes 1 to 4 in 2019–20.	This representation of the 2019–20 FESM data includes all classes of fire severity from low to extreme severity and only differentiates unburnt from burnt. As koalas are known to persist with low to moderate severity fires (Law et al. 2024a), this layer was used to see whether there was a relationship between all levels of fire severity and koala abundance.
13	fesm_4b	FESM 2019–20 class 4 (%)	FESM v3 was developed during and after the megafires in 2019–20. Created from a binary raster where 0 is unburnt or burnt at low, moderate or high severity and 1 = extreme severity. The layer represents the percentage of cells in FESM class 1 in 2019–20.	This representation of the 2019–20 FESM data only includes the areas classed as extreme severity (canopy burn). A substantial impact of high severity fire was confirmed during the 2019–20 megafires and severe impacts were localised across the landscape (Law et al. 2022a).

No.	Covariate	Name	Plain English explanation	Why is it important?
14	tc_wet	Wetness	The Tasseled Cap (TC) index is a remote sensing index used to extract information about vegetation cover, soil, and water content from multispectral imagery. The wetness component of the TC index is a measure of the water content of the surface. High wetness values are indicative of surface water, but also other objects that have low reflectance such as dense vegetation. The covariate is in raster format at a resolution of 1 arc sec (~30 × 30 m pixels). TC index was derived using Sentinel 2a timeseries median of all cloud-free 2022 images.	Koalas meet their water requirements through a combination of the moisture within browsed leaves and drinking from free water sources. Eucalypt leaves typically contain more than 50% water content by weight and herbivores should not have too much difficulty meeting their water balance in that situation. This layer was used in the models because koalas may move to moister microclimates (gullies and drainage lines, lower topographic positions) during times of high temperature and drought (OEH 2018).
15	cw_precipd	Precipitation driest period	Precipitation of driest period. Created by the department using ANUCLIM (Version 6.1 MTHCLIM module) software and the 1 second Shuttle Radar Topographic Mission (SRTM) DEM (digital elevation model) data. Climate data includes monthly mean climate values for the 1976 to 2005 period.	Precipitation of driest period – included as it is potentially an extreme or limiting environmental factors.
16	ct_tmpmtc	Min temperature	Minimum temperature of coldest period. Created by the department using ANUCLIM (Version 6.1 MTHCLIM module) software and the 1 second SRTM DEM (digital elevation model) data. Climate data includes monthly mean climate values for the 1976 to 2005 period.	Mean annual minimum temperature was used in the models because it had been shown in relevant research to have an influence on koala population density. Ashman et al. (2020) found a negative trend in koala abundance with increasing mean minimum temperature.

No.	Covariate	Name	Plain English explanation	Why is it important?
17	ct_tmpmtw	Max temperature	Maximum temperature of warmest period. Created by the department using ANUCLIM (Version 6.1 MTHCLIM module) software and the 1 second (SRTM) DEM data. Climate data includes monthly mean climate values for the 1976 to 2005 period.	Maximum temperature was used to determine whether it had an influence on koala density in the assessment area.
18	crown_max	Tree crown height	The crown height is the height from the lowest branches to the top of the tree. Layer represents maximum tree crown height (m) per 30 × 30 m pixel. Derived from light detection and ranging (LiDAR) point cloud data.	Tree crown height was used to determine whether it had an influence on koala density in the assessment area.
19	lf_dem1nnv	Elevation	The height of a place above the level of the sea in metres. Product is the national 1 second (~30 m) DEM which was produced from SRTM digital surface model (DSM). The covariate is in raster format at a resolution of 1 arc sec (~30 x 30 m pixels).	Elevation was used in our models as it had been shown in relevant research to have a strong effect on initial koala occupancy (Law et al. 2018; Law et al. 2024a) and on koala density (Heard and Ramsey 2020), with lower elevations having both greater occupancy and density in these studies.
20	TSI_06spp	Tree species Index (6 species) - probability of occurrence	A Tree Species Index (TSI) attempts to predict the collective distributions of a given set of tree species. It uses individual species distribution models (SDMs) derived from presence-absence vegetation site data to define the predicted distribution of each individual species. These SDMs are then stacked, and for each 30 × 30 m grid cell, the TSI represents the probability that at least one of those species is present. This index includes the 6 highest value koala food trees known to occur in the assessment area. This includes *Eucalyptus grandis*, *E. microcorys*, *E.*	This layer was used in the models to look at the influence of the 6 locally highest value feed trees on koala density. The list is based on local koala tree use preference information provided by J Turbill (DCCEEW) and M Fisher (3D Ecology Mapping).

No.	Covariate	Name	Plain English explanation	Why is it important?
			propinqua, *E. robusta*, *E. saligna* and *E. tereticornis* (common names are provided in Table 4). The covariate is in raster format at a resolution of 1 arc sec (~30 × 30 m pixels).	
21	TSI_06sppb	TSI (6 species) - binary thresholded version	This is a variation of the TSI above. Instead of predicting a continuous probability, the TSI is thresholded at 0.5 and converted to a 0 or 1 binary layer (cells with a value of 1 are predicted to have a probability greater than 0.5 that at least one tree species is present). The binary is then used to count the number of cells above the 0.5 threshold, and this is represented as a proportion of the total number of 30 × 30 m grid cells that make up each prediction cell (750 × 750 m). The covariate is in raster format at a resolution of 1 arc sec (~30 × 30 m pixels).	As above.
22	TSI_14spp	Tree Species Index (14 species) - probability of occurrence	Described above. The TSI includes 14 food tree species that are known importance to koalas locally. This includes the 6 species in TI_06spp and *E. signata*, *E. biturbinata*, *E. blakelyi*, *E. quadrangulata*, *E. rummeryi*, *E. globoidea*, *E. moluccana*, *E. resinifera* (common names are provided in Table 4).	This layer was used in the models to look at the influence of 14 locally important feed trees on koala density.
23	TSI_14sppb	TSI (14 species) - binary thresholded version	Described above but is a thresholded version of the 14 species TSI.	As above.

Table 11 Technical details: list of covariate options for modelling relative abundance/density in the assessment area

No.	Covariate	Name	Units	Source	Years	More information
1	sp_des0200	Soil depth	m	CSIRO	Soil profile data 1950 to2021	Soil and Landscape Grid National Soil Attribute Maps – Soil Depth (3" resolution) – Release 2 – CSIRO Data Access Portal
2	sp_soc0100	Soil organic carbon	%	CSIRO	Soil profile data 1950 to 2022	Soil and Landscape Grid National Soil Attribute Maps – Soil Organic Carbon Fractions (3" resolution) – Release 1 – CSIRO Data Access Portal
3	sp_cly0100	Soil clay content	%	CSIRO	Soil profile data 1950 to 2021	Soil and Landscape Grid National Soil Attribute Maps - Clay (3" resolution) – Release 2 – CSIRO Data Access Portal
4	rs_ndvi_q3	Normalized Difference Vegetation Index	Index	TERN	1984 to 2012	USGS Landsat 5 Level 2, Collection 2, Tier 1 – Earth Engine Data Catalog
5	rs_fmstd	Foliar moisture standard deviation	%	University of Western Sydney		Kotzur and Moore (2023) – not yet published. Plan to publish on Information Asset Register soon
6	rs_fmmean	Foliar moisture mean	%	University of Western Sydney		Kotzur and Moore (2023) – not yet published. Plan to publish on Information Asset Register soon
7	rs_fm05	Foliar moisture 5th percentage	%	University of Western Sydney		Kotzur and Moore (2023) – not yet published. Plan to publish on Information Asset Register soon
8	firet_freq	Number times burnt	Years	FireTools dataset	1927 to 2024	FireTools Cloud Results – NPWS North Coast Branch – Asset – Information Asset Register | NSW Environment & Heritage

No.	Covariate	Name	Units	Source	Years	More information
						FireTools Cloud user guide (Williamson 2021)
9	fesm_34b	FESM 2019–20 classes 3 to 4 (%)	proportion of cells	DCCEEW	2019–20	Fire Extent and Severity Mapping (FESM) (SEED data portal)
10	fesm_maxse	FESM 2016 to 2023	Index	DCCEEW	2016–23	Fire Extent and Severity Mapping (FESM) (SEED data portal)
11	fesm_24b	FESM 2019–20 classes 2 to 4 (%)	proportion of cells	DCCEEW	2019–20	Fire Extent and Severity Mapping (FESM) (SEED data portal)
12	fesm_14b	FESM 2019–20 classes 1 to 4 (%)	proportion of cells	DCCEEW	2019–20	Fire Extent and Severity Mapping (FESM) (SEED data portal)
13	fesm_4b	FESM 2019–20 class 4 (%)	proportion of cells	DCCEEW	2019–20	Fire Extent and Severity Mapping (FESM) (SEED data portal)
14	tc_wet	Wetness	Index	DCCEEW	2022	Unpublished
15	cw_precipd	Precipitation driest period	mm	DCCEEW	1976 to 2005	State Vegetation Type Map (SVTM) Modelling Grid Collection – NSW Planning Portal
16	ct_tmpmtc	Min temperature	degrees C	DCCEEW	1976 to 2005	State Vegetation Type Map (SVTM) Modelling Grid Collection – NSW Planning Portal
17	ct_tmpmtw	Max temperature	degrees C	DCCEEW	1976 to 2005	State Vegetation Type Map (SVTM) Modelling Grid Collection – NSW Planning Portal
18	crown_max	Tree crown height	m	Griffith University	2009 to 2018	Mackey et al. (unpublished). Plan to upload to Information Asset Register.
19	lf_dem1nnv	Elevation	m	DCCEEW		State Vegetation Type Map (SVTM) Modelling Grid Collection – NSW Planning Portal Gallant et al. (2011)

No.	Covariate	Name	Units	Source	Years	More information
20	TSI_06spp	Tree Species Index (6 species) – probability of occurrence	probability	DCCEEW		Unpublished
21	TSI_06sppb	Tree Species Index (6 species) – binary thresholded version	proportion of cells	DCCEEW		Unpublished
22	TSI_14spp	Tree Species Index (14 species) – probability of occurrence	probability	DCCEEW		Unpublished
23	TSI_14sppb	Tree Species Index (14 species) – binary thresholded version	proportion of cells	DCCEEW		Unpublished

Maps of covariates across the assessment area

The following maps (Figure 16 to Figure 38) depict the spatial distribution of each candidate covariate that was considered in the models to predict koala abundance across the assessment area, as follows:

Figure 16	Normalized Difference Vegetation Index (rs_ndvi_q3)
Figure 17	Foliar moisture mean (rs_fmmean)
Figure 18	Foliar moisture standard deviation (rs_fmstd)
Figure 19	Foliar moisture 5th percentile (rs_fm05)
Figure 20	Soil depth (sp_des0200)
Figure 21	Clay content (sp_cly0100)
Figure 22	Soil organic carbon (sp_soc0100)
Figure 23	Tasseled Cap wetness index (tc_wet)
Figure 24	Tree Species Index (6 species) - probability of occurrence (TSI_06spp)
Figure 25	Tree Species Index (6 species) - binary thresholded version (TSI_06sppb)
Figure 26	Tree Species Index (14 species) - probability of occurrence (TSI_14spp)
Figure 27	Tree Species Index (14 species) binary thresholded version (TSI_014sppb)
Figure 28	Minimum temperature coldest period (ct_tmpmtc)
Figure 29	Maximum temperature warmest period (ct_tmpmtw)
Figure 30	Precipitation driest period (cw_precipd)
Figure 31	Elevation (lf_dem1nnv)
Figure 32	Fire Extent and Severity Mapping (FESM) classes 1 to 4, proportion of cells (fesm_14b)
Figure 33	Fire Extent and Severity Mapping (FESM) classes 2 to 4, proportion of cells (fesm_24b)
Figure 34	Fire Extent and Severity Mapping (FESM) classes 3 and 4, proportion of cells (fesm_34b)
Figure 35	Fire Extent and Severity Mapping (FESM) class 4, proportion of cells (fesm_4b)
Figure 36	FESM 2016 to 2023 (fesm_maxse) (representing the maximum severity per pixel between 2016 and 2023)
Figure 37	FireTools fire frequency (firet_freq)
Figure 38	Canopy height (crown_max)

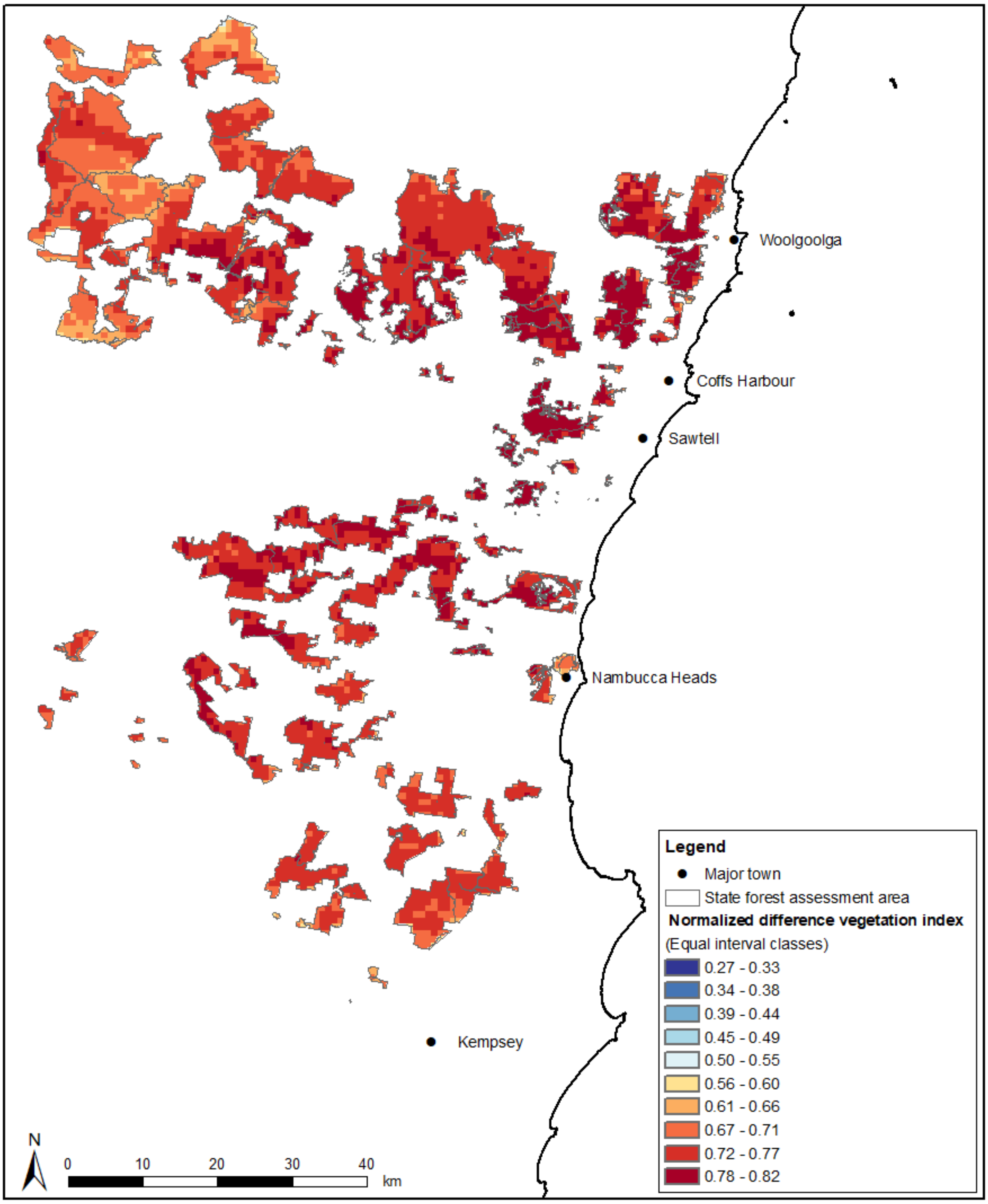


Figure 16 **The spatial distribution of the long-term Normalized Difference Vegetation Index, NDVI, third quarter (rs_ndvi_q3) covariate considered in the models of koala abundance across the assessment area**

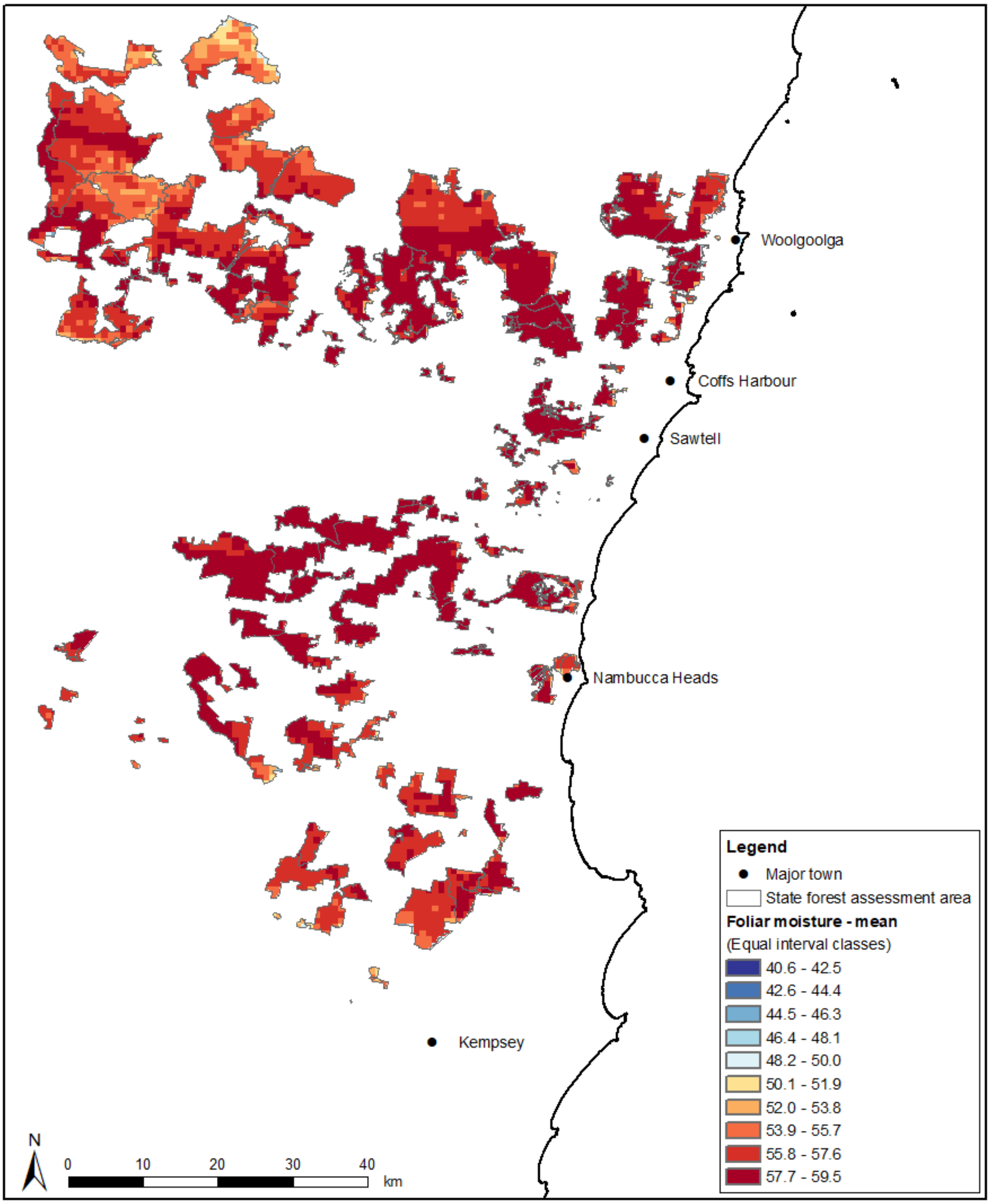


Figure 17 **The spatial distribution of the foliar moisture mean (rs_fmmean) covariate considered in the models of koala abundance across the assessment area**

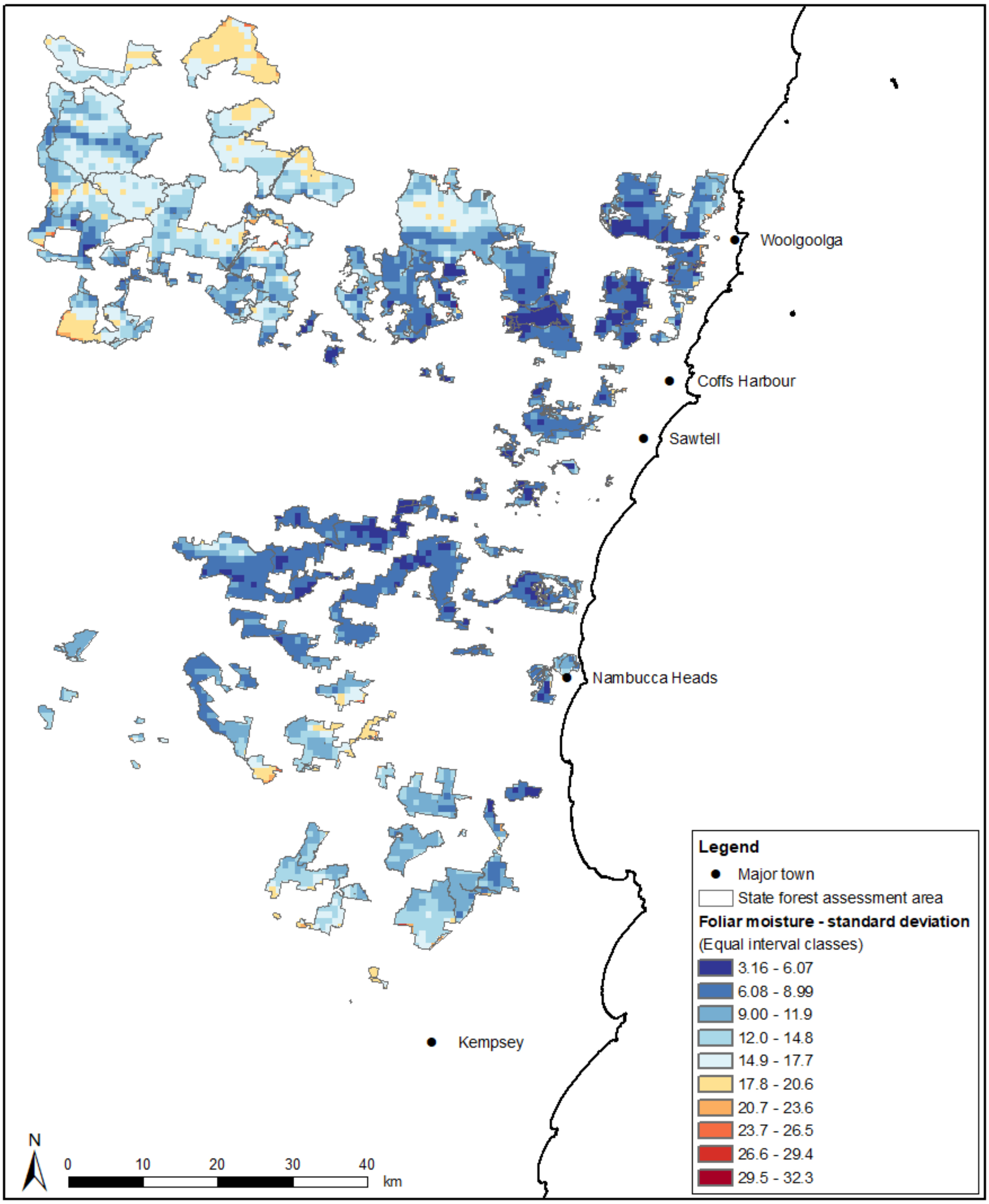


Figure 18 **The spatial distribution of the foliar moisture standard deviation (rs_fmstd) covariate considered in the models of koala abundance across the assessment area**

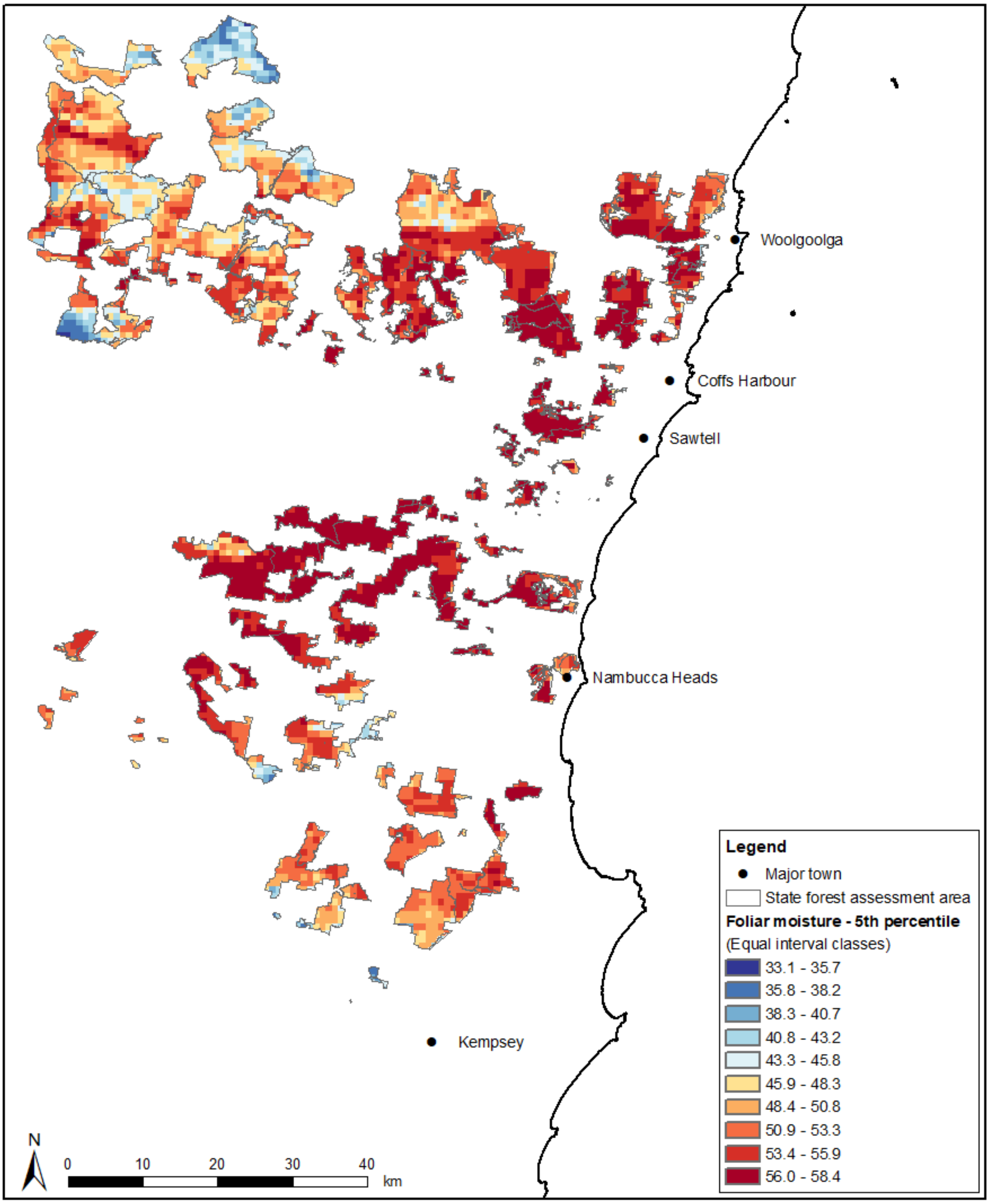


Figure 19 **The spatial distribution of the foliar moisture 5th percentile (rs_fm05) covariate considered in the models of koala abundance across the assessment area**

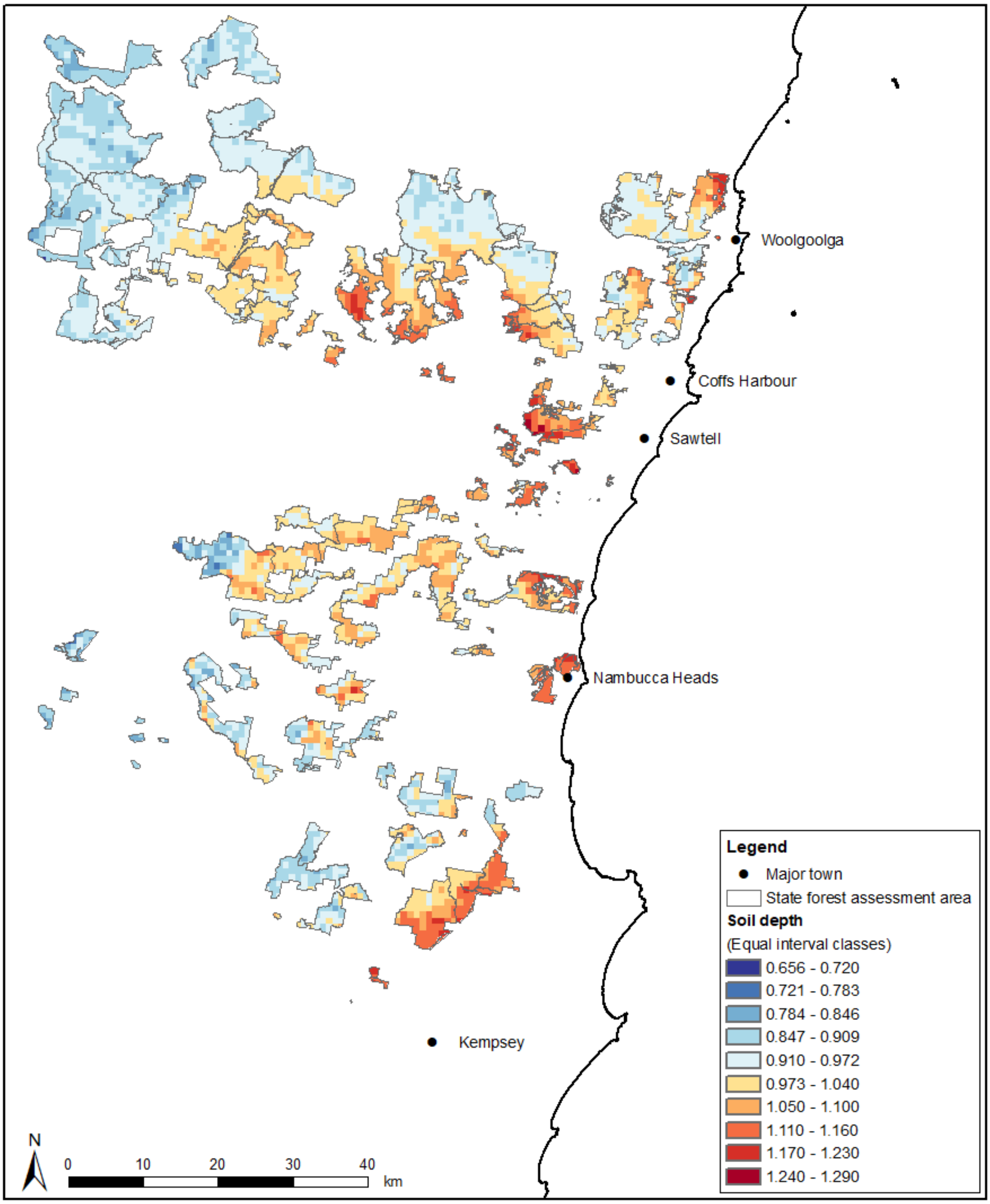


Figure 20 **The spatial distribution of the soil depth (sp_des0200) covariate considered in the models of koala abundance across the assessment area**

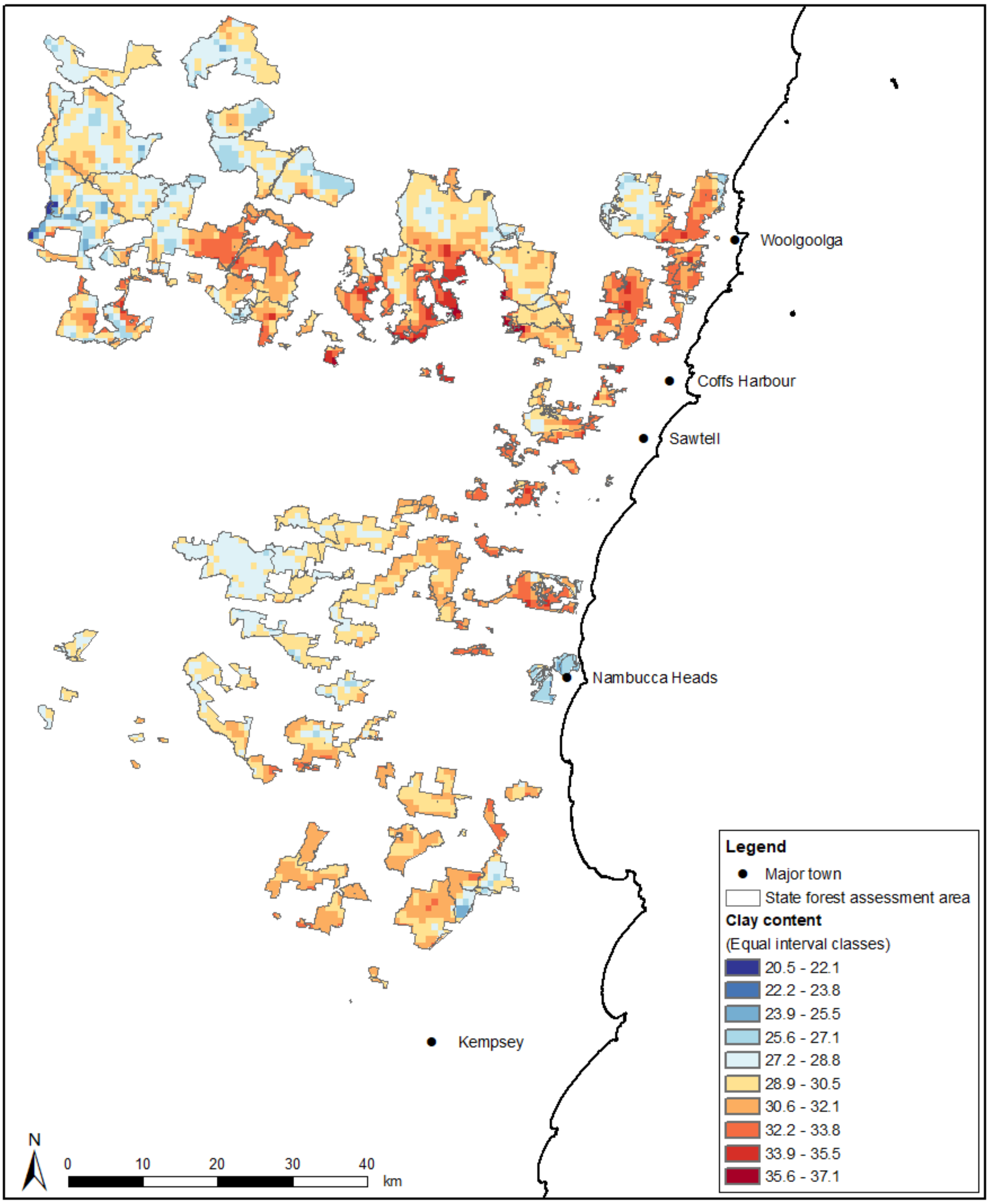


Figure 21 **The spatial distribution of the clay content (sp_cly0100) covariate considered in the models of koala abundance across the assessment area**

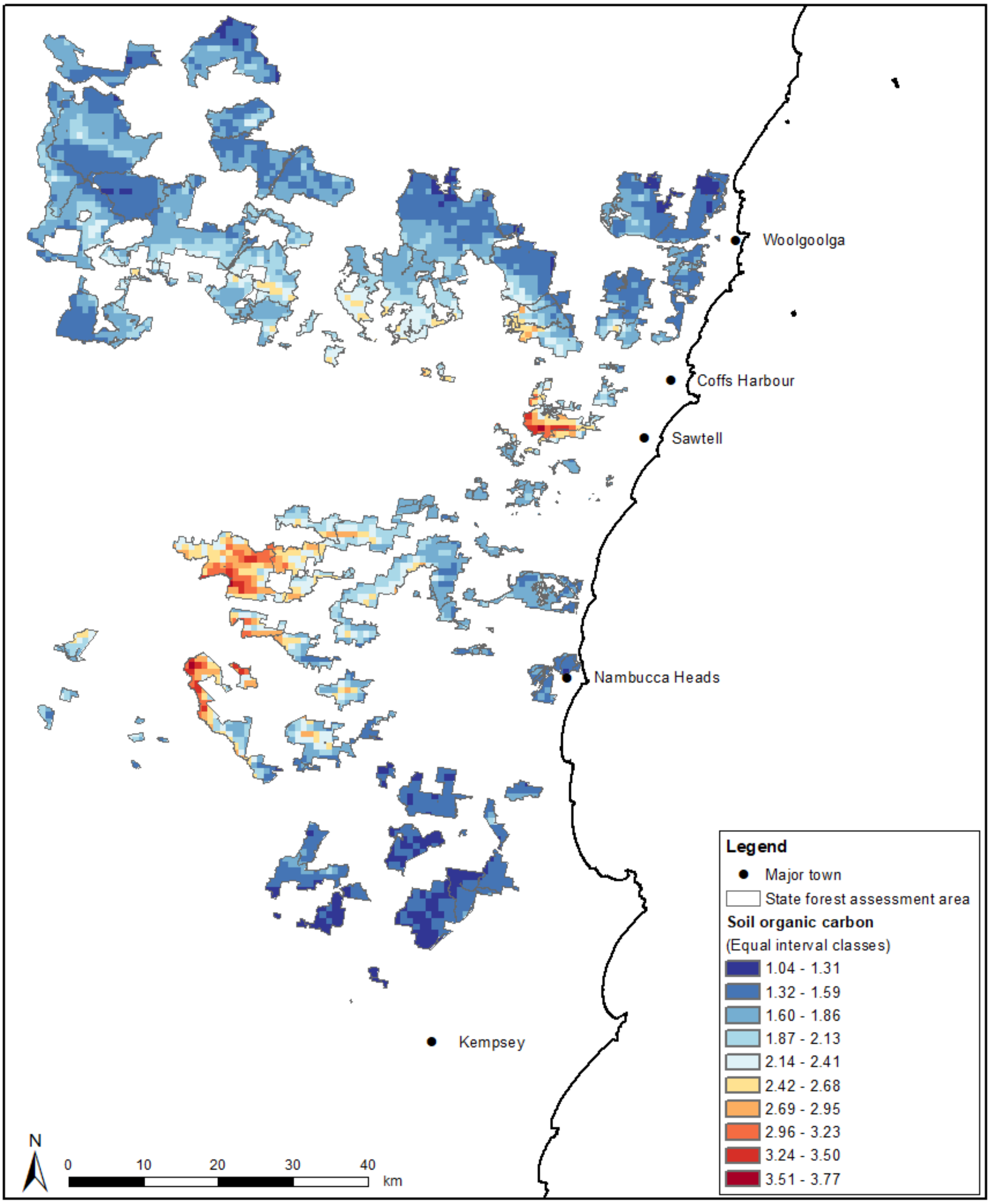


Figure 22 **The spatial distribution of the soil organic carbon (sp_soc0100) covariate considered in the models of koala abundance across the assessment area**

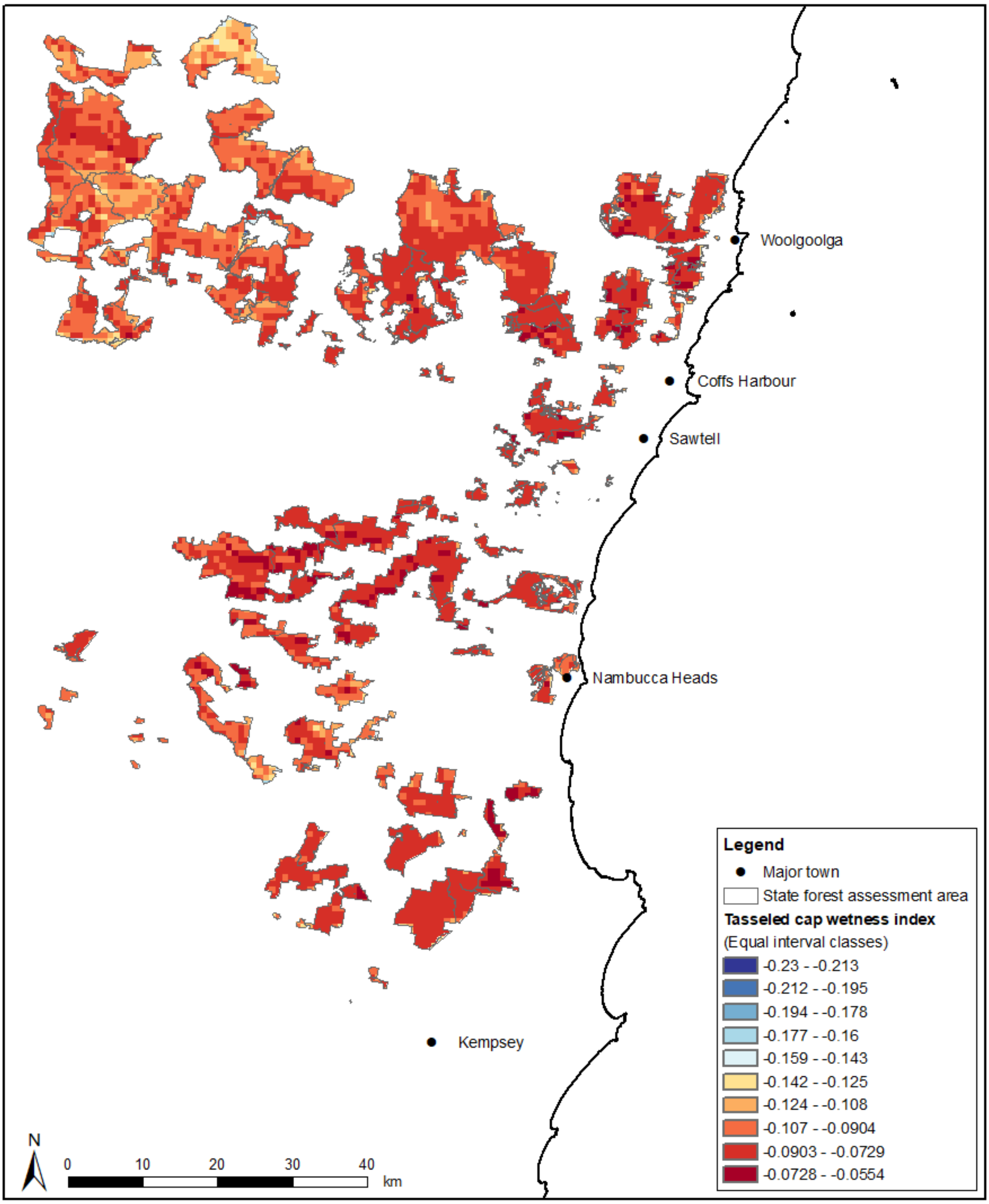


Figure 23 **The spatial distribution of the Tasseled cap wetness index (tc_wet) covariate considered in the models of koala abundance across the assessment area**

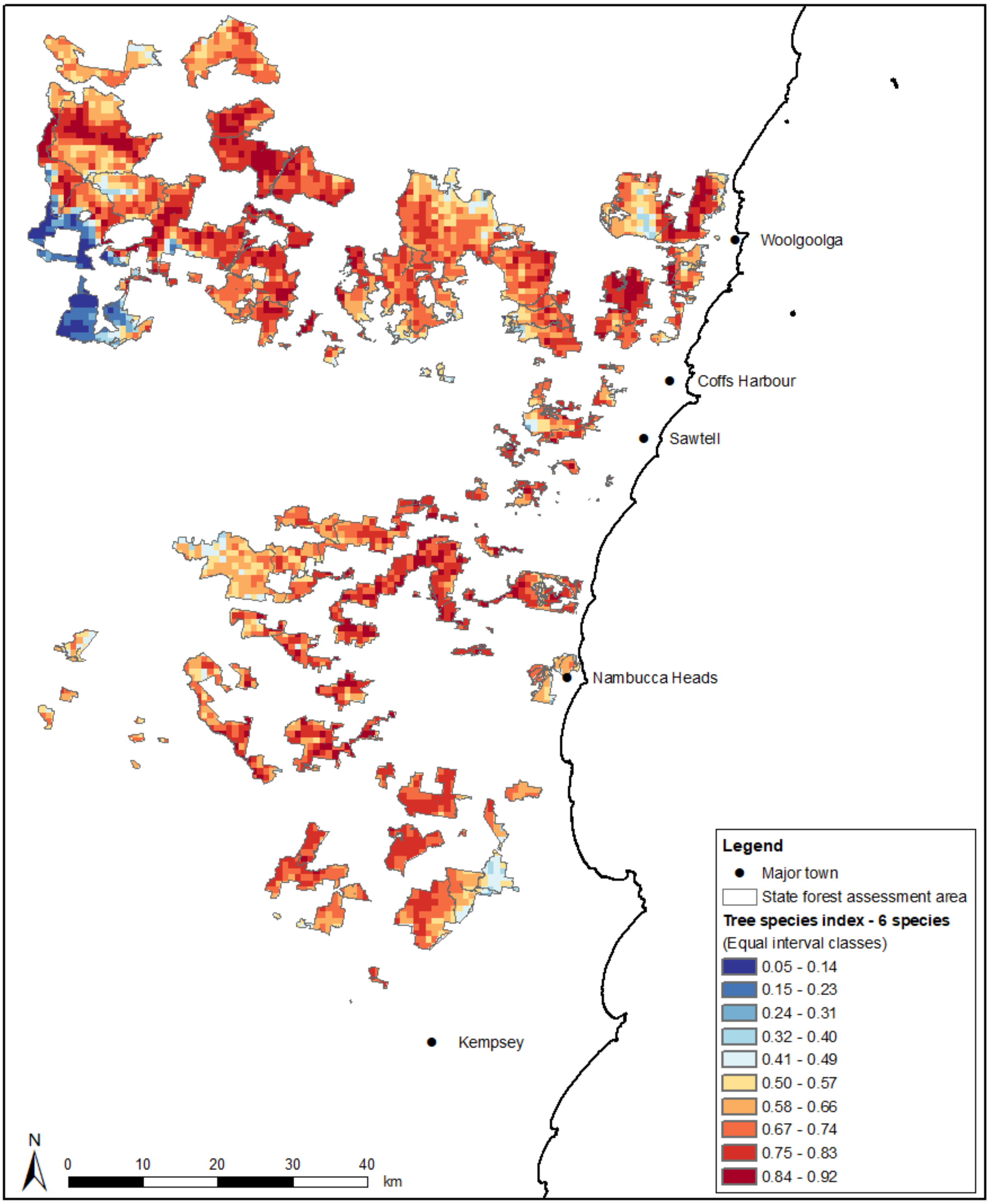


Figure 24 The spatial distribution of the Tree Species Index (6 species) - probability of occurrence (TSI_06spp) covariate considered in the models of koala abundance across the assessment area

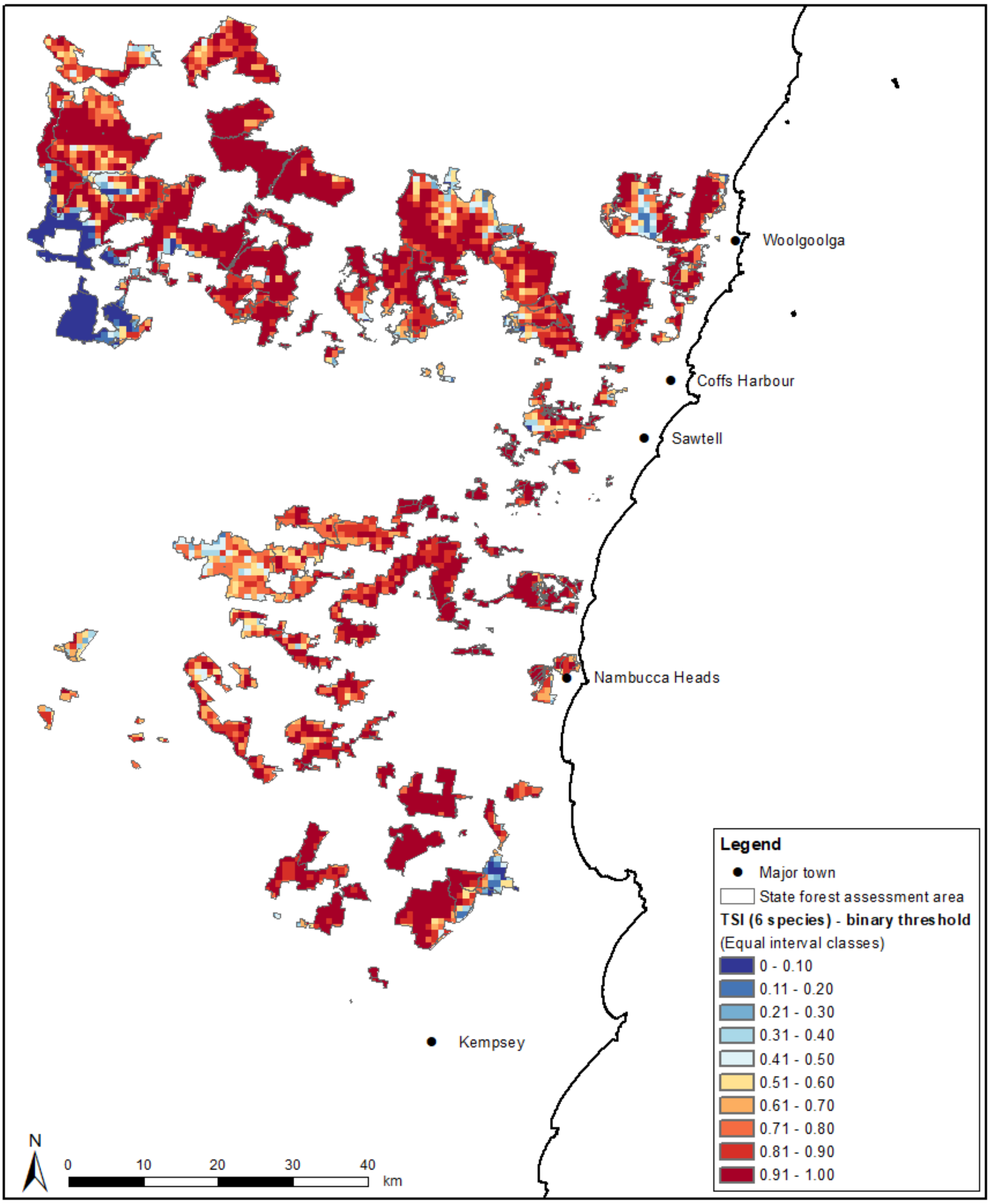


Figure 25 **The spatial distribution of the Tree Species Index (6 species) - binary thresholded version (TSI_06sppb) covariate considered in the models of koala abundance across the assessment area**

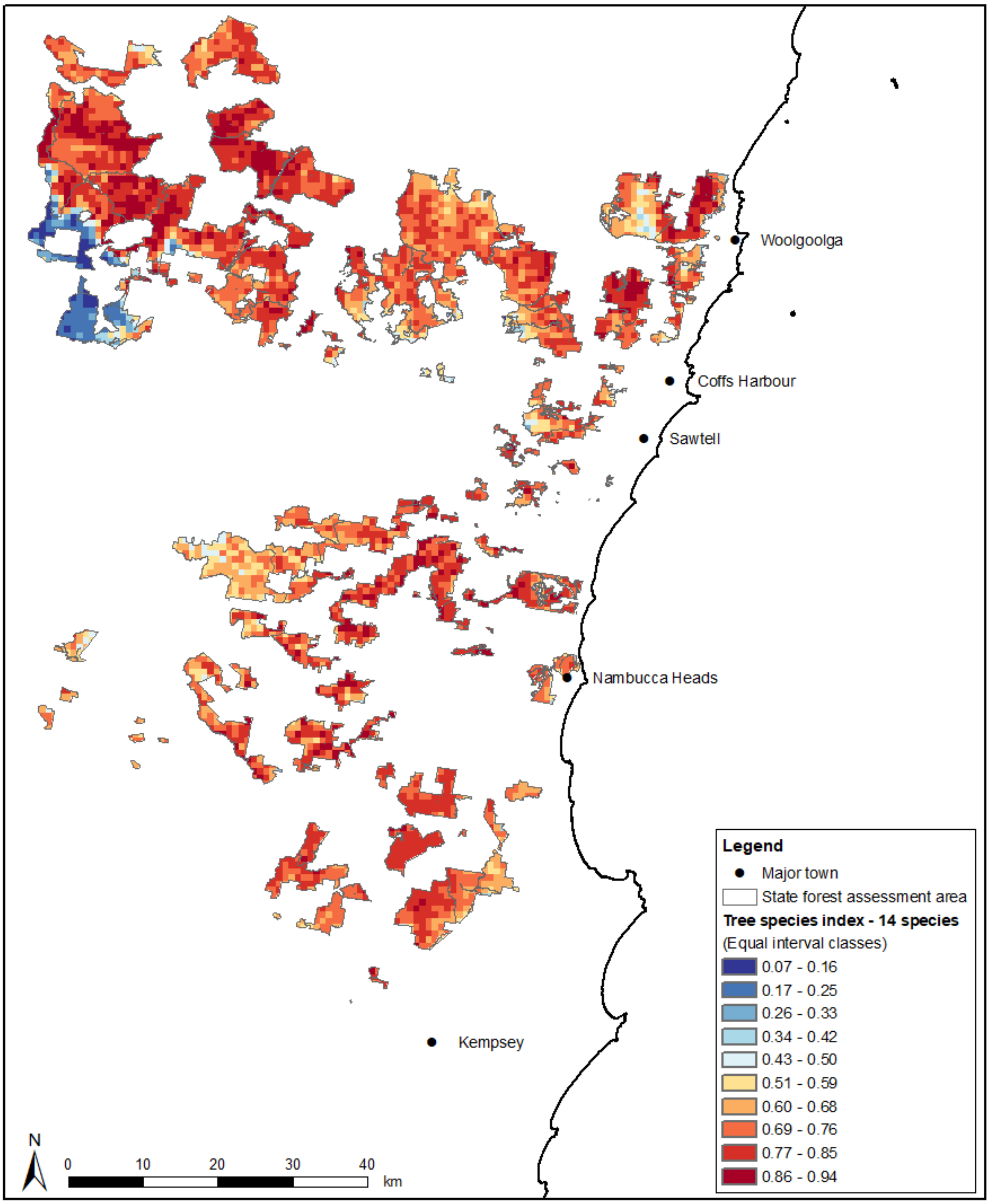


Figure 26 The spatial distribution of the Tree Species Index (14 species) - probability of occurrence (TSI_14spp) covariate considered in the models of koala abundance across the assessment area

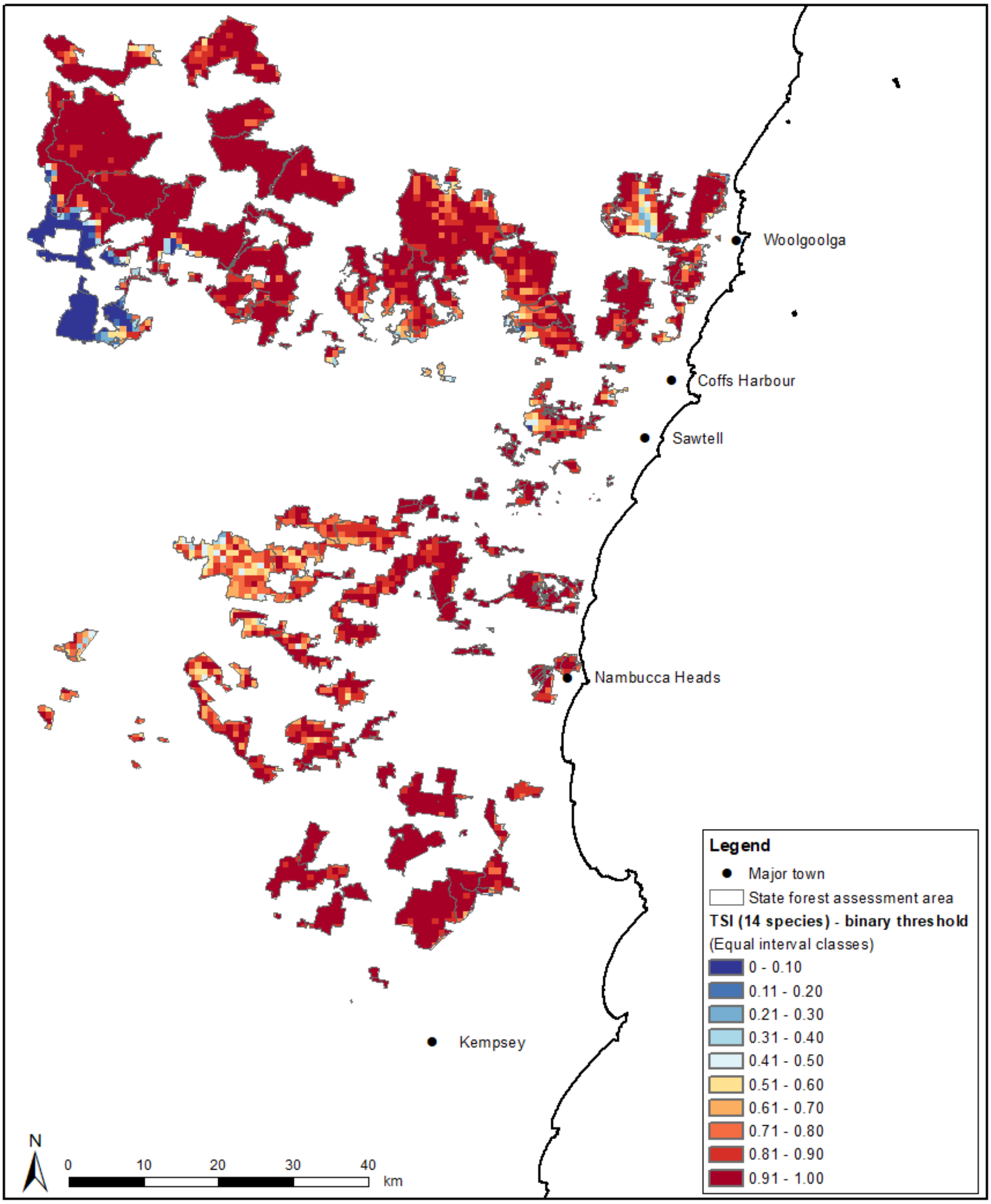


Figure 27 **The spatial distribution of the Tree Species Index (14 species) binary thresholded version (TSI_014sppb) covariate considered in the models of koala abundance across the assessment area**

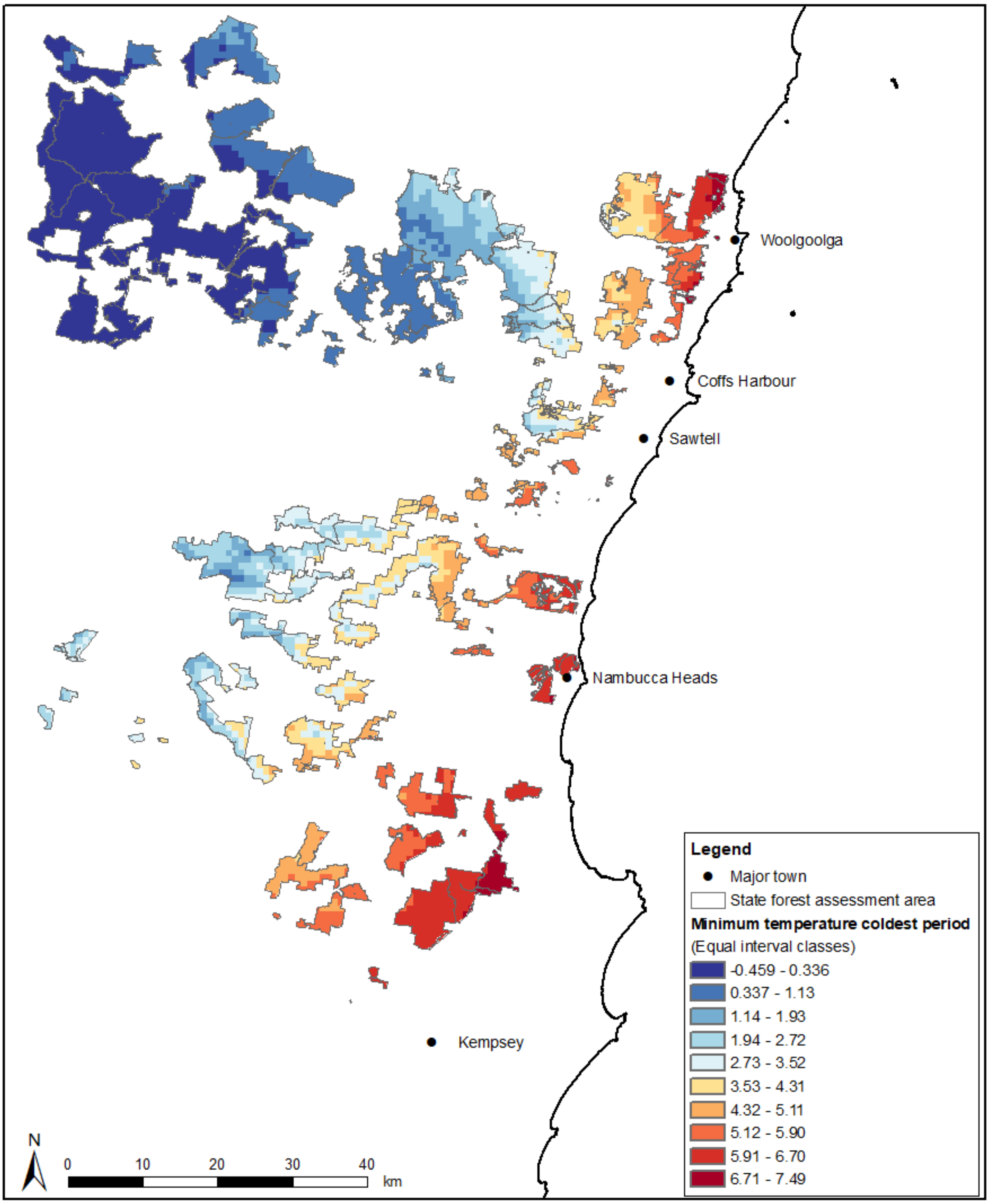


Figure 28 The spatial distribution of the minimum temperature coldest period (ct_tmpmtc) covariate considered in the models of koala abundance across the assessment area

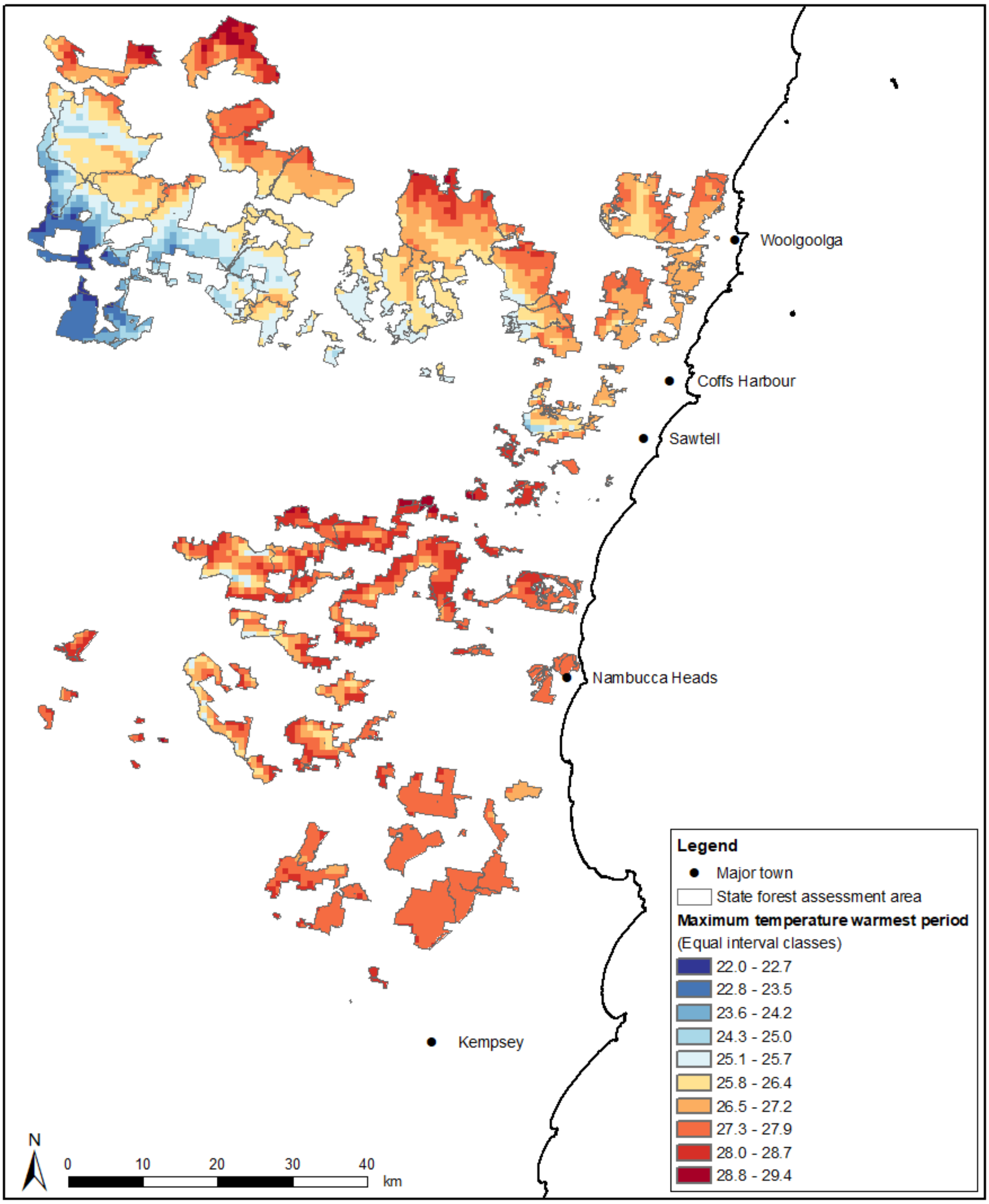


Figure 29 **The spatial distribution of the maximum temperature warmest period (ct_tmpmtw) covariate considered in the models of koala abundance across the assessment area**

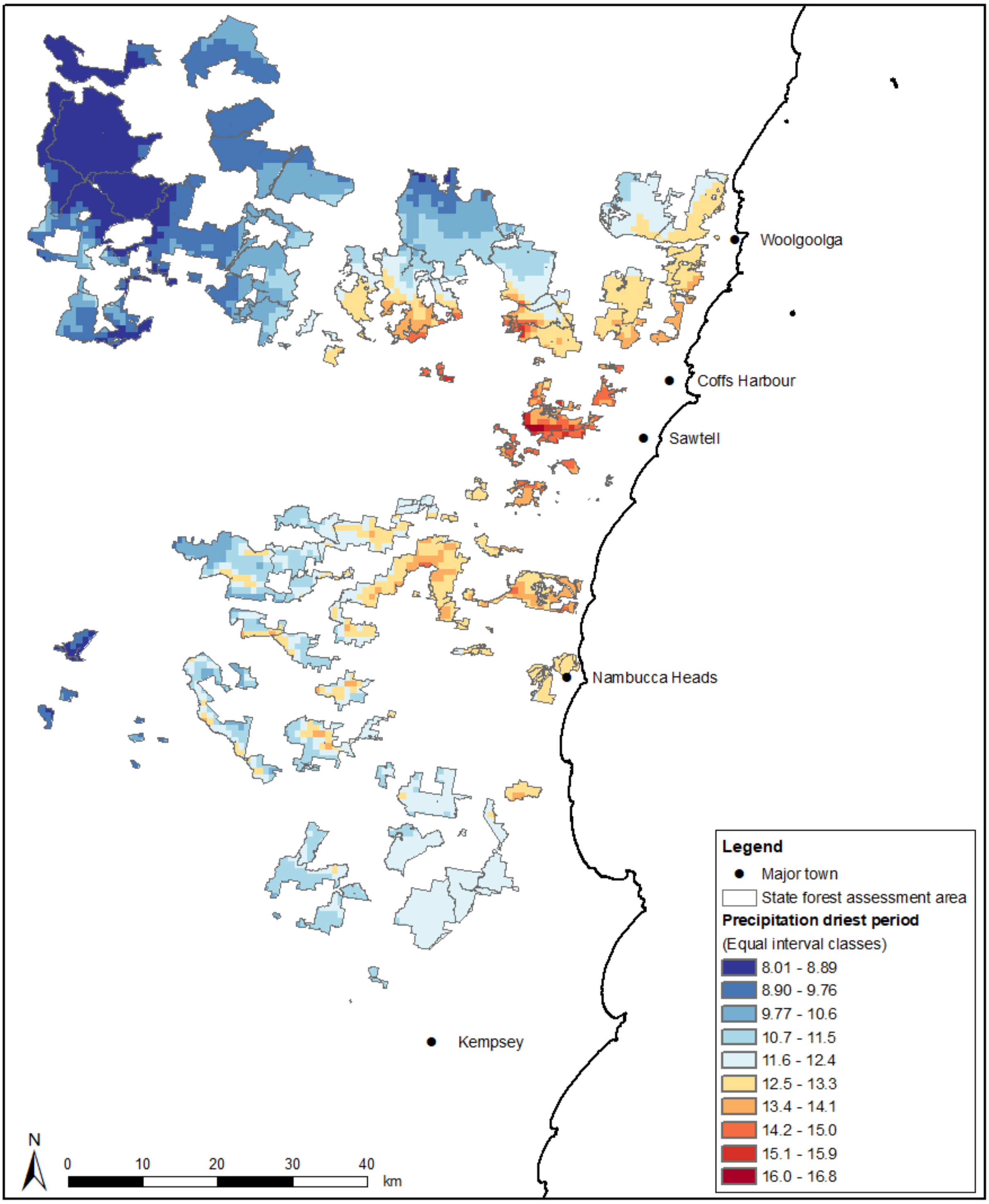


Figure 30 **The spatial distribution of the precipitation driest period (cw_precipd) covariate considered in the models of koala abundance across the assessment area**

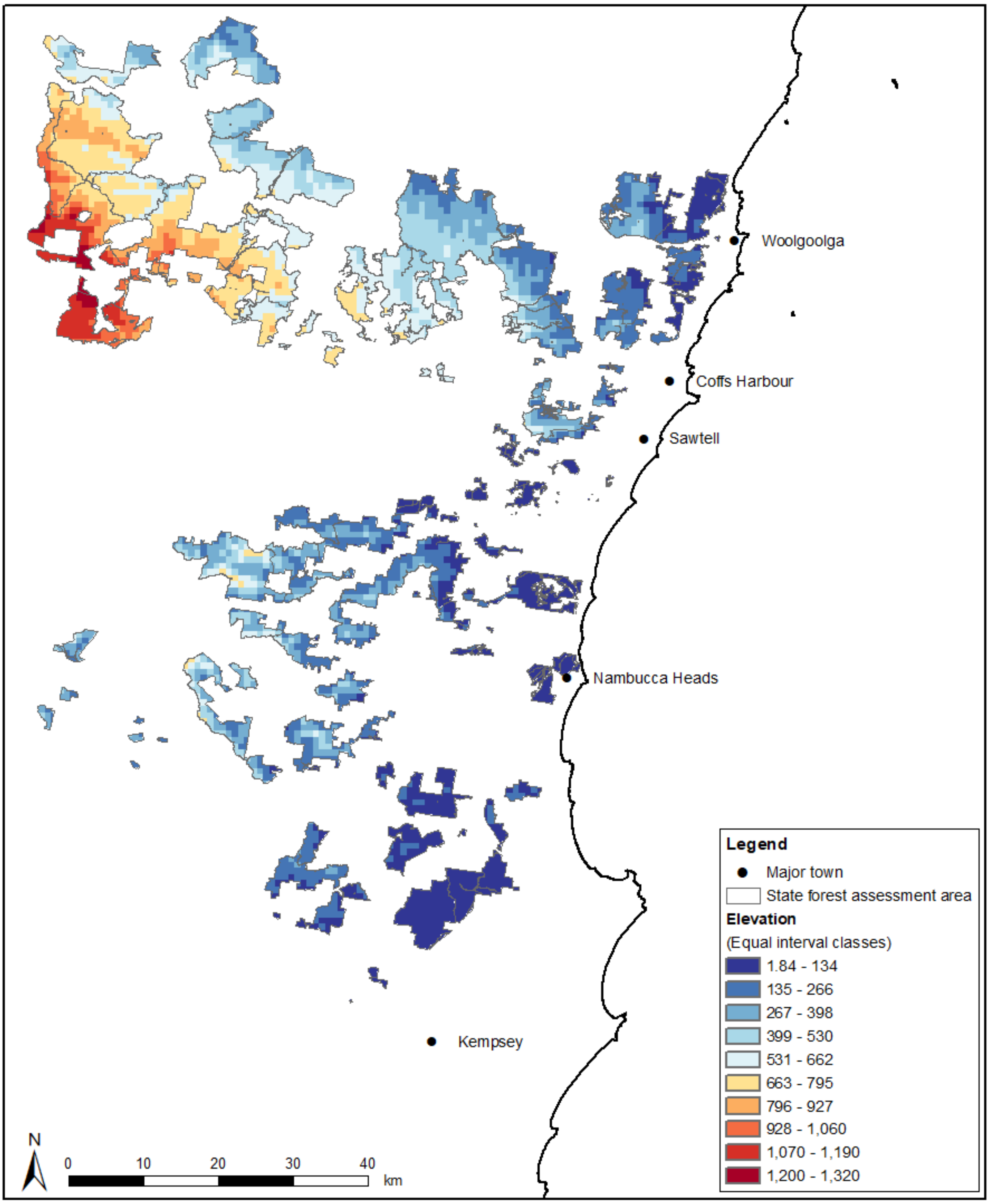


Figure 31 **The spatial distribution of the elevation (lf_dem1nnv) covariate considered in the models of koala abundance across the assessment area**

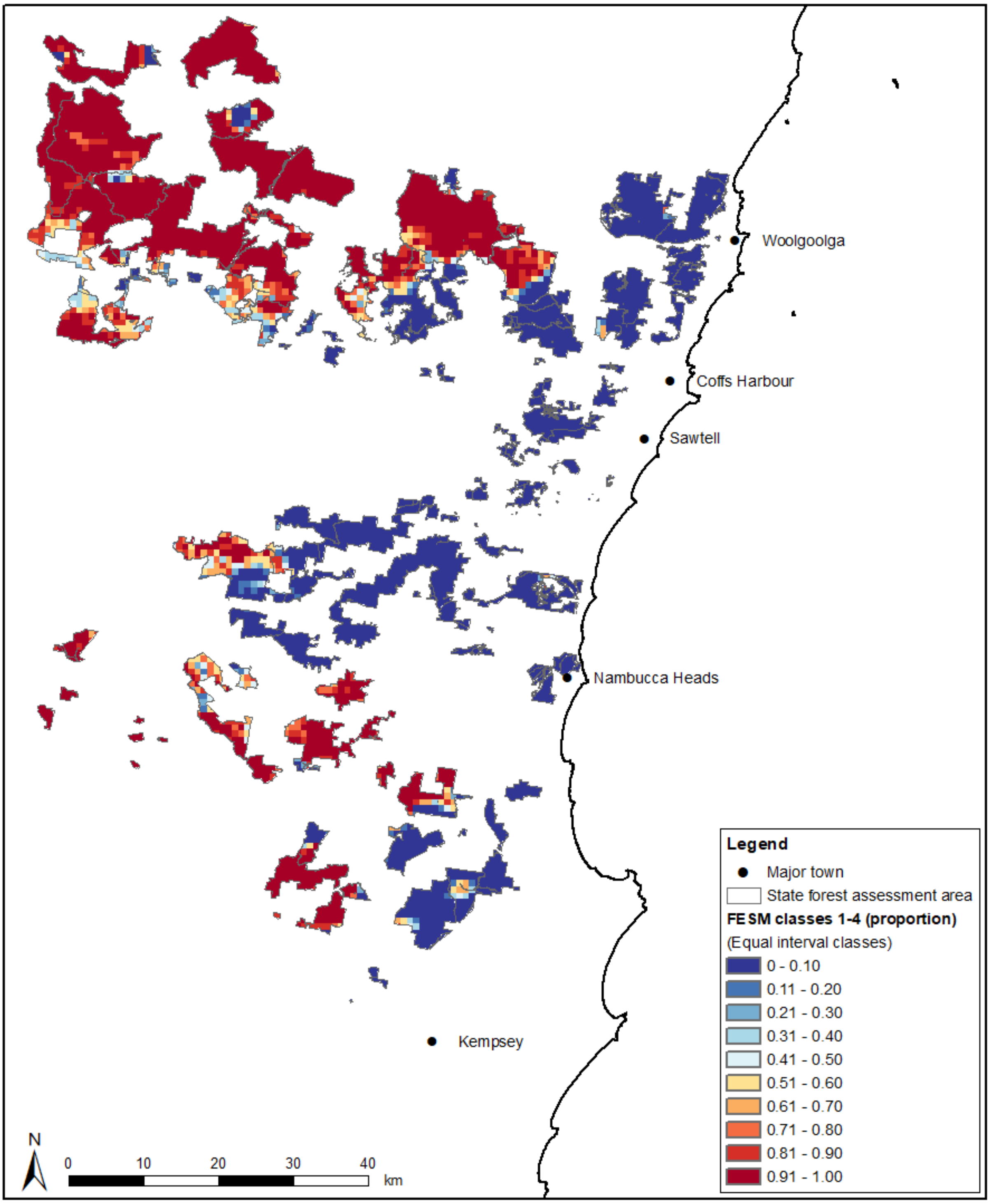


Figure 32 **The spatial distribution of the Fire Extent and Severity Mapping (FESM) classes 1 to 4, proportion of cells (fesm_14b) covariate considered in the models of koala abundance across the assessment area**

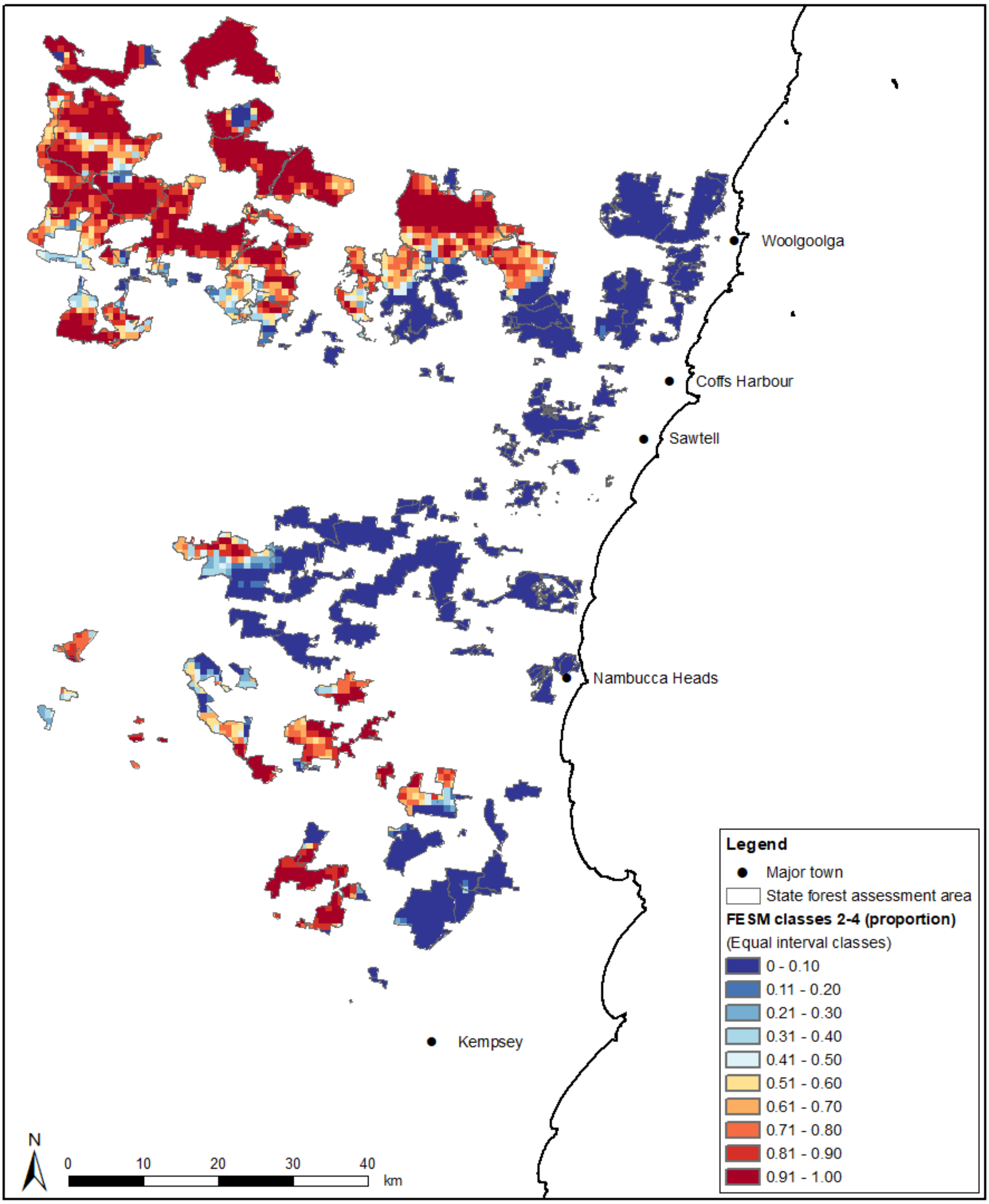


Figure 33 **The spatial distribution of the Fire Extent and Severity Mapping (FESM) classes 2 to 4, proportion of cells (fesm_24b) covariate considered in the models of koala abundance across the assessment area**

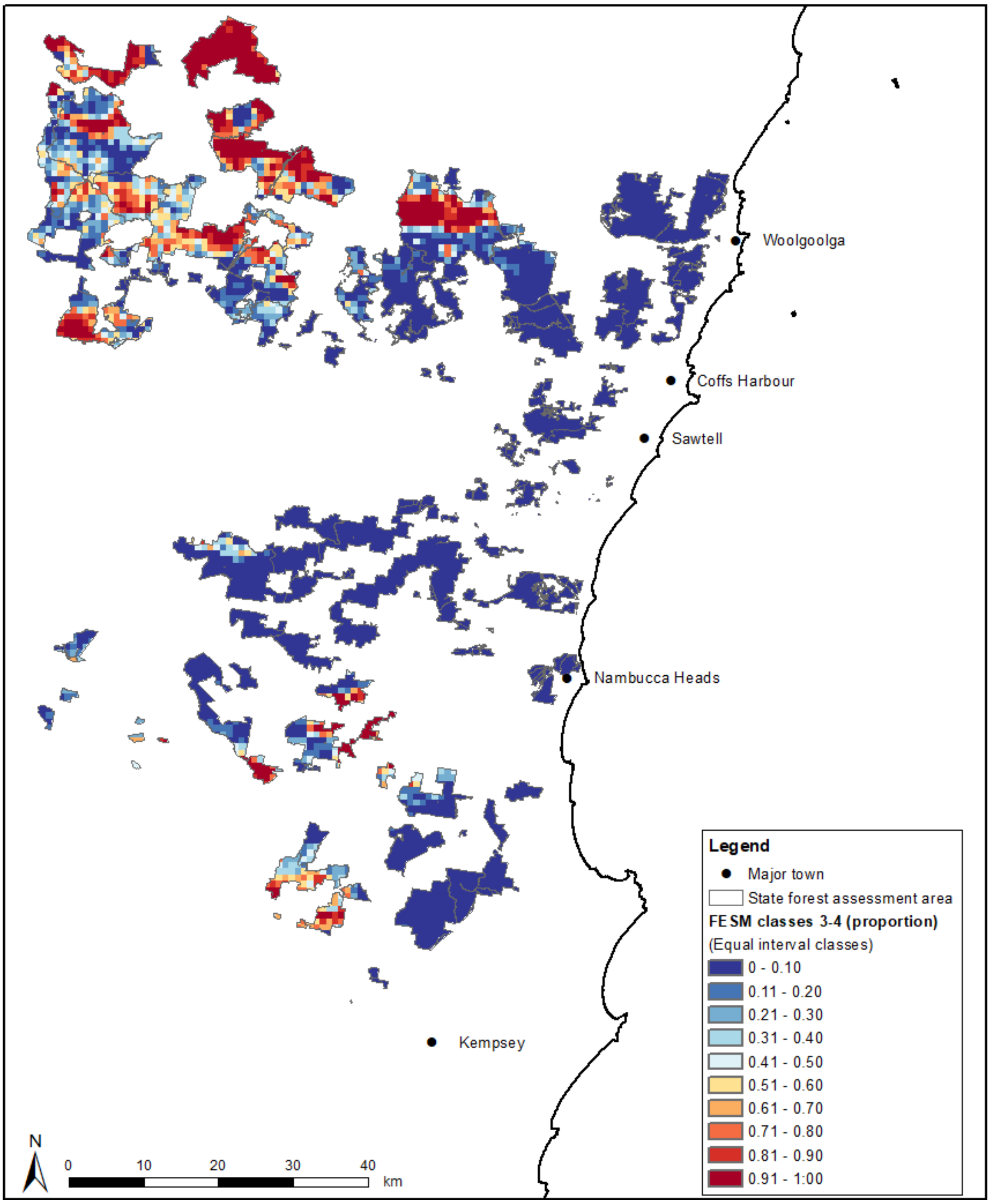


Figure 34 **The spatial distribution of the Fire Extent and Severity Mapping (FESM) classes 3 and 4, proportion of cells (fesm_34b) covariate considered in the models of koala abundance across the assessment area**

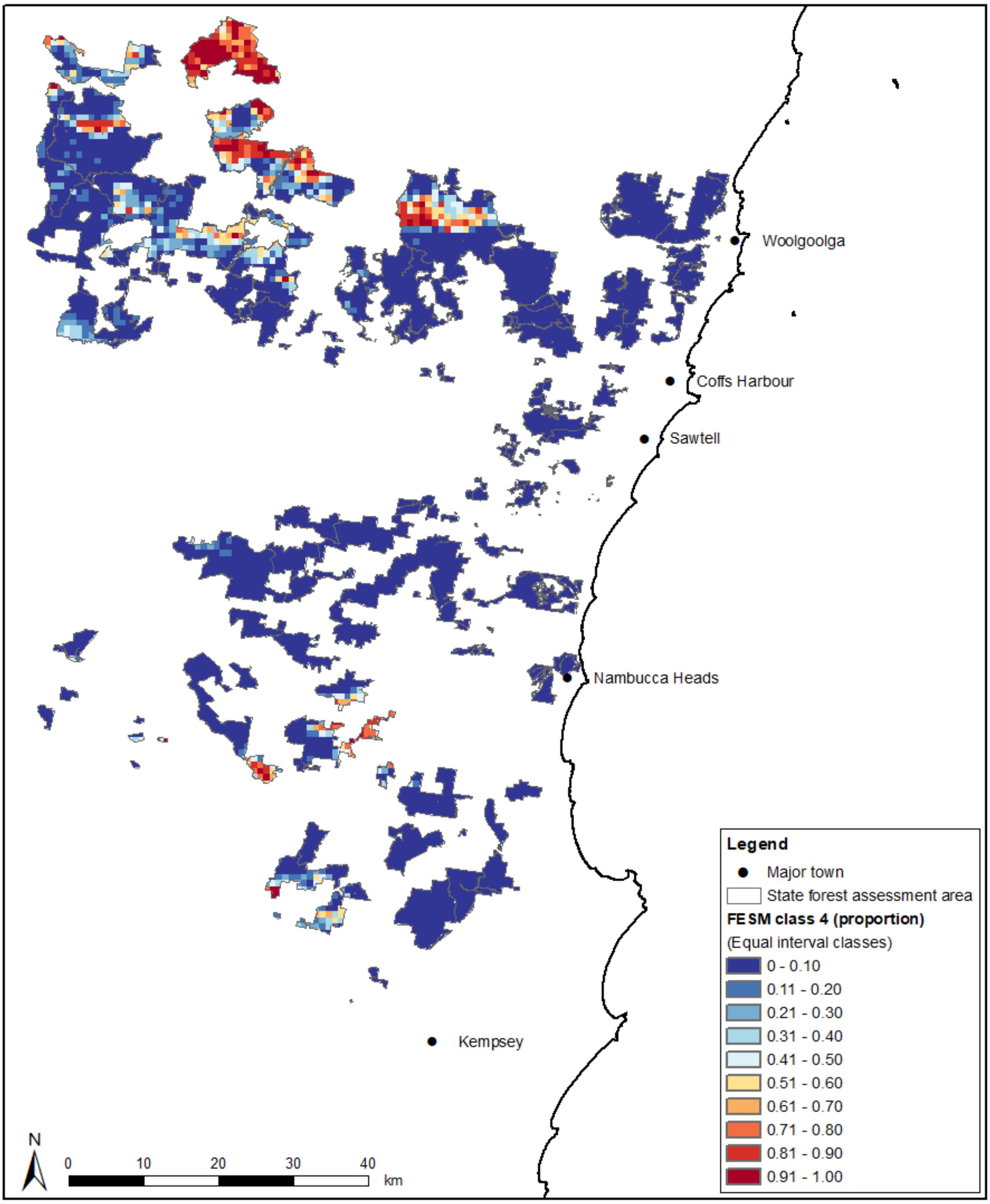


Figure 35 **The spatial distribution of the Fire Extent and Severity Mapping (FESM) class 4, proportion of cells (fesm_4b) covariate considered in the models of koala abundance across the assessment area**

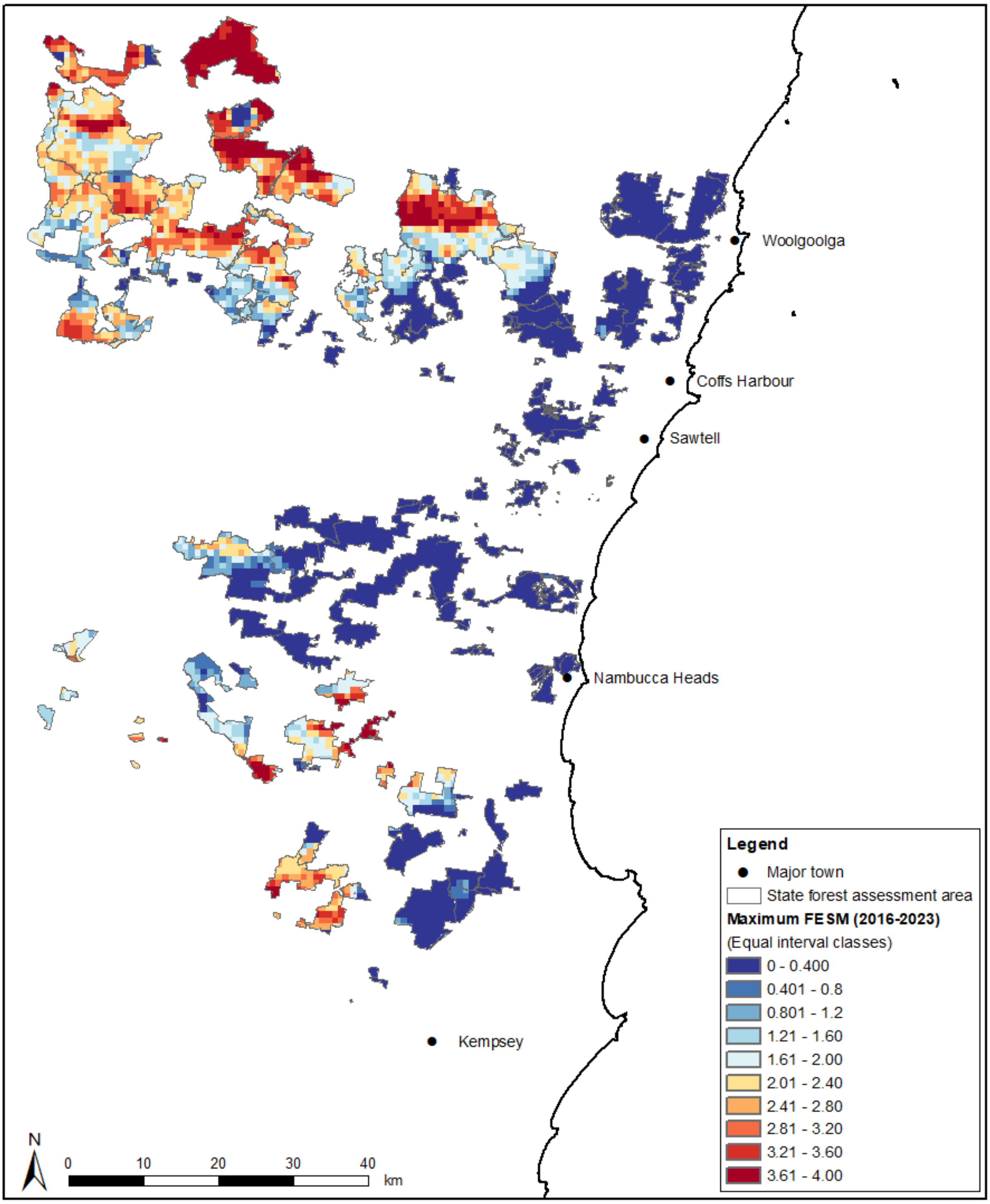


Figure 36 **The spatial distribution of the FESM 2016 to 2023 (fesm_maxse) covariate considered in the models of koala abundance across the assessment area (representing the maximum severity per pixel between 2016 and 2023)**

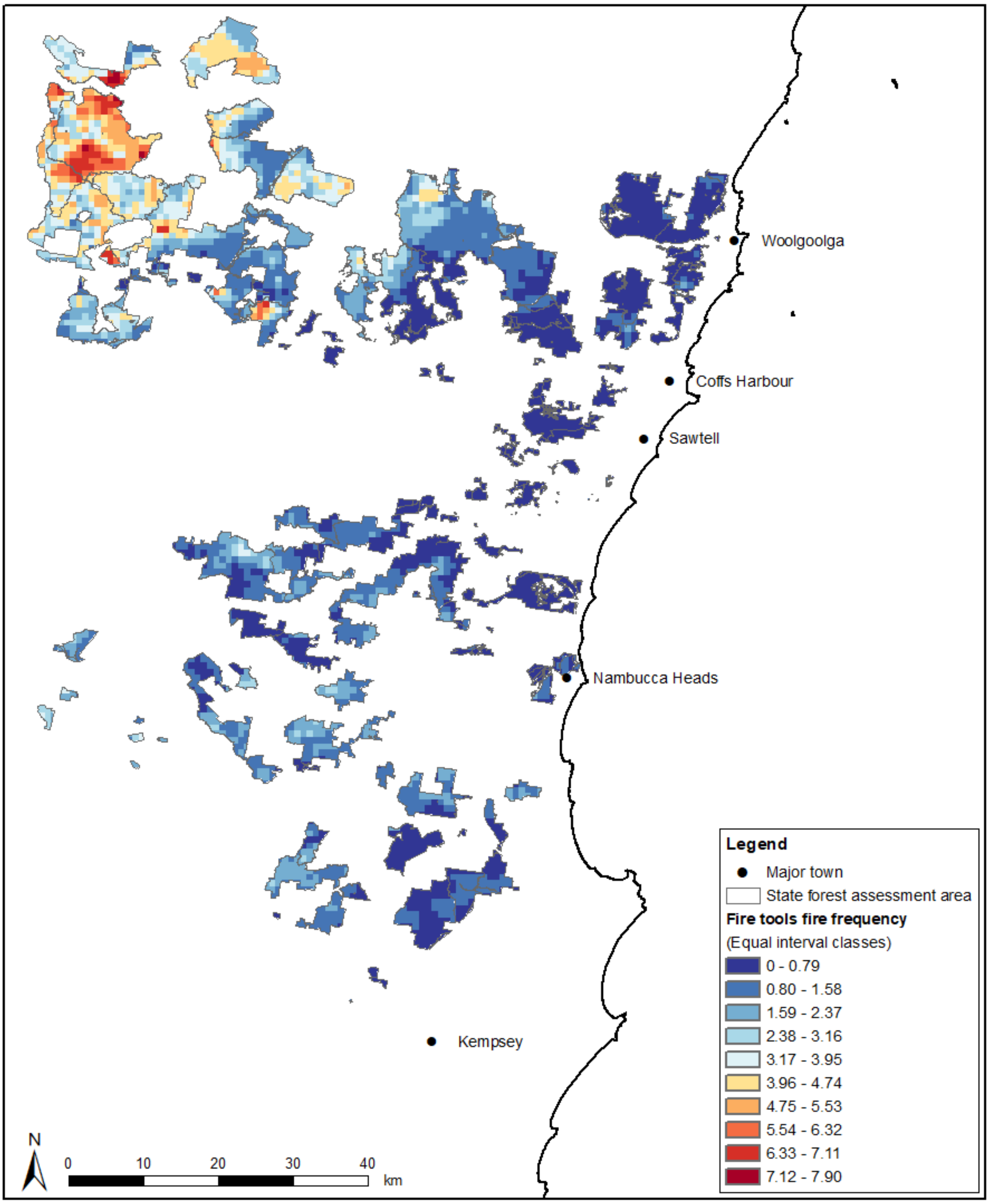


Figure 37 **The spatial distribution of the Fire Tools fire frequency (firet_freq) covariate considered in the models of koala abundance across the assessment area**

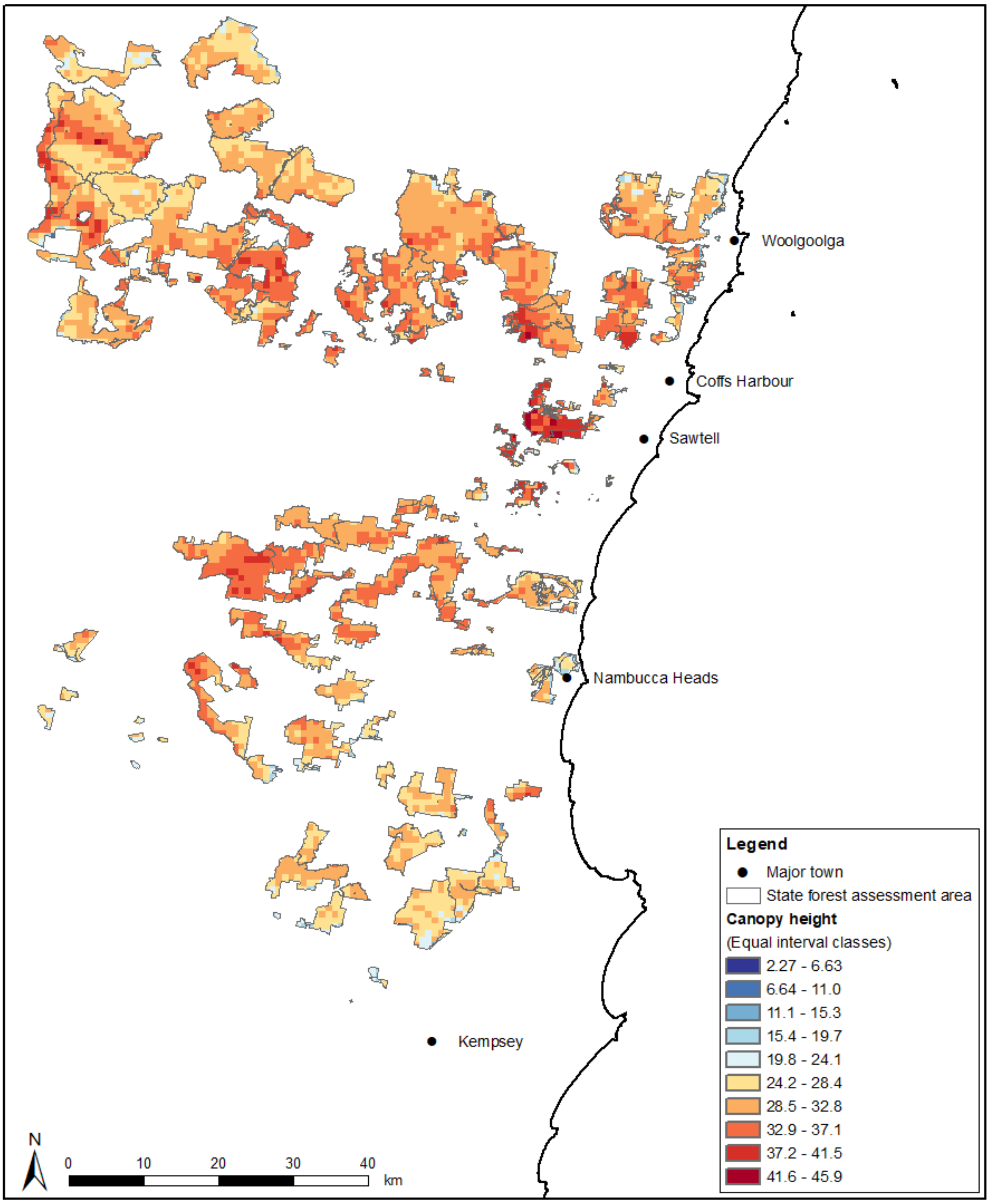


Figure 38 **The spatial distribution of the canopy height (crown_max) covariate considered in the models of koala abundance across the assessment area**

Appendix D: Koala detection and abundance modelling

To estimate spatial variation in koala abundance in the assessment area, data from double-observer koala counts were analysed using multinomial Poisson N-mixture models. This modelling approach is ideal for count data where detection probability may be less than perfect and allows for separate estimation of 2 key parameters: detection probability (p), which represents the chance of observing a koala during a survey, and mean abundance (λ), which is the average number of koalas at each survey location (Kéry and Royle 2016).

The model works by treating the actual counts as coming from a Poisson distribution, while incorporating a latent (unobserved) variable for abundance. This variable accounts for imperfect detection by integrating over possible true abundance values. Detection and abundance parameters are modelled using covariates, which may include environmental or sampling factors, and are linked to the data through mathematical functions such as the logit (for detection) or log link (for abundance).

Model building was conducted using R packages 'Unmarked' and 'UBMS', which support hierarchical modelling of ecological data. The function 'Stan_multinomPois()' was employed, configured for 'Double' data to accommodate observations from 2 independent observers, enhancing the reliability of detection probability estimates. This function fits Bayesian hierarchical models using the Stan platform, allowing for robust inference by using modern Markov chain Monte Carlo (MCMC) sampling methods to estimate model parameters.

Koala detection

Evaluating koala detection-based covariates for improving estimates of koala abundance

Hierarchical abundance models attempt to better estimate species abundance by effectively separating the biological process (true abundance) from the observation process (detection). This modelling approach is particularly valuable in ecological studies because it accounts for the fact that not all individual animals present at a site are detected during a survey. By doing so, these models enable more accurate estimates of species abundance. This is crucial when detection is imperfect and influenced by various external factors such as weather, time of day, observer experience or habitat type (Kéry and Royle 2015; MacKenzie et al. 2006).

The detection process within these models is typically modelled using either a binomial or multinomial distribution, where the observed count (y_{ij}) depends on the true abundance (N_i) and the detection probability (p_{ij}). This modelling structure effectively adjusts the observed counts to reflect detection probabilities, which vary based on survey conditions. Incorporating detection probabilities into the model ensures that the analysis accounts for imperfect detection, thereby providing a more realistic estimate of the true abundance of the species. This approach is particularly critical in studies involving cryptic or low-density species, such as the koala, where detection probabilities are often low and variable, leading to underestimates of true abundance if not properly accounted for in the modelling process (Royle and Dorazio 2008).

Assessing koala detection covariates using a global model

Relevant detection-related covariates that could influence koala detection probability during drone surveys were assessed in a global model, that is, a model containing all covariates of interest (Beranek et al. 2024). This model aimed to identify all significant associations between covariates and koala counts and to correct for imperfect detection.

To determine which detection-related covariates would be important for a global model, all pertinent covariates were evaluated to identify which covariates, if any, most influenced koala detection probability (P) during surveys. This model was specified as:

> P~ pilot+survey_order + scale(Survey_Canheight) + scale(Start_Wind65m) + I(scale(Survey_Temp)) + scale(Survey_Date) + scale(Survey_Time)~1.

These covariates were defined as follows:

- Pilot: A categorical variable representing different observers who conducted the surveys. This accounts for variability in detection probability due to differences in observer skill or experience.
- Survey_order: Accounts for when surveys were conducted in each survey site and could account for variation in observed koala detection probability due to time-related factors such as observer fatigue, changes in environmental conditions, or changes in koala behaviour over time.
- Survey_Canheight: The value represents the height of the vegetation canopy during the survey.
- Start_Wind65m: The wind speed measured at 65 m above ground level at the start of the survey. Wind speed could affect the detection probability, for example, by influencing the movement or behaviour of the species being surveyed or disrupting optimal drone function and distracting the observer from diligently seeing all koalas.
- Survey_Temp: The survey temperature could affect detection probability, potentially capturing effects like an optimal temperature range for detecting species.
- Survey_Date: This could account for seasonal effects on detection probability.
- Survey_Time: The scaled time of day when the survey was conducted, which might capture daily patterns in detection probability, for example, species are more detectable at certain times of the day.

This detection model was fitted with the following specification to run a Bayesian multinomial Poisson hierarchical model in the R package UBMS:

- chains = 3: The model is run using 3 MCMC chains. Multiple chains are used to assess the convergence of the model and ensure that the posterior distribution is accurately sampled.
- iter = 25,000: Each MCMC chain runs for 25,000 iterations, which includes both the warm-up (burn-in) period and the sampling period.
- cores = 3: The model runs in parallel on 3 CPU cores, which speeds up the computation by processing the MCMC chains simultaneously.
- umf: The data is provided in the form of an unmarked frame (umf) object, which typically contains the response variable (counts or detections) and site-specific covariates.
- seed = 123: A random seed is set for reproducibility, ensuring that the results can be replicated exactly.

The global model attempted to estimate the detection probability of koalas as a function of several environmental and observational covariates. Specifically, it examined how the pilot (observer effects), survey order (behavioural or environmental responses), canopy height, wind speed, temperature (including a quadratic effect), survey date, and survey time affected the likelihood of detecting koalas during a drone survey event. The model assumed that the abundance was constant across the study area.

The global koala detection probability model indicated that 3 detection-related parameters – pilot, survey time and survey order – were having important influences on koala detection probability, suggesting that the second survey and surveys conducted later in the night resulted in reduced koala detection. Similarly, pilots varied in their capacity to detect koalas during surveys.

Ranking models using Leave-One-Out Information Criterion

To consider if the 3 parameters identified by the global model were better than the global model, 8 models were compared and ranked by 'LOOIC' (Leave-One-Out Information Criterion) to determine which detection-related covariates should be retained to improve estimates of koala abundance. LOOIC is a metric used to evaluate the predictive accuracy of a model, with lower values indicating better performance. Here it was evident that a single 2-parameter model outperformed the second-best and the null model. This indicated that it was necessary to account for variation in koala detection probability using the **survey order** and **survey time (time of survey)** to improve koala abundance estimates (see Table 12).

Table 12 Model ranking of koala detection covariates based on Leave-One-Out Information Criterion (LOOIC)

Model rank	Model covariates	LOOIC	ΔLOOIC	LOOIC w
1	Survey_order + (Survey_Time)	1150.58	0.00	0.91
2	Survey_order	1156.05	5.47	0.06
3	Survey_order + Pilot	1159.94	9.36	0.01
4	Pilot + (Survey_Time)	1160.67	10.07	0.01
5	(Survey_Time)	1160.82	10.22	0.01
6	Null (Intercept Only)	1165.96	15.36	0.00
7	Pilot	1167.98	17.39	0.00
8	Pilot + Survey_order + (Survey_Canheight) + (Start_Wind65m) + Survey_Temp) + (Survey_Date) + (Survey_Time)	1168.79	18.19	0.00

Table note: ΔLOOIC = delta LOOIC; LOOICw = LOOIC weight. Models with lower LOOIC values indicated better predictive performance. The delta LOOIC (ΔLOOIC) column represents the difference in LOOIC values between each model and the best-performing model (Rank 1). The LOOIC weight (LOOICw) provides a measure of relative support for each model given the data.

Survey_order and Survey_Time were associated with negative effects on koala detection probability. Koala detection probability decreased with the second survey in a site and with the time at which the survey was conducted, indicating that surveys conducted later in the night or those closest to dawn were associated with reduced koala detection (Figure 39).

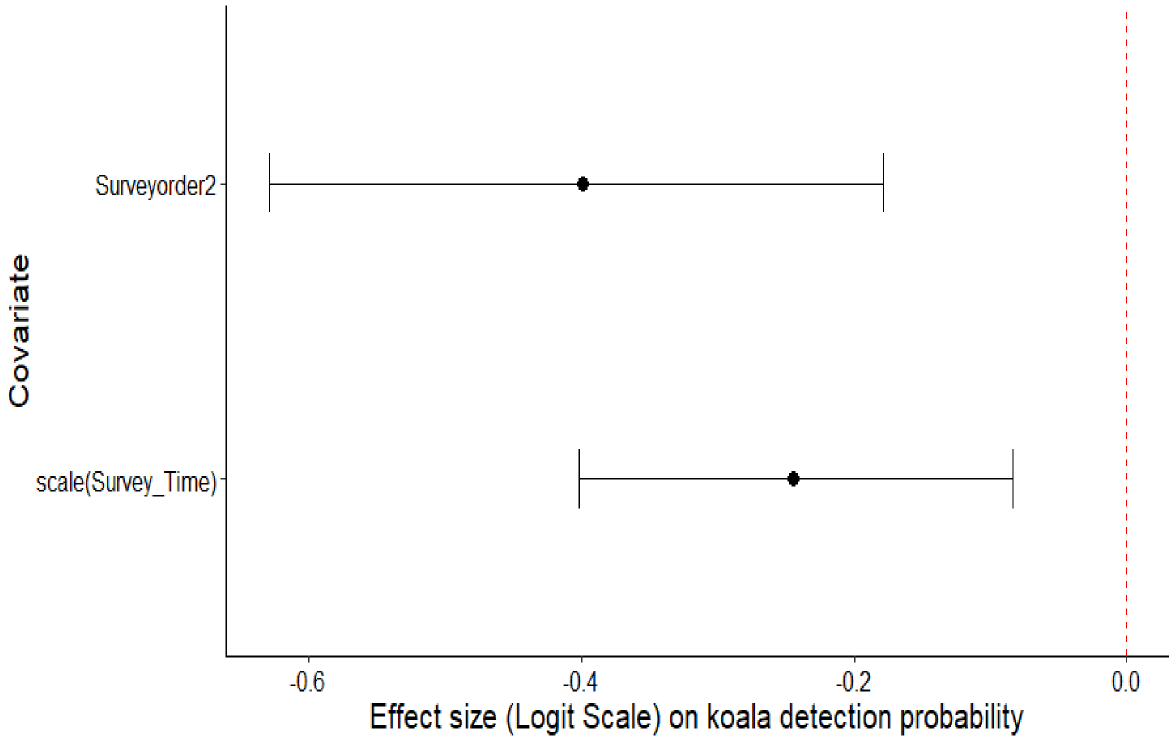


Figure 39 **Effect sizes of survey order and survey time on koala detection probability with 95% confidence intervals (logit scale)**

Koala abundance

A stepwise process was undertaken to narrow down an initial set of 23 candidate covariates as follows (more detail is provided in the following sections):

- modelling covariate effects using a Bayesian multinomial Poisson regression model to calculate each covariate's effect size
- avoiding multicollinearity by removing covariates that are highly correlated
- modelling the most important variables.

Once the final set of predictor variables were decided, koala abundance was estimated.

Modelling covariate effect size on koala abundance

A total of 23 candidate covariates were initially selected for modelling koala abundance, with each based on theoretical and empirical knowledge to represent positive or negative influences on koala abundance (see Table 10 in Appendix C). However, a range of factors related to data quality, model structure, scale, and ecological complexity could prevent covariates from influencing koala abundance. Addressing covariate limitations is crucial for interpreting model results and making informed conservation or management decisions. For example, Dormann et al. (2013) discuss how multicollinearity can obscure the effects of important variables in ecological models, while Zuur et al. (2010) emphasise the importance of correctly specifying models to capture complex ecological relationships. Recognising these challenges can help improve model accuracy and reliability, leading to better ecological insights and conservation outcomes.

Each of the 23 predictor variables was coded as univariate abundance-based hierarchical models (including the null model) using the 'stan_multinomPois' function in the program R package UBMS. This function fitted a Bayesian multinomial Poisson regression model, which is appropriate for count data such as species abundance. The response variable in these models was the koala count data comprising:

1. the number of koalas observed by pilot 1 and not pilot 2
2. the number detected by pilot 2 and not pilot 1
3. the number detected by both pilots (that is, joint observation or resightings) on both surveys.

This Bayesian inference was executed using MCMC with 3 chains, 25,000 iterations, and 3 cores for efficient computation. A null model, which included only the intercept for abundance and the detection process covariates (survey order and standardised survey time), was also fitted. This model served as a baseline, to demonstrate if selected covariates had a stronger influence on koala abundance compared to the null model. This was important to eliminate any uninformative parameters prior to model selection (Leroux 2019).

Table 13 Initial exploratory model ranking of selected variables, highlighting the predictive performance of each variable to influence koala abundance. All model variables ranked above the null model to indicate validity for modelling consideration

Model rank	Covariate	Name	LOOIC	ΔLOOIC
1	sp_des0200	Soil depth	1,012.388	0
2	rs_ndvi_q3	Normalized Difference Vegetation Index	1,015.570	3.182
3	rs_fmstd	Foliar moisture standard deviation	1,028.094	15.706
4	rs_fmmean	Foliar moisture mean	1,037.294	24.906
5	firet_freq	Number times burnt	1,037.816	25.428
6	rs_fm05	Foliar moisture 5th percentage	1,044.242	31.854
7	fesmaxse	FESM 201 to 2023	1,051.57	39.182
8	fesm34b	FESM 2019–20 classes 3 and 4 (%)	1,051.788	39.4
9	cw_precipd	Precipitation driest period	1,056.888	44.5
10	fesm24b	FESM 2019–20 classes 2 to 4 (%)	1,058.716	46.328
11	fesm14b	FESM 2019–20 classes 1 to 4 (%)	1,064.088	51.7
12	fesm4b	FESM 2019–20 class 4 (%)	1,065.648	53.26
13	sp_soc0100	Soil organic carbon	1,080.286	67.898
14	tc_wet	Wetness	1,081.006	68.618
15	crown_max	Tree crown height	1,089.12	76.732

Model rank	Covariate	Name	LOOIC	∆LOOIC
16	sp_cly0100	Soil clay content	1,089.862	77.474
17	lf_dem1nnv	Elevation	1,098.584	86.196
18	TSI_06spp	Tree Species Index (6 species) - probability of occurrence	1,101.324	88.936
19	TSI_14sppb	Tree Species Index (14 species) - binary thresholded version	1,102.138	89.75
20	ct_tmpmtc	Minimum temperature	1,102.53	90.142
21	TSI_06sppb	Tree Species Index (6 species) - binary thresholded version	1,104.314	91.926
22	TSI_14spp	Tree Species Index (14 species) - probability of occurrence	1,107.874	95.486
23	ct_tmpmtw	Maximum temperature	1,110.88	98.492
24	Null		1,111.68	99.292

Table note: ∆LOOIC = delta LOOIC.

Evaluation of each covariate's effect size indicated that it was associated with minor to moderate but otherwise significant (that is, non-overlapping error bars) influence for explaining variation in koala abundance (Figure 40).

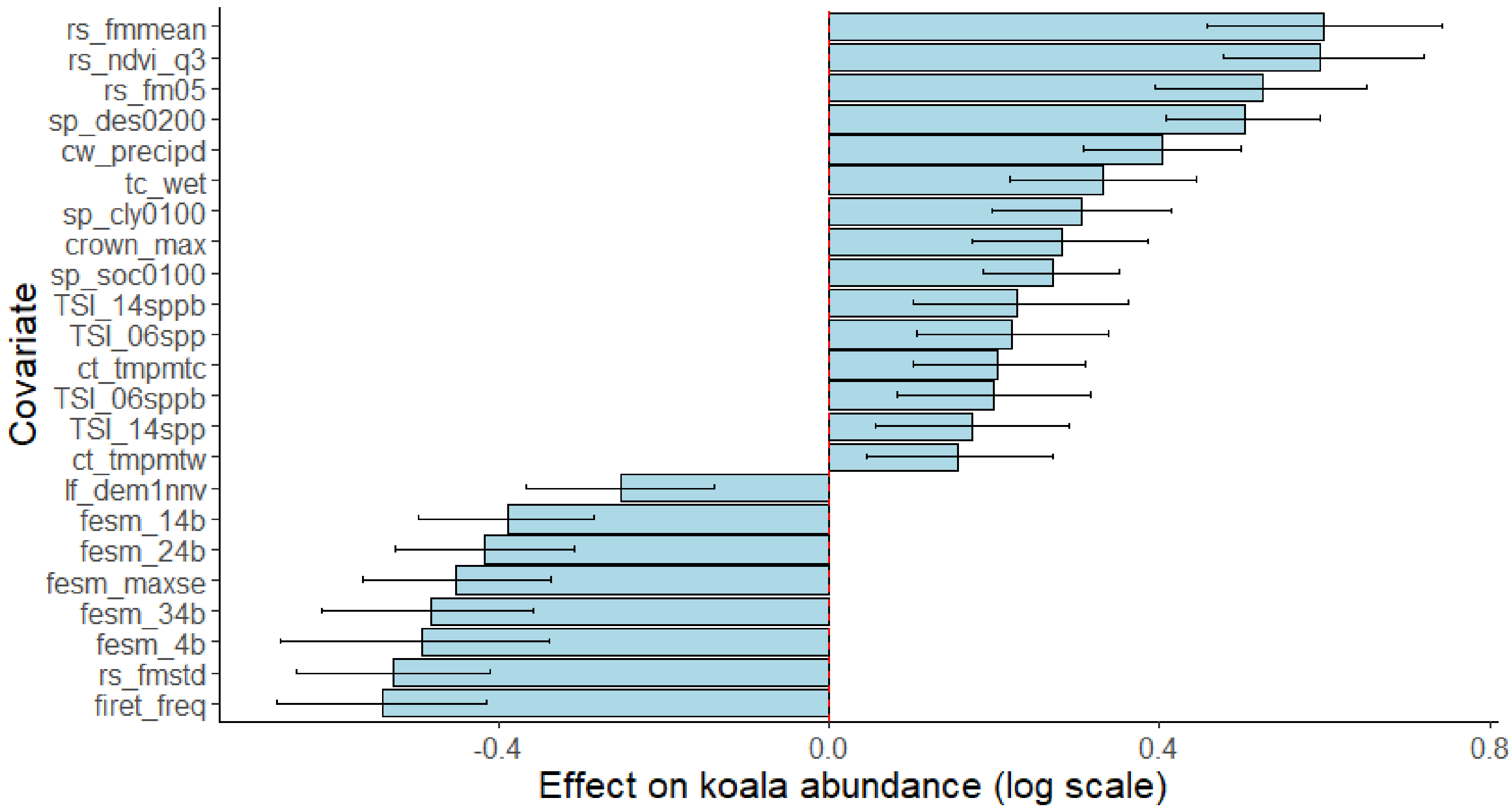


Figure 40 **Effect sizes (log scale) with 95% credible intervals for all candidate predictor covariates and their respective influence on koala abundance**

Avoiding multicollinearity

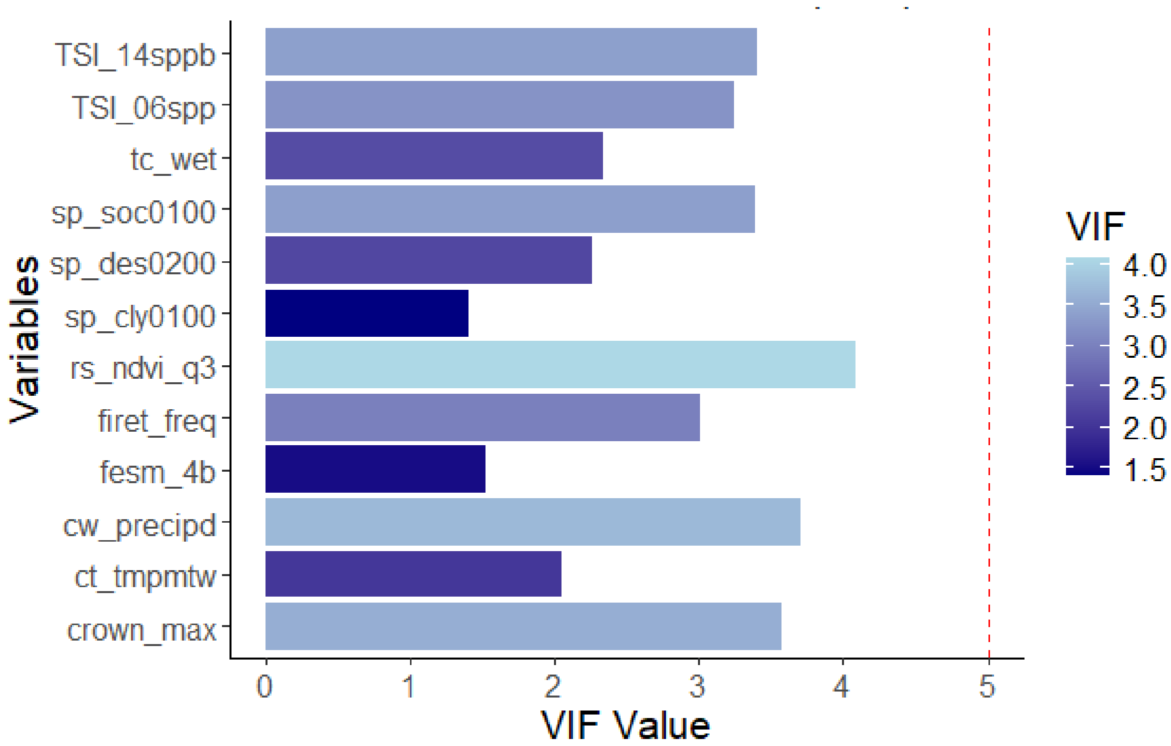
A multivariate model requiring multiple covariates was expected to best explain variation in koala abundance across the assessment area (for example, Law et al. 2024a). However, before it was possible to test this multivariate model it was important to ensure that all candidate covariates were not subject to multicollinearity.

Multicollinearity occurs when multiple covariates within a model are highly correlated and can distort the model's estimates and even produce spurious results (Dormann et al. 2013). To prevent this, multiple steps were taken to remove those covariates that were overly correlated. This ensured that the remaining variables provided independent information about any influences on koala abundance. To address potential multicollinearity, particularly among variables that represented similar ecological or environmental processes, each variable had to demonstrate that it had a low variance inflation factor (VIF) (that is, <5), no excessive correlation (>0.7) with any other variable and was not influenced by collider bias that would affect its influence on koala abundance (Figure 41). Of the 23 covariates, 11 were found to have high VIF scores of >5 and were removed from further modelling consideration.

The VIF score for each covariate measured its sensitivity to multicollinearity in the hierarchical model. VIF values of <5 are considered good and indicate that each covariate in a model is unlikely to be affected by multicollinearity. It is, however, still possible to retain variables with low VIF scores that may be correlated and hence another 4 variables with correlation >70% were discarded: tree crown height (Crown_Max), number of times burnt (Fire_Freq), maximum temperature (ct_tmptw), and the 6-species TSI (TI_06spp) (Figure 42). A final 2 variables – wetness (TC_Wet) and precipitation driest period (cw_precipd) – provided evidence of collider bias and they were similarly removed from the set of candidate variables used to predict koala abundance across the assessment area.

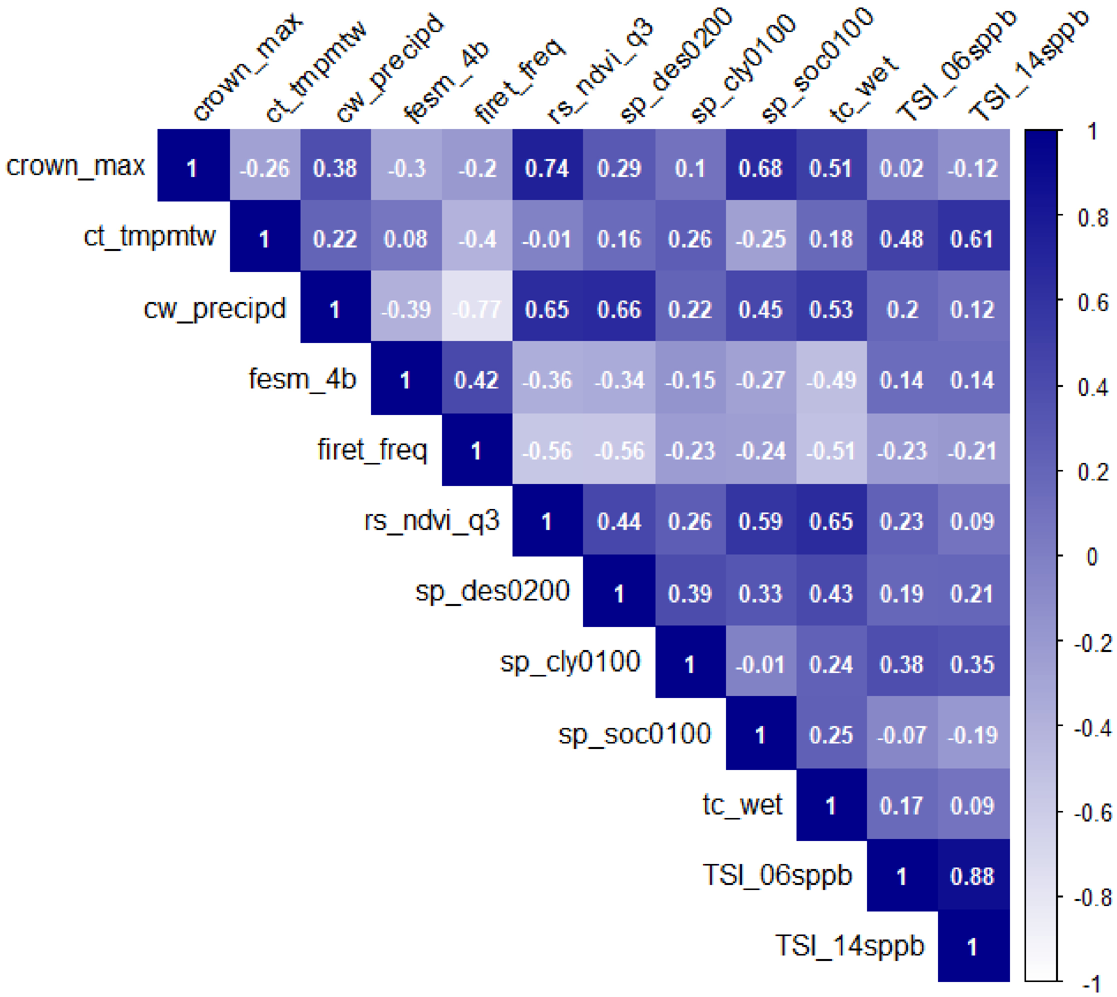
These covariate quality checks resulted in the candidate 23 covariates becoming a set of 6 covariates comprising:

1. NDVI (Normalized Difference Vegetation Index third quarter (rs_ndvi_q3), an indicator of vegetation health and productivity
2. FESM 2019–20 class 4 (fesm_4b) – this comprises FESM data classed as extreme severity (canopy burn)
3. soil depth (sp_des0200) – soil depth at 200 cm, related to soil fertility and vegetation health
4. soil organic carbon (sp_soc0100) – soil organic carbon content at 100 cm, related to soil fertility and vegetation health
5. soil clay content (sp_cly0100) – clay content at 100 cm depth, affecting soil structure and water retention.
6. 14-species Tree Species Index – binary thresholded version (TSI_14sppb) – includes the top 14 koala food trees known across the assessment area, including *Eucalyptus grandis, E. microcorys, E. propinqua, E. robusta, E. saligna* and *E. tereticornis*.



Note: Refer to Table 10 for full names of variables shown on y-axis.

Figure 41 **Of the 23 candidate variables, 12 had variance inflation factors (VIF) scores <5 that were retained in the first of 3 steps to assess the suitability of covariates for koala abundance modelling**



Note: Refer to Table 10 for full names of variables shown on y-axis.

Figure 42 **Correlation among covariates with variance inflation scores <5**

Modelling the most important covariate effects to explain koala abundance

A model dredging, or comprehensive model selection process, is an automated model selection process that evaluates subsets of the maximum model. Model dredging was used to identify the most influential covariates from the remaining 6 covariates to identify the most parsimonious model that could best explain koala abundance in the assessment area. This approach was selected because in ecological studies multiple factors can influence species abundance, and the relationships between these factors can be complex and interdependent and rely on the evaluation of a large number of plausible model combinations

The rationale for model dredging is based on the following:

1. **Complex ecological systems:** Koala abundance is influenced by a wide range of factors, including habitat quality, climate conditions, fire history and anthropogenic impacts. These variables often interact in non-linear ways, making it difficult to identify the most important predictors a priori. Model dredging allows researchers to

explore a wide range of candidate models, each representing different combinations of variables, to identify which set best predicts koala abundance.

2. **Model uncertainty:** In ecological modelling, there is often uncertainty about which variables should be included in the model due to the complexity of ecosystems. Model dredging provides a systematic way to address this uncertainty by evaluating multiple models based on their fit and predictive power. This helps avoid overfitting a single model that may not generalise well to new data (Burnham and Anderson 2002).
3. **Information–theoretic approach:** The use of criteria such as the Akaike Information Criterion (AIC) or Leave-One-Out Information Criterion (LOOIC) in model dredging allows for the comparison of models based on their trade-off between goodness-of-fit and model complexity (Burnham et al. 2011). Models that explain the most variation in koala abundance and are of good fit will be those expected to retain fewer parameters than those represented in the global model leading to a more interpretable and generalisable model.
4. **Model averaging:** In cases where no single model is superior, model averaging can be employed, where predictions are based on a weighted average of several models. This approach helps to account for model selection uncertainty and provides more robust estimates of the effects of different variables on koala abundance (Burnham and Anderson 2002).

In the context of this analysis, it was crucial to perform model dredging on the 6 covariates resulting from the covariate quality checks using the Unmarked package rather than UBMS to expedite computational time. The decision to use Unmarked was driven by the need for efficiency, as UBMS, while powerful, can be computationally intensive, particularly when dealing with many models and covariates (Fiske and Chandler 2011). Despite the shift from UBMS to Unmarked for this specific task (using function 'dredge' from the MuMIn package), the core findings and inferences remain robust and reliable. This is due to the similarity in effect sizes observed between models produced by both packages and the equivalencies in model ranking when using AIC in Unmarked compared to LOOIC in UBMS (Burnham and Anderson 2002; Vehtari et al. 2017). These similarities ensure that the shift in methodology does not compromise the integrity of the model selection process or the subsequent ecological interpretations of the factors influencing koala abundance.

Following dredging of all possible covariate combinations, 3 models (<4 AIC corrected, or AICc) were considered to accurately determine the best set of parameters to fit into the final Bayesian model (Table 14). Here it was evident that there was a strong consensus to retain the 4 best variables to use in the final Bayesian model estimation of covariate effects on koala abundance, that is:

1. FESM 2019–20 Class 4 (fesm_4b)
2. Normalized Difference Vegetation Index (rs_ndvi_q3)
3. soil depth (sp_des0200)
4. Tree Species Index (14 spp.) – binary thresholded version (TSI_14sppb).

The 2 variables not used/eliminated by model dredging were soil clay (sp_cly0100) and soil carbon (sp_soc0100).

Table 14 Model ranking and identification of best model to evaluate covariate effects on koala abundance obtained using package Unmarked

Model rank	1	2	3
Model	Abundance = FESM4+NDVI+SOIL DEPTH+ TSI	Abundance = FESM4+NDVI+SOIL DEPTH+ TSI+ SOIL_CLAY	Abundance = FESM4+NDVI+SOIL DEPTH+ TSI+ SOIL_CARBON
df	8	9	9
logLik	−482.27	−482.16	−482.27
AICc	981.8	983.9	984.1
∆AICc	0	2.1	2.32
weight	0.6	0.21	0.19
Model covariates: koala abundance			
Intercept	1.52	1.52	1.52
FESM 2019–20 Class 4 (fesm_4b)	−0.21	−0.21	−0.21
Normalized Difference Vegetation Index 3rd quarter (rs_ndvi_q3)	0.35	0.34	0.35
Soil clay content (sp_cly0100)		0.01	
Soil depth (sp_des0200)	0.3	0.3	0.3
Soil carbon (sp_soc0100)			-0.01
TSI (14 species) – binary thresholded (TSI_14sppb)	0.25	0.25	0.25
Model covariates: koala detection			
Intercept	−0.54	−0.54	−0.54
Time of survey	−0.43	−0.45	−0.44
Survey order	+	+	+

Table notes: df: degrees of freedom; logLik: log-likelihood; AICc: Akaike Information Criterion corrected; ∆AICc: delta Akaike Information Criterion corrected.

All final model rankings were then re-estimated in UBMS to ensure consistency of model inference used throughout the study. This step was essential to confirm that the conclusions drawn from the Unmarked-based dredging process were consistent with those from the UBMS framework, thereby validating the robustness of the selected models and ensuring that the most parsimonious models were indeed those that best explained the observed variation in koala abundance. To further refine the final model performance, each covariate was evaluated to assess if a linear-link or quadratic fit was better in recognition, that it, is ecologically plausible for these covariations to have both linear and non-linear influences on koala abundance. Only the FESM4 class 4 covariate was found to benefit from a quadratic parameterisation, and this is represented in the final model specification to assess the multivariate effects of 4 best variables on koala abundance. This final model exhibited a good fit based on ‘Rhat’ values and MCMC chain convergence (Figure 43 and Figure 44).

```
> Final_Model_UBMS_Bayesian

Call:
stan_multinomPois(formula = ~scale(Survey_Time) + Surveyorder ~
    scale(rs_ndvi_q3) + scale(sp_des0200) + scale(TI_14sppb) +
        scale(I(fesm_4b^2)), data = umf, chains = 3, iter = 25000,
    cores = 3, seed = 123)

Abundance (log-scale):
                    Estimate     SD   2.5%  97.5% n_eff Rhat
(Intercept)            1.505 0.0905  1.331 1.6839 31085    1
scale(rs_ndvi_q3)      0.357 0.0698  0.222 0.4965 34307    1
scale(sp_des0200)      0.295 0.0579  0.181 0.4080 35121    1
scale(TI_14sppb)       0.263 0.0734  0.122 0.4104 39328    1
scale(I(fesm_4b^2))   -0.277 0.0972 -0.479 -0.0986 35067   1

Detection (logit-scale):
                   Estimate     SD   2.5%  97.5% n_eff Rhat
(Intercept)          -0.534 0.1416 -0.812 -0.259 29401    1
scale(Survey_Time)   -0.449 0.0779 -0.603 -0.299 40406    1
Surveyorder2         -0.377 0.1179 -0.610 -0.147 36724    1

LOOIC: 971.725
Runtime: 45.250 sec
```

Figure 43 **Screenshot of final model output and performance depicting the effects of Normalised Difference Vegetation Index (NDVI), Tree Species Index (TSI), soil depth and Fire Extent and Severity Mapping 2019–20 class 4 quadratic parameterisation (FESM4b^2) on koala abundance (log scale) in the assessment area**

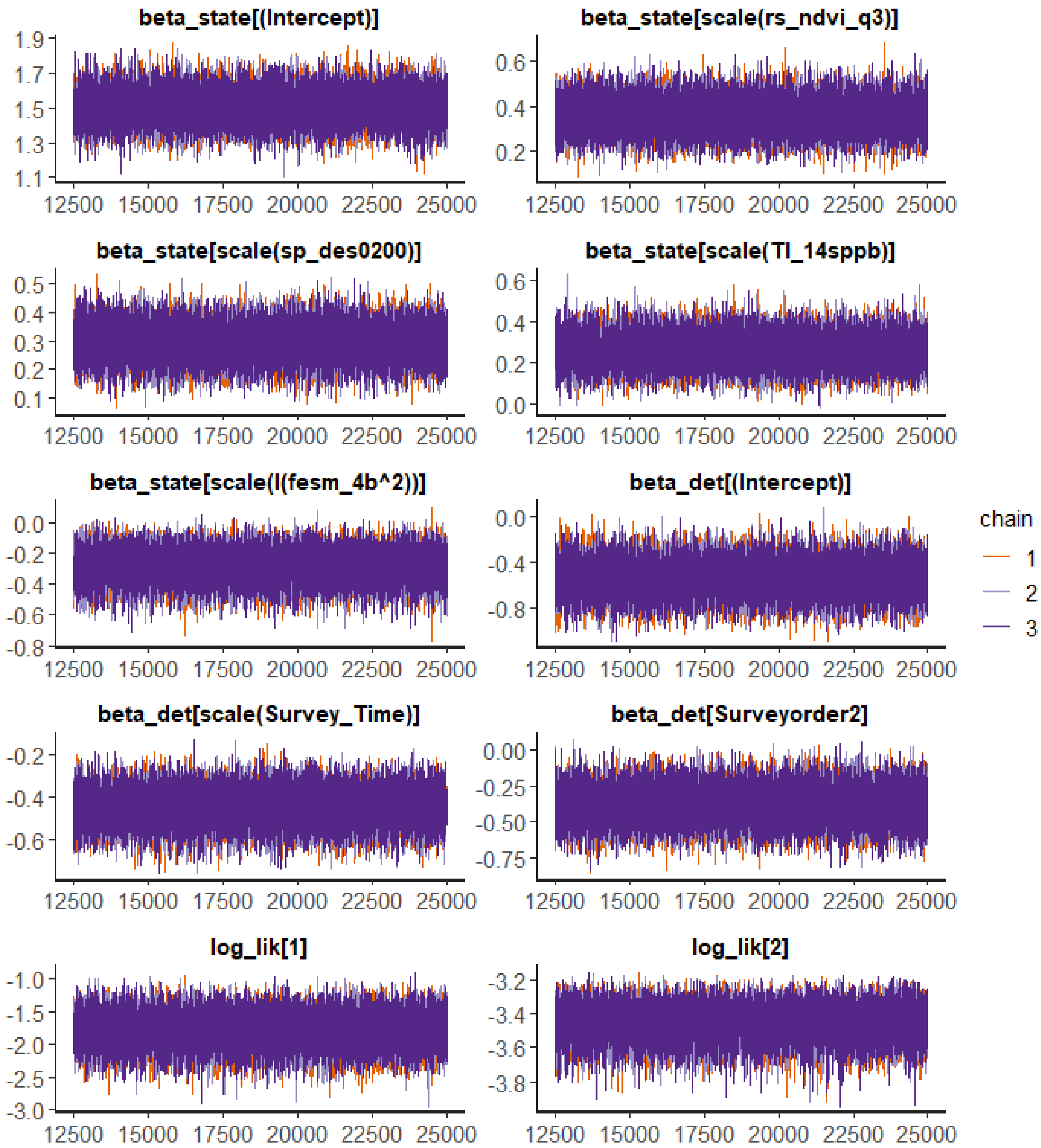


Figure 44 **Trace plots for the Markov chain Monte Carlo (MCMC) sampling of the final model parameters**

Each subplot in Figure 44 represents the trace for one parameter, showing iterations from 3 chains (coloured in orange, purple and blue) across 25,000 iterations. The parameters include model coefficients such as scale (rs_ndvi_q3: Normalised Difference Vegetation Index), scale (sp_des0200: soil depth), scale (TI_14sppb: Tree Species Index 14 spp. – binary thresholded), and scale (I(fesm_4b^2: FESM 2019–20 Class)), as well as the 2 detection model coefficients scale (Survey_Time) and Surveyorder. The convergence and mixing of the chains can be assessed, with a stable trend indicating well-behaved sampling and proper convergence across the chains. The log_lik traces represent the log-likelihood for each data point in the model.

Estimating koala abundance in the assessment area

To estimate the total koala abundance across the assessment area, it was decided a consensus estimate, as opposed to a single model estimate, would be advantageous. In ecological modelling, consensus estimates are widely used to improve the reliability and accuracy of predictions by integrating multiple models, which is essential for understanding and predicting ecological patterns or for dealing with uncertainty in conservation decision-making. To derive a mean consensus estimate of **population abundance and error** for the assessment area, the independent estimates for naive density, 2 closed mark-resighting models (Huggins 1989; Otis et al. 1978), and a multinomial Poisson hierarchical model (Royle and Nichols 2003; Borchers et al. 1998) were averaged. These models are described in Table 15. This consensus estimate represented the mean koala density per hectare ± 95% confidence intervals. The consensus density estimate (that is, koalas/ha) was then multiplied by 176,000 ha to calculate the total koala abundance for the entire assessment area.

This consensus approach was particularly advantageous because drone surveys using the double-independent observer method provided robust data for estimating detection probabilities and population size using various closed population models. These included the Huggins and Otis models (Huggins 1989; Otis et al. 1978; Rexstad and Burnham 1991), which account for factors like individual heterogeneity, behavioural responses and time effects. Additionally, hierarchical models offered greater flexibility by incorporating covariates to enhance detection and abundance estimates, especially when extrapolating beyond the surveyed area. These different models were used to produce independent estimates of **koala density and total abundance** that were then averaged with the naive density estimate to produce a **consensus density estimate** (Table 16). The model-specific estimates are provided in Table 16.

This consensus total population estimate of 10,311 to 14,541 koalas in the assessment area is higher than the naive total population estimate of 4,752 to 6,160 koalas (Table 16) for reasons related to imperfect detection and covariate influences. First, abundance estimation models accounted for imperfect detection by using the koala resighting probability to correct estimates. For example, the koala resighting probability for the multinomial model was much less than one (that is, P = 0.46, meaning fewer than half of koalas seen on the first survey were then observed on the second survey). So naive abundance estimates were effectively corrected for each abundance model using the resighting probability to model koala abundance estimates. Second, using covariates in the multinomial abundance estimation model further increased the estimate of total koala abundance by predicting that koalas were likely to be in higher abundance than what was directly observed or adjusted for imperfect detection. This occurs because covariates can capture underlying environmental and ecological relationships that are correlated with koala abundance. For example, covariates such as NDVI, soil depth and TSI 14 species were positively associated with koala density. When these covariates are included in the model they can predict higher koala abundance in areas that have favourable conditions (for example, high NDVI and deeper soils), even if fewer koalas were observed during the study. Consequently, in areas where conditions are similar, but observations are lower, the model may estimate a higher true abundance than what was directly counted, correcting for potential under-detection. Thus, the inclusion of correlated covariates enhances the model's ability to estimate koala abundance more accurately, reflecting both observed data and the predicted abundance based on key environmental factors. This would explain why the multinomial model total koala population estimate of 14,236 to 23,154 koalas was higher than the 3 other estimates.

Table 15 Koala abundance models that were used to estimate koala abundance, using double-independent observer koala count data obtained from drone surveys in the assessment area

Model	Description	Application
Huggins model	A likelihood-based capture-recapture model that estimates population size using conditional likelihoods, allowing for individual heterogeneity through covariates.	Estimating koala abundance when individuals are identifiable through unique markings or tags.
Otis model	A capture-recapture model for closed populations, accounting for variation in capture probability over time or among individuals. It includes variants based on assumptions like constant or time-varying capture probabilities.	Applicable to koala populations assumed to be closed during the study period, with varying capture probabilities.
Multinomial Poisson model	A model used for estimating abundance in point counts. It combines Poisson and multinomial distributions to handle over-dispersion and variable detection probabilities.	Used in koala abundance studies involving observations at different points, where detection probability varies.

Table 16 **Model-specific estimates of koala density and total koala abundance across the assessment area used to report the consensus density and total abundance estimate**

Abundance method	Koalas/ha ± 95% CI	Total koala abundance assessment area (176,000 ha)	Lower confidence interval (2.5%)	Upper confidence interval (97.5%)
Naive estimate	0.031 ± 0.024 to 0.038 (95% CI)	5,528	4,752	6,160
Huggins model	0.069 ± 0.063 to 0.081 (95% CI)	12,359	11,160	14,497
Otis model	0.069 ± 0.062 to 0.080 (95% CI)	12,255	11,097	14,353
Multinomial Poisson model	0.104 ± 0.081 to 0.131 (95% CI)	18,304	14,236	23,154
Consensus estimate	**0.066 ± 0.056 to 0.078 (95%CI)**	**12,111**	**10,311**	**14,541**

Appendix E: Koala density values per hectare for other studies, with different methods in NSW

Table 17 includes examples of koala abundance or density values (per hectare) estimated using different methods at a range of locations to demonstrate comparable densities from the literature.

Table 17 Examples of koala abundance/density values (per ha) using different methods

Method	Location	Sex	Koalas/ha	Category	References
Drone survey (RPAS)	Port Stephens	Male and/or female	Mean 0.033 ± 0.014	–	Witt et al. (2020)
Acoustic sensor array	North-east forests	Male koala/ha	0.03–0.07	Average	Law et al. (2022b)
	North-east forests	Male koala/ha	0.3	Above	Law et al. (2022b)
	North-east forests	Male koala/ha	<0.01	Below	Law et al. (2022b)
	Upper Nepean SCA	Primarily male	0.04 (0.01–0.13)	–	Law et al. (2021)
	Canyonleigh	Primarily male	0.04 (0.01–0.11)	Minimum	Law et al. (2021)
	Bongil Bongil NP	Primarily male	0.07 (0.03–0.18)	–	Law et al. (2021)
	Murrah Flora Reserve	Primarily male	0.05 (0.03–0.10)	–	Law et al. (2021)
	Gunnedah	Primarily male	0.30 (0.14–0.40)	Maximum	Law et al. (2021)
	Bril Bril SF	Male koala/ha	0.05 (2018) 0.04 (after fire)	Low severity	Law et al. (2022a)
	Kiwarrak SF	Male koala/ha	0.08 (2019) 0.04 (after fire)	Moderate severity	Law et al. (2022a)
	Bellangry SF	Male koala/ha	0.04 (2018) 0.016 (after fire)	High severity	Law et al. (2022a)
Spotlighting	Pine Creek SF, Bongil Bongil NP	Male and/or female	0.02-0.20	–	Smith and Pile (2024)

Method	Location	Sex	Koalas/ha	Category	References
Scat survey	East Coast S/E Forests Campbelltown	Male and/or female	≤ 0.1	Low	Phillips and Callaghan (2011)
	East Coast Port Stephens Noosa	Male and/or female	–	Med–high	Phillips and Callaghan (2011)
	Western Slopes & Plains Pilliga Walgett	Male and/or female	–	Med-high	Phillips and Callaghan (2011)
	Campbelltown	Male and/or female	>0.5	High	Phillips (2018)
	Campbelltown	Male and/or female	<0.1	Low	Phillips (2018)

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