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Department of **Biodiversity, Conservation and Attractions**

Ngwayir associations with management and environmental factors in the Upper Warren.

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Ngwayir associations with management and environmental factors in the Upper Warren.

Adrian F. Wayne, Marika A. Maxwell, Joanne Potts, Adrian Barrett, Billy Geary

June 2022

Department of Biodiversity, Conservation and Attractions

GOVERNMENT OF WESTERN AUSTRALIA

Department of Biodiversity, Conservation and Attractions
Locked Bag 104
Bentley Delivery Centre WA 6983
Phone: (08) 9219 9000
Fax: (08) 9334 0498

www.dbca.wa.gov.au

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Questions regarding the use of this material should be directed to:
Position: Program Leader
Section: Animal Science Program
Department of Biodiversity, Conservation and Attractions
Locked Bag 104
Bentley Delivery Centre WA 6983
Email: lesley.gibson.wa.gov.au

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Cover image: ngwayir in *Banksia grandis* (Photo by Adrian Wayne)

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Acknowledgments

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Summary

The pedestrian-based spotlighting using the distance sampling method has provided the best available information on the ngwayir population in the Upper Warren region to date. Population density varies greatly across the region and is extremely patchy, with most of the current population being located between the Yerraminup and Perup Rivers. Elsewhere in the region, substantial and rapid declines in ngwayir have been observed over the last 20 years. The population estimate of 7,103 (6,052 – 8,335 95%CI) across the 38,349 ha surveyed in 2022 encompasses most of the regional hotspot and most of the known population within the region. The size of this population is significant given total species estimates of at least 20,000 (Teale and Potts, 2020).

Elevation and the incidence of severe fire over the last 20 years were the best factors in the density surface models at explaining spatial variation in ngwayir densities across the broader region (2019 survey) and ngwayir 'hotspot' (2022 survey), respectively. However, the importance of these factors should not be overstated given that most of the variation remained unexplained and other management, anthropogenic and environmental factors explored in this study explained similar amounts of the spatial variation. The current distribution and abundance of ngwayir within the region is very likely strongly influenced by recent declines, the cause(s) of which remains unknown. Interactions between multiple agents of population change are likely but were not investigated here. Dedicated studies investigating the factors driving population change are recommended, including a focus on the effects of fire and insect outbreak. Adequate monitoring of the spatiotemporal changes in the population are also highly recommended. Experiences from these surveys also provide opportunities to improve the methods used to survey and monitor ngwayir in these and similar habitats across their range.

1 Introduction

The ngwayir or western ringtail possum (*Pseudocheirus occidentalis*) is currently listed as '*Critically Endangered*' due principally in response to the rapid and substantial decline of the species in the Upper Warren region (Wayne *et al.* 2005; Wayne *et al.* 2017; Wayne *et al.* 2012; Woinarski *et al.* 2014). This region supports the largest remaining ngwayir population in the jarrah forest and a substantial portion of the extant population and its genetic diversity (White *et al.* 2021). Understanding the factors that affect the distribution and abundance of ngwayir is fundamental to inform effective management and conservation efforts for this species in this region. Research 20 years ago found that the relative abundance of the ngwayir across the Upper Warren was patchy and related to fire, timber harvesting, fox control and forest fragmentation (Wayne *et al.* 2006). However, the ngwayir population in the region is expected to have changed considerably since, with declines continuing or being sustained in some areas and numbers potentially being higher in other areas.

In 2019, Biota Environmental Services (Biota) undertook an extensive survey of ngwayir throughout the species' range (Teale and Potts 2020).The purpose of this work was to estimate the density of ngwayir at over 40 study sites across the species' geographic range (Teale and Potts 2020). This works constituted the most thorough, systematic, and extensive survey of the species undertaken to date. With regards to the Upper Warren, the survey involved 251 km of walked transect that resulted in the detection of 175 ngwayir individuals. The distance sampling model estimated the ngwayir population to be 8,423 individuals (5,472 – 12,966, 95% confidence interval (CI)), across an area of 95,142 ha (Teale and Potts 2020).

In 2022, Biodiversity and Conservation Science (BCS) conducted a follow-up, more detailed survey (Wayne *et al.* 2022) of a smaller northern portion of the Upper Warren, focussing on the so called 'ngwayir hotspot' - the area that had relatively high detection rates of ngwayir in the 2019 survey. Using the same methods as the 2019 survey but at a higher spatial resolution (1 km spacing between parallel transects in 2022 compared with 2.5 km spacing in 2019), a total of 371.5 km walked transect resulted in a total of 438 ngwayir individuals being detected. A distance sampling model estimated the population size to be 8,341 individuals (7068 – 9842 95% Confidence Interval) across the 38,349 ha survey area (Wayne *et al.* 2022).

Both surveys demonstrate that the spatial variation in the density of ngwayir is large, and that the vast majority of the ngwayir are within the so -called 'hotspot'.

The aim of this study is to use density surface modelling to relate the density of ngwayir across the Upper Warren in 2019 and 2022, to environmental and management-related factors including;

1. management activities (fire, timber harvesting and fox baiting),
2. other anthropogenic factors (e.g. proximity to agriculture and the density of roads), and
3. environmental factors (e.g. proximity to surface water features, primary productivity, site moisture and forest type)

The purpose of this is to better understand what factors may best explain the distribution and abundance of ngwayir. This can be used to inform management to improve the conservation and recovery of the ngwayir population.

The project contributes to the delivery on the highest priority recovery objectives in the western ringtail possum (ngwayir) recovery plan (Department of Parks and Wildlife 2017):

- Habitat critical for survival for ngwayir is identified and protected in each key management zone.
- Threatening processes that are constraining the recovery of ngwayir are mitigated in each key management zone.
- An evidence-based approach is applied to the management and recovery of ngwayir.

2 Methods

2.1 Study area

The Upper Warren refers to the river catchments of the Wilgarup, Yerraminnup, Perup and Tone Rivers, all tributaries of the Warren River, in southwestern Australia. For practical purposes it is considered here as the Department of Biodiversity, Conservation and Attractions (DBCA)-managed lands within the DBCA Warren Region east of the Southwest Highway between Bridgetown, Manjimup and Quinninup, and north and west of Lake Muir (Figure 1). At about 177,000 hectares, this includes some contiguous areas of DBCA-managed land within the Blackwood River catchment and Donnelly River catchment. The area includes State Forest, the Tone-Perup Nature Reserve (56,000 ha), Kingston National Park (21,000 ha) and several other smaller reserves.

The study area is situated in the Southern Jarrah Forest Interim Biogeographic Regionalisation for Australia (IBRA) subregion (JAF02), the forests and woodlands of the area are dominated by jarrah (*Eucalyptus marginata*), marri (*Corymbia calophylla*) and wandoo (*Eucalyptus wandoo*). The area is particularly important for the conservation of several native mammals including the *Critically Endangered* woylie (*Bettongia penicillata*) and ngwayir, the *Endangered* numbat (*Myrmecobius fasciatus*), the *Vulnerable* chuditch (*Dasyurus geoffroii*) and quokka (*Setonix brachyurus*), the *Conservation dependent* wambenger (*Phascogale tapoatafa wambenger*), and Priority 4 species including quenda (*Isoodon fusciventer*), tammar wallaby (*Notamacropus eugenii derbianus*), and kwara or western brush wallaby (*Notamacropus irma*). Several of these species, including ngwayir, and others such as dunnarts (*Sminthopsis* spp.) and mootit or bush rat (*Rattus fuscipes*) have undergone significant and sustained declines since the 1990s, while others, such as the koomal (southwestern subspecies of common brushtail possum, *Trichosurus vulpecula hypoleucus*) have increased (Wayne *et al.* 2015; Wayne *et al.* 2017). The introduced red fox (*Vulpes vulpes*) and cat (*Felis catus*) are a significant threat to many native mammals. Other introduced species in the area that are of management interest include pig (*Sus scrofa*), goat (*Capra hircus*) and red deer (*Cervus elaphus*).

Fox baiting for conservation purposes began in some areas in 1977 (Burrows and Christensen 2002). It became broadscale, covering most of the study area in 1996 as part of the Western Shield program (Wayne *et al.* 2017; Wyre 2004). Other major management activities in the region include prescribed burning (McCaw *et al.* 2005), timber harvesting (Wayne *et al.* 2006; Wayne *et al.* 2016 and references therein) and dieback hygiene (i.e. reducing the spread of the plant pathogen *Phytophthora cinnamomi*).

Land uses of the freehold land around the DBCA-managed lands in the Upper Warren are primarily agricultural (sheep, cattle, grain and oil crops), plantation forestry (blue gums and pine), viticultural (wine grapes), and horticultural (fruit tree orchards and vegetables).

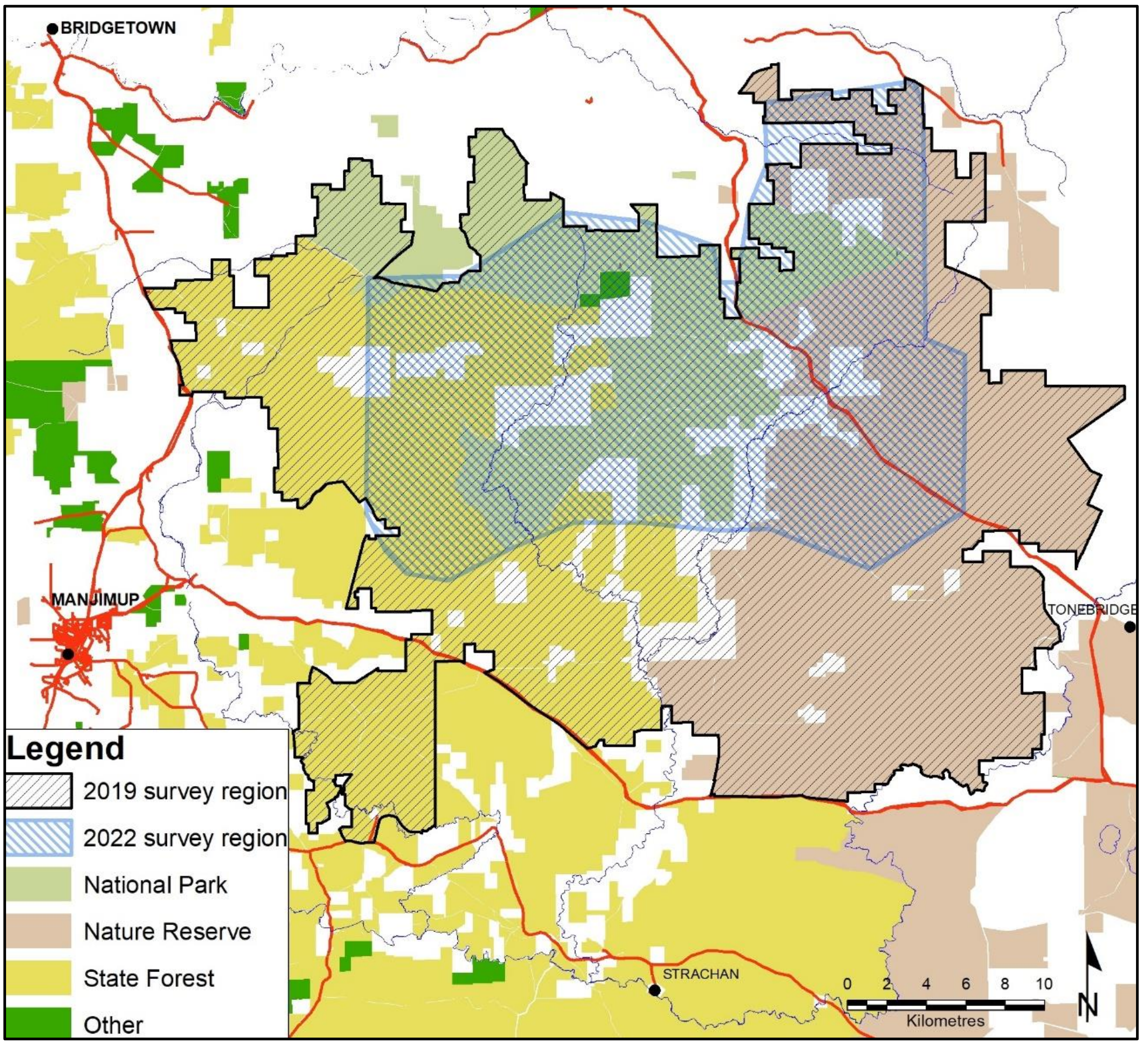

Figure 1. *Ngwayir survey regions of 2019 (black forward diagonal hatching) and 2022 (blue and backward diagonal hatching), within the Upper Warren, Western Australia.*

Main sealed roads (red lines) and major hydrography (blue lines) are also depicted. Non-DBCA managed land (white areas) was not included in the surveys and is mostly freehold (private property) used for agriculture.

2.2 Survey methods

Line transect distance sampling surveys were undertaken February – March 2019 and January - April 2022 using methods described in Teale and Potts (2020) and Wayne *et al.* (2022). In 2019, the surveys were undertaken by Biota on transects spaced 2.5 km on DBCA-managed land across the northern portion of the Upper Warren (Figure 2). In 2022, the surveys were conducted by BCS on transects spaced 1 km apart within a smaller northern portion of the Upper Warren, focussing on the so called 'ngwayir hotspot' - the area that had relatively high detection rates of ngwayir in the 2019 survey (Figure 3). Each transect was surveyed by a single observer, following the transect using a GPS and walking quietly at approximately 1 km per hour. Animals were searched for using a high-powered head torch (Led Lenser XEO 19R or H19R Core models). A GPS was used to record the location for each animal observation.

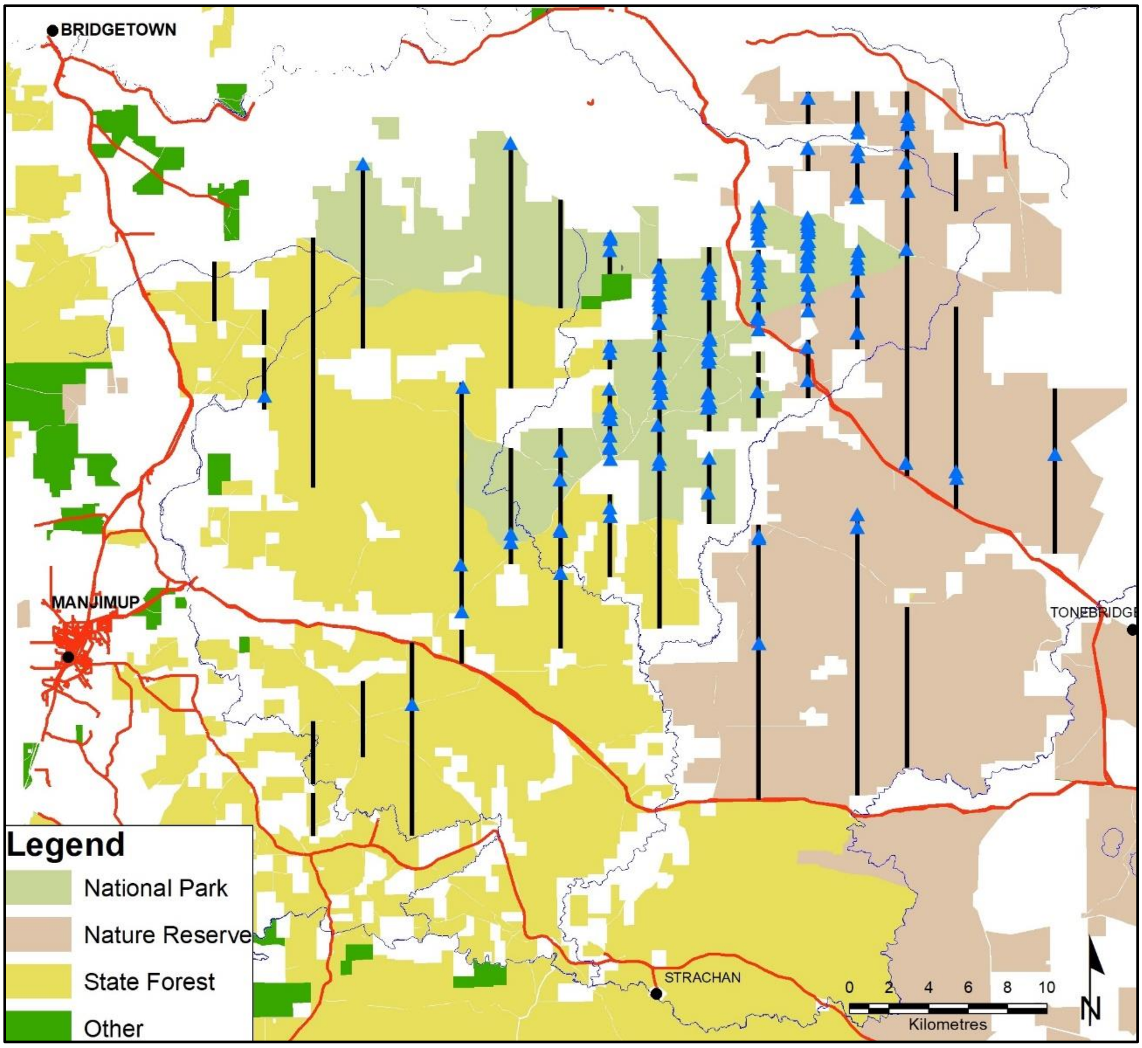

Figure 2. *Spotlight transects (black parallel lines, running north-south, spaced 2.5 km apart), in the Upper Warren, surveyed in 2019.*

Independent sightings of ngwayir on transect during distance sampling spotlight surveys (blue triangles), main sealed roads (red lines) and major hydrography (blue lines) are also depicted. Non-DBCA managed land (white areas) was not included in the surveys and is mostly freehold (private property) used for agriculture.

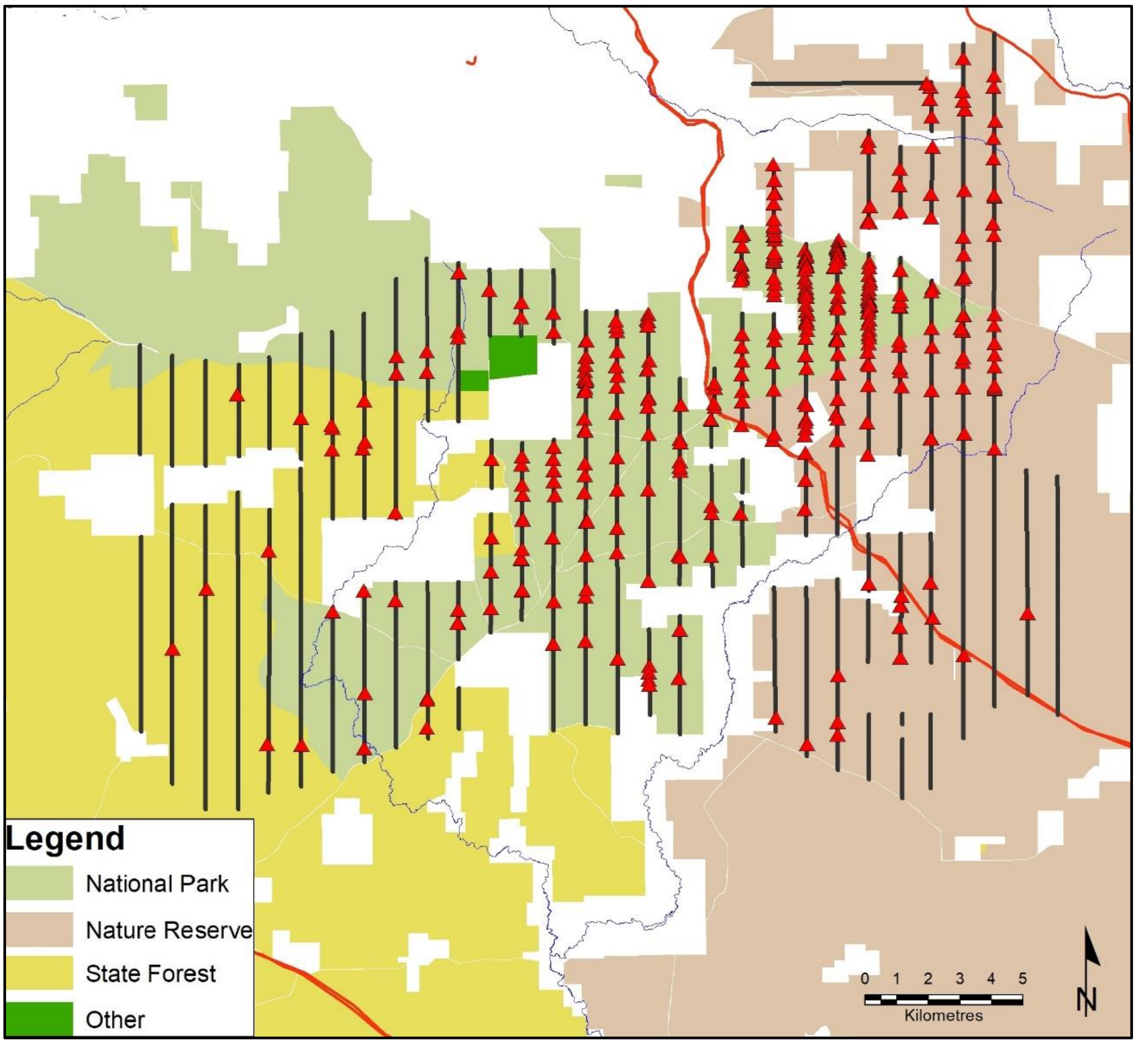

Figure 3. *Spotlight transects (black parallel lines most running north-south, spaced 1 km apart), in the Upper Warren, surveyed in 2022.*

Independent sightings of ngwayir on transect during distance sampling spotlight surveys (red triangles), main sealed roads (red lines) and major hydrography (blue lines) are also depicted. Non-DBCA managed land (white areas) was not included in the surveys and is mostly freehold (private property) used for agriculture. Note this is a subset of the area surveyed in 2019 but at a finer spatial scale.

2.3 Analyses

Distance sampling analysis (Buckland *et al.* 2001) was undertaken using the 'Distance' package (v. 1.0.4, Miller *et al.* 2019) in R (v. 4.1.2, R Core Team 2021) on both the 2019 and 2022 data separately. Details of these analyses are provided in Wayne *et al.* (2022). Density estimates derived from the distance sampling can be used to estimate total population size across the survey region (i.e., 'mod.ds' in Tables 2 and 3), by extrapolating the density estimate in the areas actually surveyed and applying this across the survey region (i.e., it is assumed the estimated density of animals in the covered region applies to the uncovered region).

Alternatively, population estimates can be derived using a density surface modelling approach (Miller *et al.* 2013). In this case, the spatial locations of detected animals (obtained via distance sampling) can be modelled according to a 2-dimensional spatial smooth (i.e., 'mod.xy' in Tables 2 and 3). To do this, the survey region is discretised. Line transects may have fallen within some grid cells in the discretised survey region (in which case, the encounter rate of animals within that grid cell is known, as is the survey effort, i.e. the transect length within each grid cell), or not (in which case there was no survey effort in the grid cell). The encounter rate of animals within each surveyed grid cell is corrected upwards based on distance sampling theory (i.e. detection function), to account for animals that were present but not detected.

Explanatory variables within each grid cell across the survey region are known (e.g. latitude and longitude). The relationship between the estimated density in each surveyed grid cell is modelled, accounting for survey effort, and extrapolated to grid cells that were not surveyed. This results in a spatial 'map' of where the animals are located within the survey region. The predicted abundance of the survey region can be obtained by summing the estimated abundance in each grid cell. This result differs slightly to that obtained via distance sampling, because as outlined above, it assumes that the estimated density in the covered region is applicable to the entire survey region. However, note that if survey coverage in the region is high, the estimates from density surface modelling and distance sampling will become approximately equal.

Here, the density surface modelling was done using the 'dsm' package (v.2.3.1, Miller *et al.* 2021) in R. A bivariate smooth of x (Easting) and y (Northing) was used with an initial basis complexity of 50 (i.e., s(x, y, k=50)). To account for overdispersion of counts (i.e., when the mean is greater than the variance), two distributions were investigated (Tweedie versus negative binomial), and analysis proceeded using the negative binomial because model assumptions were better met (results not presented).

The influence of 17 spatial covariates on density estimates were explored in the density surface modelling (Table 1, Appendix 1). The definitions of levels within a covariate were specified based on the frequency distribution of ngwayir records within classes (Appendix 2), and what was biologically meaningful. A spatial grid cell of 500 m and 100 m was used for the 2019 and 2022 models, respectively (due to spatial scale of the prediction area and processing time). The same prediction area was used for all covariates within a given year by removing grid cells that had incomplete data for at least one covariate (i.e. to allow for direct comparability between models within a given year). The percentage deviance explained was calculated for each model, and spatial autocorrelation for each density surface model was checked. Model selection between the covariates was based on AIC.

Table 1. *Spatial covariates explored in relation to ngwayir density estimates derived from the density surface modelling.*

* denotes covariates that were time sensitive and therefore had a different time-specific covariate for the 2019 and 2022 models, based on the situation as it was at the start of the surveys (i.e. 1st April 2019 and 27 January 2022, respectively).

Subject	**Covariate name**	**Details (covariate type and levels)**
*Fire age	FSW_YSLB	Year since last burned. (Continuous).
*Fire severity (10 years)	sev10yrs	Fire severity of all fires in the 10 years prior to survey. (Categorical: 0= no record (i.e. not burnt in previous 10 years), 1= unburnt, 2= low, 3=medium, 4= high, 5= very high fire severity class).
*Severe fire count (20 years)	sev20yrs	The number of times each 50 m grid cell was burnt severely (class 4 or 5) in the 20 years prior to survey. (Count: 0-2).
*Fox bait intensity	bait.2019 / 2022	Average number of baits per km^2 deployed in the 38 months prior to survey. (Continuous)
*Timber harvesting period	Decade	When last timber harvesting was recorded. (Categorical: 0 = <1970, including areas with no record of timber harvesting (e.g., not cut), 1= 1970-1979, 2= 1980 to current.
Road density	prop.roads	The proportion of 50 m cells within a 3 km buffer that contain a mapped road.
Agriculture proportion	prop.ag.5	The proportion of 50 m cells within a 5 km that were not mapped as DBCA-managed tenure
Agriculture proximity	dist.ag	The distance of each cell to the nearest cell that is not mapped as DBCA-managed tenure. (Continuous)
Remnant vegetation proportion	remnant.veg3	The proportion of 50 m cells within a 3 km buffer that contain mapped remnant vegetation
Elevation	elev	Height above sea level (m). (Continuous)

Subject	**Covariate name**	**Details (covariate type and levels)**
Distance to all surface water features	dist.allhydro	The distance (m) from each 50 m cell to the nearest cell with a mapped hydrological feature (stream or wetland). (Continuous)
Distance to major surface water feature	dist.majhydro	The distance (m) from each 50 m cell to the nearest cell with a mapped major hydrological feature (river). (Continuous)
*Vegetation density (2022 model only)	veg.dens	Landsat satellite imagery vegetation index (using imagery data from 17/02/2022), classified (1-10), with values 4& 5 corresponding to thickets and riparian vegetation on DBCA managed land in the Upper Warren.
*Primary productivity	ndvi.apr2019 / ndvi.jan2022	Average monthly NDVI for the 36 months (3 years) prior to survey (Source: https://lpdaac.usgs.gov/products/mod13a3v006/). Rescaled to 50 m resolution. (Continuous)
Site wetness	topo.wetness	Topographic Wetness Index from CSIRO (https://data.csiro.au/collection/csiro:5588) rescaled to 50 m resolution. (Continuous)
Forest type	forest	Dominant vegetation type (Categorical: 1= Jarrah dominant with other species >20% of canopy; 2= Other eucalypts; 3= Nonhabitat (non-forest shrub; cleared, not rehabilitated; swamp; rock, exotics (pine, exotic eucalypts); karri; water bodies); 4= Jarrah dominant with other species <20% of canopy; 5= Marri dominant; 6= Blackbutt dominant.
Landscape position	landscape	Landscape position (Categorical: NA: Needs to be reviewed; 1= Depressions and Swamps on Uplands; 2= Uplands; 3= Valley Floors and Swamps; 4= Valleys). Source: Matiske and Havel Vegetation complex layer.

3 Results

In 2019, the area actually surveyed was 2,756 ha (251.4 km x 110 m truncated transect width) across a survey region of 95,142 ha, which after removal of cells with missing covariate data was reduced to a prediction area of 87,478 ha. In 2022, the area actually surveyed was 3,344 ha (371.5 km x 90 m truncated transect width) across a survey region of 43,594 ha, and a prediction area of 38,349 ha. The covariate space sampled in 2019 and 2022 don't appear biased (i.e., they reflect what is available in the survey region, see Appendix 2) and presence records seem to reflect available covariate space rather than preferentially selecting one region of the covariate (see Appendix 2).

3.1 Models of 2019 data

Density surface model selection results are in Table 2. Based on AIC model selection, mod.elev, (elevation) was the best model of those investigated. Based on this model, abundance of ngwayir in this survey region is 4,187 individuals (95% CI: 3151, 5563). Model structure uncertainty was low (i.e., the next model had a difference in AIC of >2, i.e., these models are not equivalent). The percentage deviance explained by all models is comparable and moderate (~45%, Table 2). Also note, the difference in estimated abundance between the models is relatively small, especially when considering the confidence interval range.

When investigating mod.elev, the coefficient of the explanatory variable was -0.02 (s.e., 0.007) and significant (p-value = 0.002). A map of the predicted abundance of ngwayir based on mod.elev is provided in Figure 4.

Table 2. *Density surface model (DSM) selection results for the 2019 survey data, ranked by AIC (i.e., model with the lowest AIC).*

Estimated abundance ($\hat{N}$) and 95% confidence interval is provided, and the percent deviance explained by the model (%dev). Abundance estimates from distance sampling are provided for comparison (mod.ds). 'mod.xy' is a DSM spatial model. Area to which these abundance estimates apply is 87,478 ha (i.e., smaller than the total survey area of 95,142 ha due to missing covariates – predictions cannot be made to grid cells without complete covariate information).

Model	$\hat{N}$	95% CI	%dev	AIC	ΔAIC
mod.elev	4,187	(3151, 5563)	46.64	463.12	0
mod.Decade	4,233	(3185, 5624)	45.96	466.47	3.35
mod.landscape	4,163	(3131, 5534)	46.88	468.87	5.75
mod.forest	4,210	(3155, 5617)	46.68	469.39	6.28
mod.dist.allhydro	4,238	(3184, 5639)	44.95	470.27	7.16
mod.topo.wetness	4,203	(3160, 5587)	45.25	470.36	7.24
ndvi.jan2019	4,192	(3150, 5577)	45.13	470.98	7.86
mod.xy	5,060	(3793, 6747)	44.42	471.09	7.97
mod.dist.majhydro	4,219	(3170, 5615.)	42.41	472.48	9.36
mod.sev10yrs	4,133	(3111, 5489.)	44.44	472.53	9.41
mod.prop.ag.5	4,211	(3158, 5613.)	44.29	472.81	9.7
mod.FSW_YSLB	4,161	(3129, 5533.)	44.59	472.82	9.71
mod.remnant.veg3	4,187	(3144, 5576.)	44.52	472.83	9.72
mod.dist.ag	4,178	(3139, 5559)	44.52	472.89	9.78
mod.prop.roads	4,155	(3125, 5523.)	44.37	472.92	9.8
mod.sev20yrs	4,121	(3097, 5482)	44.29	473.06	9.95
mod.bait.2019	4,169	(3134, 5544)	44.33	473.21	10.09
mod.ds	5,773	(4232, 7873)			

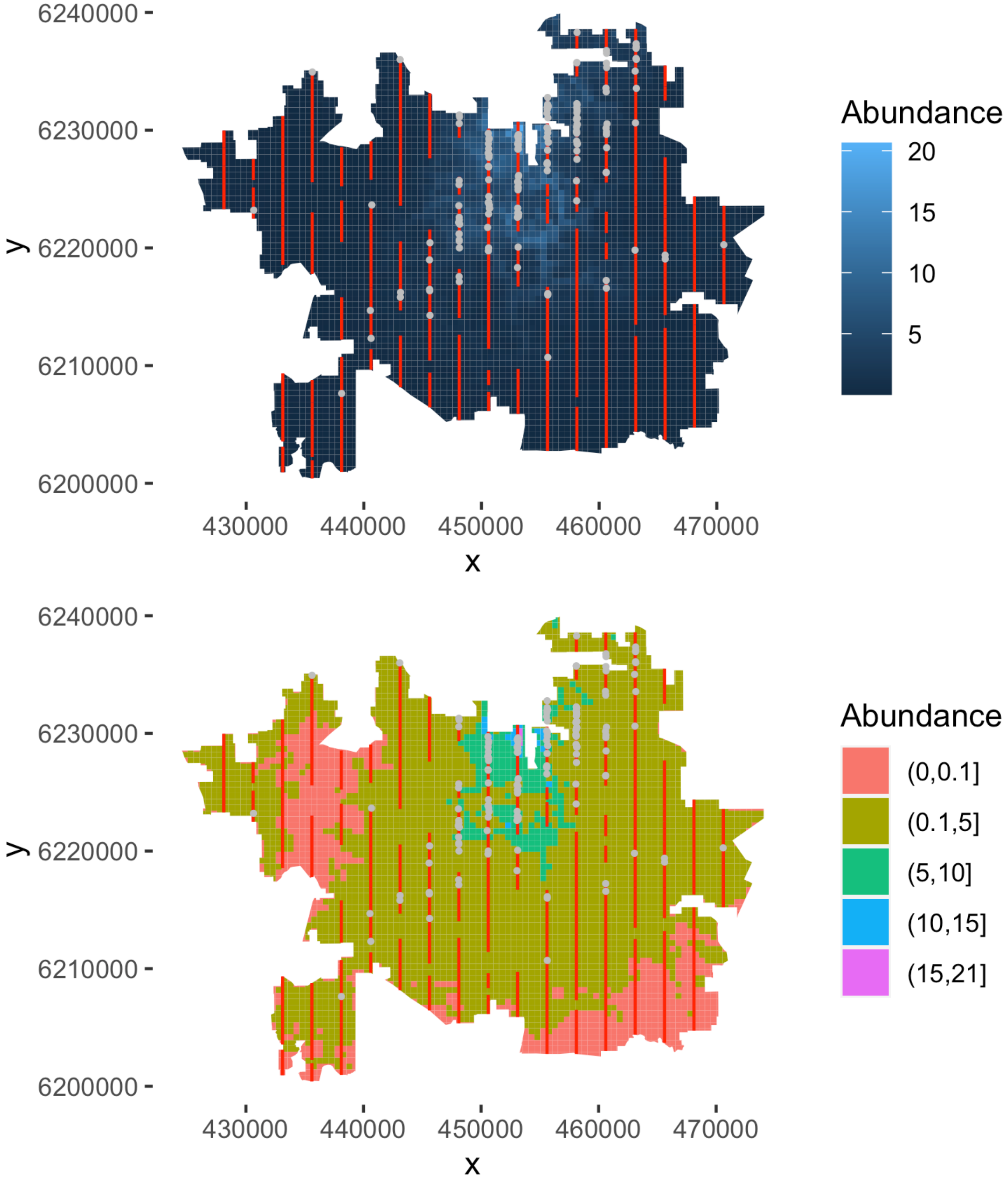

Figure 4. *Map of estimated ngwayir abundance in the Upper Warren in 2019, based on spatial predictions from mod.elev (see Table 2) either continuous (top panel) or categorical (bottom panel).*

Estimated abundance is the number of individuals per 25 hectare grid cell. Overlaid are the detection events of ngwayir (small light grey dots).

3.2 Models of 2022 data

Density surface model selection results for the 2022 data are in Table 3. Based on AIC model selection, ‘severe fire count (20 years)’ (mod.sev20yrs) was the best model of those investigated and based on this model, abundance of ngwayir in this survey region was 7,103 individuals (95% CI: 6052, 8335). Model structure uncertainty was low (i.e., the next model had a difference in AIC of >2, i.e., these models are not equivalent), however, the percentage deviance explained by all models is comparable and low (~29%, Table 3). Also note, the difference in estimated abundance between the models is relatively small, especially when considering the confidence interval range.

When investigating ‘severe fire count (20 years)’, the coefficient of the explanatory variable was -0.57 (s.e., 0.21) and significant (p-value = 0.006). A map of the predicted abundance of ngwayir based on this model is provided in Figure 5.

3.3 Population estimates

Differences with the estimates from distance sampling and differences between datasets merit explaining.

The population estimate based on the best density surface model of the 2019 data was 4,187 ngwayir (3,151- 5,563 95% CI) across 87,478 ha. This estimate and survey region is smaller than the figures from a distance sampling model reported in Teale and Potts (2020) and Wayne et al. (2022): 8,423 individuals (5,472 – 12,966, 95% CI) across 95,142 ha. It is also smaller than the distance sampling model reported here: 5,773 (4232 – 7873 95% CI) across the same 87,478 ha. The difference in survey region is due to some missing covariate data for some prediction grid cells and the need for model comparisons in this study to have the same area of prediction (i.e. only those grid cells with complete information for all covariates were included). The difference in estimates between model approaches is due to fundamental differences in the modelling and the assumptions within. Density surface models should provide more accurate population estimates because they account for differences in density according to covariate variation across the survey region. Whereas the population estimate from distance sampling assumes a uniform survey region with the densities being the same in the areas not surveyed to those that were.

Substantial differences also exist in the population estimates derived from density surface modelling between 2019 and 2022 (7,103 with 6,052 – 8,335 95%CI, from 38,349 ha). Despite the 2022 survey region being 44% the size of the 2019 survey region, the population estimate is 170%. However, the estimates between years are not comparable. This is due, at least in part, to differences in the survey design, with a higher spatial resolution of the sampling in 2022 (i.e. 1 km spacing between transects instead of 2.5 km), focussing on the ‘hotspot’ within the region. The 2022 survey of the hotspot should, therefore, produce a more accurate estimate of the ngwayir population within this area.

Table 3. *Density surface model (DSM) selection results for the 2022 survey data, ranked by AIC.*

Estimated abundance ($\hat{N}$) and 95% confidence interval is provided, and the percent deviance explained by the model (%dev). Abundance estimates from distance sampling are provided for comparison (mod.ds). 'mod.xy' is a DSM spatial model. Area to which these abundance estimates apply is 38,349 ha (i.e., smaller than the total survey area of 43,594 ha due to missing covariates – predictions cannot be made to grid cells without complete covariate information).

Model	$\hat{N}$	95% CI	%dev	AIC	ΔAIC
mod.sev20yrs	7,103	(6052, 8335)	29.72	1,890.57	0
mod.landscape	7,064	(6059, 8356)	29.77	1,894.03	3.46
mod.dist.allhydro	7,116	(6080, 8393)	29.52	1,895.20	4.63
mod.elev	7,144	(6039, 8321)	29.48	1,895.37	4.8
mod.xy	7,089	(6065, 8361)	29.33	1,895.84	5.27
mod.forest	7,122	(6035, 8318)	29.65	1,896.22	5.65
mod.prop.ag.5	7,085	(6047, 8335)	29.41	1,896.49	5.92
mod.sev10yrs	7,100	(6057, 8352)	29.38	1,896.56	5.99
mod.dist.ag	7,113	(6032, 8313)	29.38	1,896.60	6.03
mod.FSW_YSLB	7,082	(6045, 8336)	29.41	1,897.00	6.43
mod.remnant.veg3	7,099	(6043, 8329)	29.35	1,897.00	6.43
mod.prop.roads	7,095	(6052, 8348)	29.38	1,897.06	6.49
mod.ndvi.jan2022	7,108	(6041, 8327)	29.37	1,897.16	6.59
mod.dist.majhydro	7,093	(6052, 8335)	29.31	1,897.29	6.73
mod.bait.2022	7,075	(6024, 8307)	29.31	1,897.79	7.22
mod.veg.dens	7,090	(6038, 8324)	29.33	1,897.79	7.22
mod.topo.wetness	7,091	(6039, 8324)	29.33	1,897.86	7.29
mod.Decade	7,095	(6041, 8332)	29.34	1,899.25	8.68
mod.ds	8,341	(7068, 9842)			

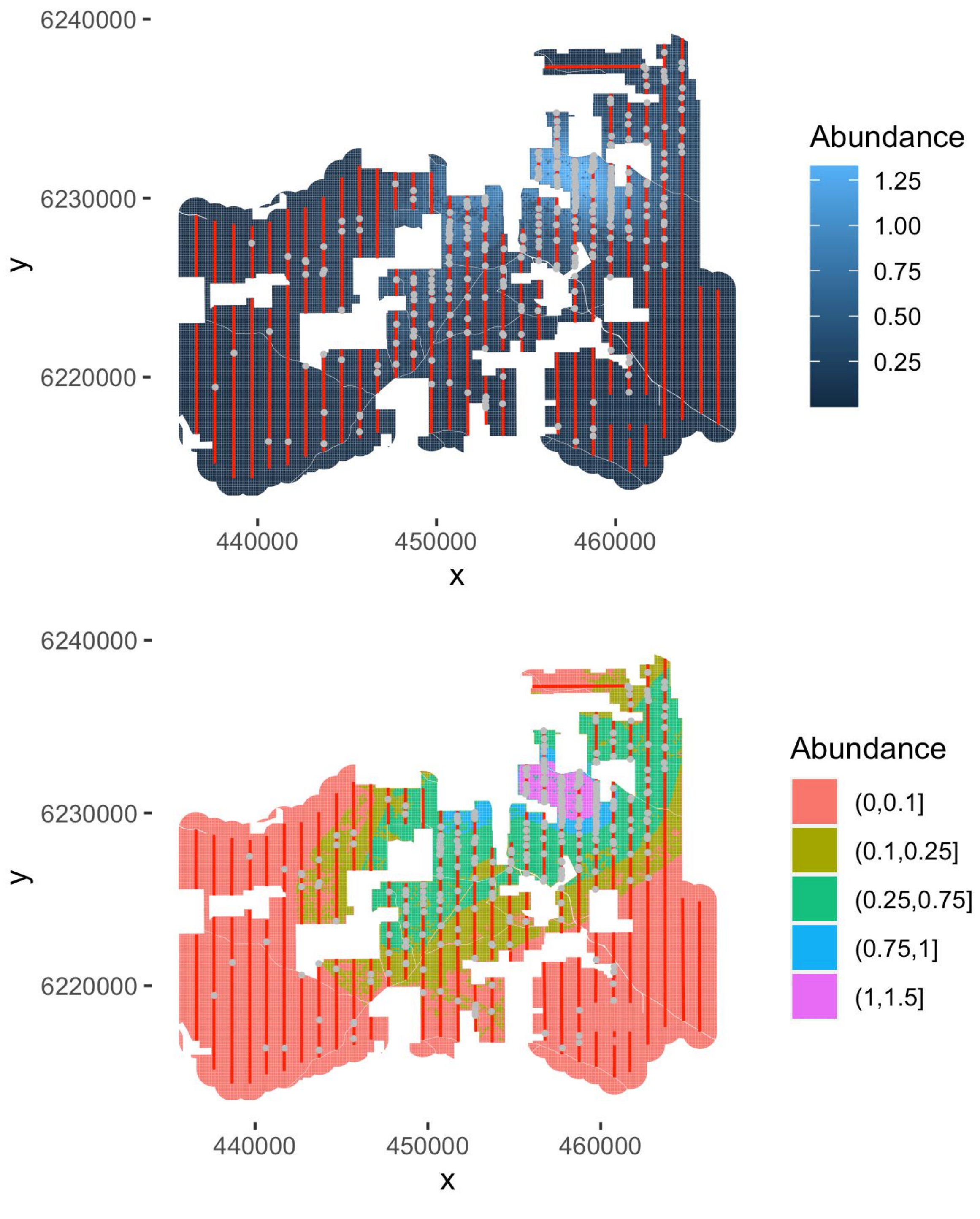

Figure 5. *Map of estimated ngwayir abundance in the Upper Warren hotspot in 2022, based on spatial predictions from mod.sev20yrs (see Table 3) either continuous (top panel) or categorical (bottom panel).*

Estimated abundance is the number of individuals per 1 hectare grid cell. Overlaid are the detection events of ngwayir (small light grey dots).

4 Discussion

4.1 Spatial variation in densities

The densities of ngwayir varied substantially over the areas surveyed in 2019 and 2022. However, the spatial patterns of density were similar within the area covered by both surveys: with the 2019 survey covering a much larger portion of the Upper Warren (<95,000 ha) and the 2022 survey providing more detail in and around the 'hotspot' in the north of the region (<43,000 ha).

Elevation best explained the variation of ngwayir density across the broader region, among the covariates investigated in this study (2019 data). The increase in ngwayir density associated with a decrease in elevation (-0.02 ngwayir per 25 ha with every 1 m increase in elevation, s.e. 0.007), was statistically significant and potentially biologically meaningful. While the effect size is small relative to the predicted densities across the region (mean 1.18 ngwayir per 25 ha, s.e. 0.028; maximum density was 20.6 ngwayir per 25 ha), the variation in elevation across the region (mean = 241 m, range 111 m – 358 m) means the overall effect may be modest. However, the importance of this covariate should not be overstated given that the percentage deviance explained by this model (47%) and the estimated abundances across the survey region were both comparable to every other explanatory variable investigated.

The incidence of severe fire over the last 20 years best explained the variation of ngwayir density across the smaller 'hotspot' area surveyed in 2022 in northern Upper Warren. The effect size was statistically significant and is biologically likely to be important, with a reduction of 0.57 (s.e. 0.21) ngwayir per hectare in those areas that experienced a severe fire in the past 20 years. This is significant given the average predicted density across the 2022 'hotspot' survey region was 0.17 ngwayir/ha (s.e. 0.001). However, further investigation is needed to better understand the effect of fire severity on ngwayir density, particularly given limitations of this study (discussed below).

Like the 2019 modelling, the percentage deviance explained (30%) by the best 2022 model and the estimated abundances were comparable to every other explanatory variable investigated. The similarity in the percentage deviance explained within both the 2019 and 2022 model sets is intriguing and merits further investigation. But it also suggests that most of the variation in the possum densities remains unexplained.

At its simplest, these surveys clearly identify the location and extent of the ngwayir 'hotspot' within the region with predicted densities (up to 1.3 ngwayir per hectare in 2022) being relatively high on the DBCA-managed land approximately between the Yerraminnup and Perup Rivers and at their highest in Dwalgan and Balban forest blocks in Kingston National Park and Tone-Perup Nature Reserve (Figure 6). This is useful for informing conservation and management. For example, management activities, such as prescribed burning, can readily identify *where* it is particularly important to consider the needs of ngwayir.

However, a good understanding of *what*, *how* and *why* factors are affecting ngwayir populations is vastly more valuable to informing conservation and management. Currently, the driver(s) of this very strong spatial ‘pattern’ to ngwayir density remains unclear. It is highly likely be an historical artefact, at least in part a result of the substantial declines that have occurred across the region over the last 24 years (Wayne *et al.* 2005; Wayne *et al.* 2017; Wayne *et al.* 2012).

The cause(s) of these declines remains unverified, however, introduced predators (feral cat and red fox), drought and climate change more generally, have been speculated (Wayne *et al.* 2017). Determining the drivers of population decline and the influence this has had on current population densities and distribution is very difficult without good information of the spatiotemporal changes in the population and the factors that may have been involved. Doing this retrospectively can be even more challenging (Caughley 1994; Caughley and Gunn 1996).

The strong spatial pattern currently evident and the fact that it may be strongly influenced by historical factors makes it more difficult to investigate the current role of covariates. Part of the rationale of the 2022 surveys to focus on the ‘hotspot’ was to address the influence of the strong spatial pattern (by looking at what factors might be associated with ngwayir density just within the hotspot). This also may explain (as was expected), why the best model for the ‘hotspot’ (in 2022) had a different covariate to the best model based on data across more of the Upper Warren (in 2019). The different spatial resolution of the prediction grid cells (500 m for the 2019 models and 100 m for the 2022 models) may also influence model performance because the influence of covariates may also vary across spatial scales. For instance, ngwayir responses to finer scale variation of potentially important factors (e.g., vegetation density and distance to a surface water feature), may be better modelled at a similarly finer scale.

The strong association with fire severity found within the ngwayir ‘hotspot’ is consistent with the findings of an earlier well-designed scientific study with stratified sampling to investigate the effects of fire and timber harvesting on ngwayir relative abundance (Wayne *et al.* 2006). Wayne *et al.* (2006) showed that ngwayir abundance was negatively associated with greater fire intensity at the local scale. At the landscape-scale, ngwayir were positively associated with fox control and negatively associated with forest fragmentation and distance from non-remnant vegetation (i.e., agriculture and tree plantations). Abundance was also greatest in predominantly unlogged landscapes and in regrowth forests where logging was historically least intense and on average 40 years old. Interactions between fox control efforts and forest fragmentation were also important (Wayne *et al.* 2006).

By comparison, the models in our study relating to fox-baiting intensity, forest fragmentation and timber harvesting history were no better at explaining ngwayir density than the other covariates investigated. It is interesting to note however, that while the fox bait intensity models in our study had relatively high delta AIC values (10.1 for 2019 and 7.2 for 2022 model), the highest densities of ngwayir in Dwalgan and Balban forest blocks, coincided with the areas of highest bait intensity (Appendix 1). While spatial autocorrelation was investigated for all covariates, it remains possible that the effect of baiting intensity may be less pronounced in a model that includes a spatial covariate, particularly given the strong spatial pattern to ngwayir density across the region and the strong spatial pattern to baiting intensity.

Position in the landscape is generally thought to be an important factor for ngwayir. Valley sites in the jarrah forest are generally believed to support higher densities of ngwayir, because they are relatively moist, well-draining, fertile areas that result in more productive and higher quality habitats (Department of Parks and Wildlife 2017). These sites are also more likely to support larger trees with greater canopy connectivity, which is also important for den site selection (Wayne 2005) but may also be important habitat features for improving resilience from introduced terrestrial predators. The results in this study may provide some support to this with landscape position being the second (2022) or third (2019) best models., That these models indicated ngwayir densities were least in the 'Depressions and Swamps on Uplands' (i.e., poor draining, low fertile sites with more open and scrubby vegetation) is consistent with our observations.

We were surprised that the covariate 'fire age' (year since last burned) did not perform better than it did in both datasets (2019 and 2022). There were numerous experiences where observers had a striking impression of detecting much fewer ngwayir in sites that had been recently burned, than along otherwise comparable, adjacent sections of transect in older fuel ages. However, it was equally striking how some areas with older fuel ages that had seemingly good ngwayir habitat had relatively few or no ngwayir detected (i.e., not all sites with older fire ages detected good numbers of ngwayir). A better understanding of ngwayir responses to time since fire is needed.

That the highest densities of ngwayir were observed in the relatively drier areas of the Upper Warren is particularly interesting and suggestive that there may be circumstances where they can flourish in relatively drier climates and conditions. Dwalgan and Balban forest blocks, where the peak densities of ngwayir were observed, have a long-term average rainfall of 604 mm compared to a regional range of 562 – 923 mm and mean of 682 mm. These areas are also not traditionally considered to be optimum habitat for ngwayir in regards to several other attributes including, being predominantly upland sites, at relatively high elevation (260 – 300 m), including the watershed boundaries at the top of the local catchments (i.e. away from valleys and higher order drainage lines), with a relatively high proportion of wandoo woodland on poor shallow soils over clay, and being close to agriculture with a high perimeter to area ratio (Appendix 2). These somewhat surprising results demonstrate how much more we still must learn to better understand what factors drive spatiotemporal changes in ngwayir populations.

It is also possible that other contemporary factors that have not been investigated here, may better explain the current distribution and density of ngwayir. For example, large areas that detected few or no ngwayir (e.g. Kingston and Warrup forest blocks) were anecdotally observed to have much poorer condition tree foliage, particularly in midstorey saplings (otherwise generally preferred by ngwayir for browsing), due to high levels of insect damage. While data on the quality, cover or extent of insect damage to tree foliage were not measured or readily available to be included as covariates in this study, it is recommended that these be considered in relation to future surveys.

Similarly, investigating the strength of association with any particular covariate may be improved by a greater consideration of context. This is because a species' distribution and abundance is likely to be the function of multiple factors (e.g., Caughley 1994; Caughley and Gunn 1996). Therefore, a multivariate approach may be of value and provides the opportunity to investigate the potential role of interactions between factors (e.g., fire severity, predation, vegetation type and structure and position in the landscape).

All covariates need to be carefully considered in terms of their potential ability to inform our understanding of their relative importance. This includes careful consideration of data accuracy and precision, spatial resolution, temporal scale, what the covariate is actually measuring, and how it may inform our biological and ecological understanding. For instance, a measure fox baiting intensity does not necessarily relate to the predation pressure from foxes. Despite this seemingly obvious distinction, these sorts of errors in inference are often made.

4.2 Population estimates and temporal variation

Some confidence in the population estimates can be gained from the similarities between the different density surface models (covariates) within each dataset (2019 and 2022). The best estimates are 4,187 ngwayir (3,151- 5,563 95% CI) across 87,478 ha in 2019 and 7,103 (6,052 – 8,335 95%CI), within the smaller area (38,349 ha) surveyed in 2022. The 2022 estimate of the ngwayir population within the regional 'hotspot' is likely to be more accurate given the finer spatial resolution of sampling, the greater survey effort and relatively large number of detection events. Nonetheless, it is not appropriate to compare these population estimates between years because of the differences in the survey design (e.g. different survey areas and transects). And therefore, we do not currently have an adequate region-wide appreciation of population trends over time.

The best temporal information currently available comes from several long-term monitoring sites (in Warrup, Kingston, Balban, Yendicup, Moopinup, Yackelup, Boyicup and Chariup forest blocks, some of which are no longer surveyed; that have used various vehicle-based spotlighting methods). All of these have shown substantial declines in ngwayir detection rates to undetectable or near undetectable levels (Wayne *et al.* 2005; Wayne *et al.* 2017; Wayne *et al.* 2012). Recent increases in the detection of ngwayir along the Keninup vehicle-based spotlight transect are supported by the relatively high densities observed in the 2022 pedestrian spotlight survey. The more extensive pedestrian-based surveys of 2019 and 2022 also provide supporting evidence that the ngwayir densities are currently low along the other vehicle-based spotlight transects (Figure 6), but also provide a far greater understanding of the spatial variation in ngwayir densities.

Adequate information of the temporal trends within the high-density area is particularly important given the risks of decline (i.e., surrounded by areas that have undergone recent declines) and the significance of this population to the conservation of the species. None of the existing vehicle-based spotlight transects adequately cover the current area supporting relatively high ngwayir densities (> 0.25 ngwayir per ha; Figure 6). This includes a relatively newly established transect (2017) in Corbal forest block.

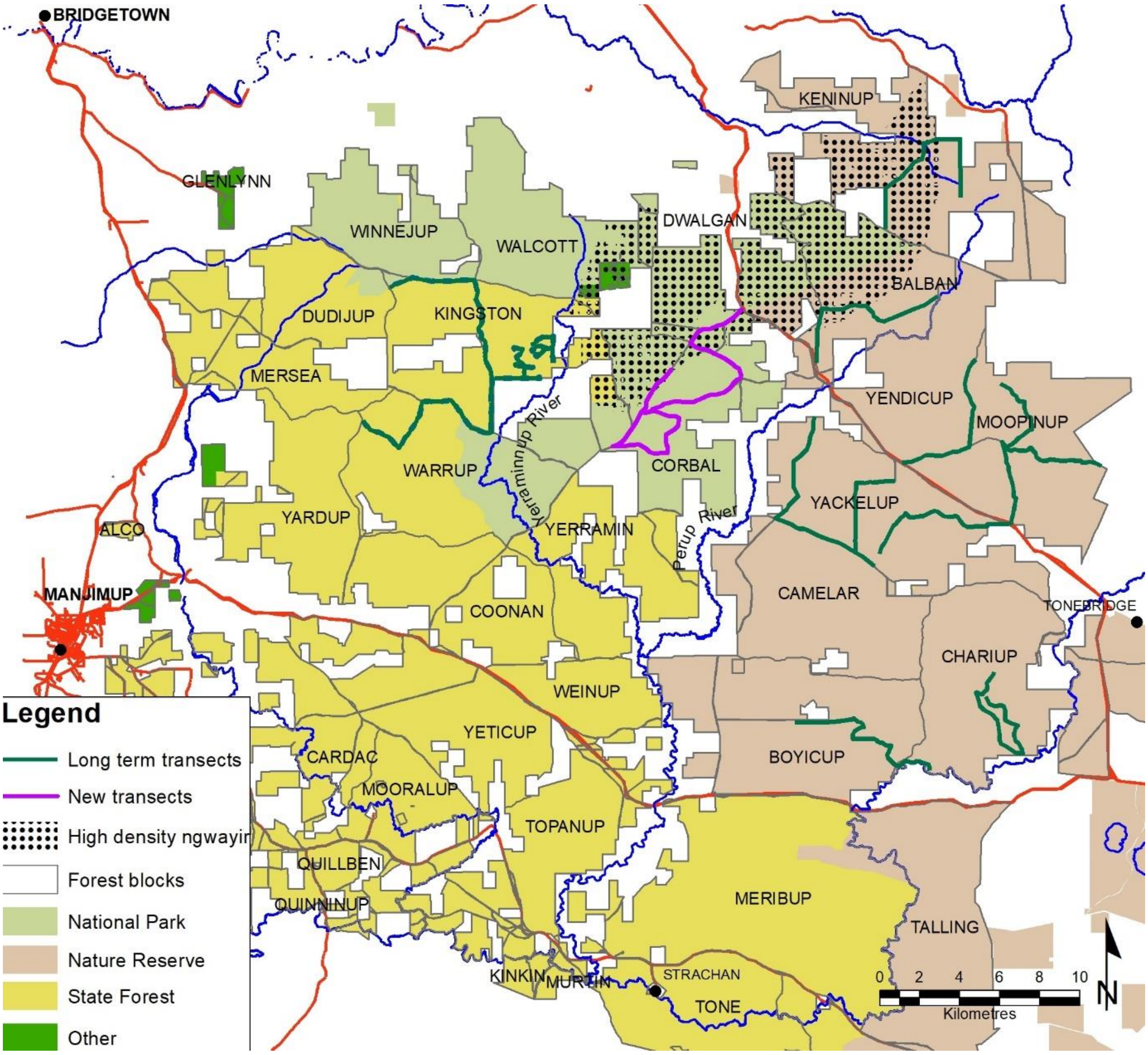

Figure 6. *Map of the current and historic long-term vehicle-based spotlight transects (dark green lines) across the Upper Warren in relation to the area where ngwayir densities in 2022 are predicted to be greater than 0.25 /ha (black stipple).*

Names are forest blocks. The Corbal vehicle-based spotlight transects (purple lines) were established in 2017. Main sealed roads (red lines) and major hydrography (blue lines) are also depicted. Areas not included in this study (white areas) includes DBCA-managed land and private property.

The ngwayir population in the Upper Warren remains very important to the conservation and recovery of the species given its size and genetics. Despite having undergone substantial declines (>99% in some areas) since 1998 (Wayne et al. 2005 b, 2012 and 2017), the Upper Warren population remains large relative to other extant populations on the west coast and south coast of Western Australia, which combined, total more than 20,000 individuals (Teale and Potts 2020). The ngwayir in the Upper Warren also contain the highest levels of genetic diversity within the species (White *et al.* 2021).

4.3 Limitations of this study

While the 2019 and 2022 surveys have profoundly improved our understanding of the ngwayir population distribution and abundance within the Upper Warren, these data and the insights they provide have their limitations. For example, more targeted and structured sampling designs are better able to assess the associations between ngwayir density and specific factors of interest, such as fire. Also factors likely to be important to ngwayir populations were not measured or investigated here including predation, competition, resource quality and quantity (including food and shelter), and site level information on vegetation structure and floristics. Furthermore, investigations into associations provide relatively weak inference since they do not distinguish between coincidental and related associations, and they do not inform the nature of the relationship (e.g. cause or effect or the ecological processes in play; Caughley 1994; Caughley and Gunn1996). However, associative studies such as this can help direct and inform what future scientific, conservation and management efforts should focus on.

4.4 Recommendations

A good understanding of the size, trends and drivers of population change over space and time are essential to effective species conservation and recovery and management of important habitat. The surveys conducted in 2019 and 2022 demonstrate that adequate spatiotemporal information on the ngwayir population at a regional scale is entirely feasible and that these datasets constitute by far the best information available to date. They may also be an excellent opportunity and foundation for future work. These opportunities include improving our understanding of the factors related to the distribution and abundance of ngwayir, establishing a monitoring program and improving the methodology used in these activities.

4.4.1 Factors affecting the distribution and abundance of ngwayir

The existing data and modelling could be improved or developed upon including,

- Improve the coverage and quality of covariate data including spatial resolution. This includes, reducing the number of cells in the prediction grid that have missing data (i.e., cells with ‘NA’ as a value). Missing data can influence both the predictions and ability to extract useful covariate information.

- Investigate the merits of increasing the spatial resolution of the modelling. This is because the spatial scale of the models used (100 m grid cell in 2022 and 500 m grid cell in 2019) may not be fine enough to quantify small-scale spatial changes that the ngwayir might be responding too.
- For particular covariates of interest, determine what spatial scale best relates to ngwayir density (e.g. proportion of agriculture within 500m, 1000m, 3000m, or 5000m; only the latter was investigated here)
- Explore other covariates not investigated here, such as the frequency and season of fire.
- Conduct multivariate analyses that also investigate interactions between factors given that few factors act in isolation and the interactive effects may be large. Note that more complex, multivariate analyses require larger sample sizes than simpler univariate tests.

New targeted studies should include investigating,

- Ngwayir responses to fire, given the species' sensitivities to fire and the extent and frequency with which fire is applied within and around ngwayir populations.
- The occurrence and characteristics of insect outbreak on the forest foliage and ngwayir populations, given that the ngwayir is a specialist foliavore, highly reliant on leaves of a few species, particularly jarrah.
- The full extent of the current 'hotspot' with the highest densities of ngwayir in the region by conducting surveys to the northeast of the area surveyed in 2022 (i.e., eastern parts of Keninup and Balban forest blocks).

Note that specific questions about fauna responses to a factor (e.g., fire management) are best investigated directly using an experimental design. This includes using structured sampling across the range of values for the factor(s) of interest (i.e., use strata to allocate survey effort differently in different regions). It may also include using a replicated before/after/control/impact (BACI) design or other manipulative experimental designs that may provide stronger inference.

4.4.2 Population monitoring

Ngwayir population changes have been substantial and rapid in the last few decades (e.g. Wayne *et al.* 2017). Which means that circumstances for this species may change substantially and rapidly in the future. There is also a high risk of extinction both locally (given recent declines) and at the species level (currently listed as *Critically Endangered* under the EPBC Act). Therefore, an effective monitoring program at appropriate spatial and temporal scales is essential for species conservation and recovery and appropriate habitat management.

Pedestrian spotlighting using distance sampling methods are demonstrably the most robust and effective methods currently available for monitoring population change over space and time. The surveys conducted in 2019 and 2022 also demonstrate that they can be successfully applied at the regional scale.

The same transects should be surveyed over time to assess temporal changes in the population more accurately. Good spatial coverage across the region is needed to provide a region-wide understanding of the population and how it may change over space and time. This is particularly important given the high variation and patchiness in the ngwayir densities across the region. Spatial resolution of the monitoring should be sufficient to detect changes in the spatial extent of the population (both range contractions and recoveries). Given the recent history of declines of ngwayir across the region it is important to have a good and timely understanding of any changes particularly in and around the areas that currently have high densities.

The transects used in 2019 and 2022 can be used to form the basis of an ongoing monitoring program, thereby building on the data collected to date.

4.4.3 Survey Methodology

Several aspects of the survey method used here can be improved upon. This includes,

- Standardise the use of appropriate head torches for detecting possums. The difference in detection distances between the 2019 and 2022 surveys were likely due to differences in the use of headtorches. Detection probability was approximately 15% at 45 m in 2022 (using lower light intensities), compared to 60 m in 2019.
- Use experienced observers that each conduct enough surveys to derive a reasonable assessment of the detection function (e.g., at least 20, but ideally more than 60 detection events of a given species per observer).
- Use GPS devices that have a high degree of accuracy (<2m).
- Given the detection truncation distances of 45 m (in 2022) and 55 m (in 2019), future surveys should consider infilling the space between transects: transects were 1 km apart in 2022, and 2.5 km apart in 2019.
- Collect vegetation density data along surveyed transects to better account for variation in the detection probabilities. Dense *Gastrolobium* and *Melaleuca* thickets and regrowth forests after recent timber harvesting may reduce the detectability of possums, particularly at distance.
- Provide frequent feedback to observers on their survey results to maintain quality and consistency of data collection. This includes checking the shape of the detection curve (i.e., frequency histogram of the number of detection events by distance from the transect).

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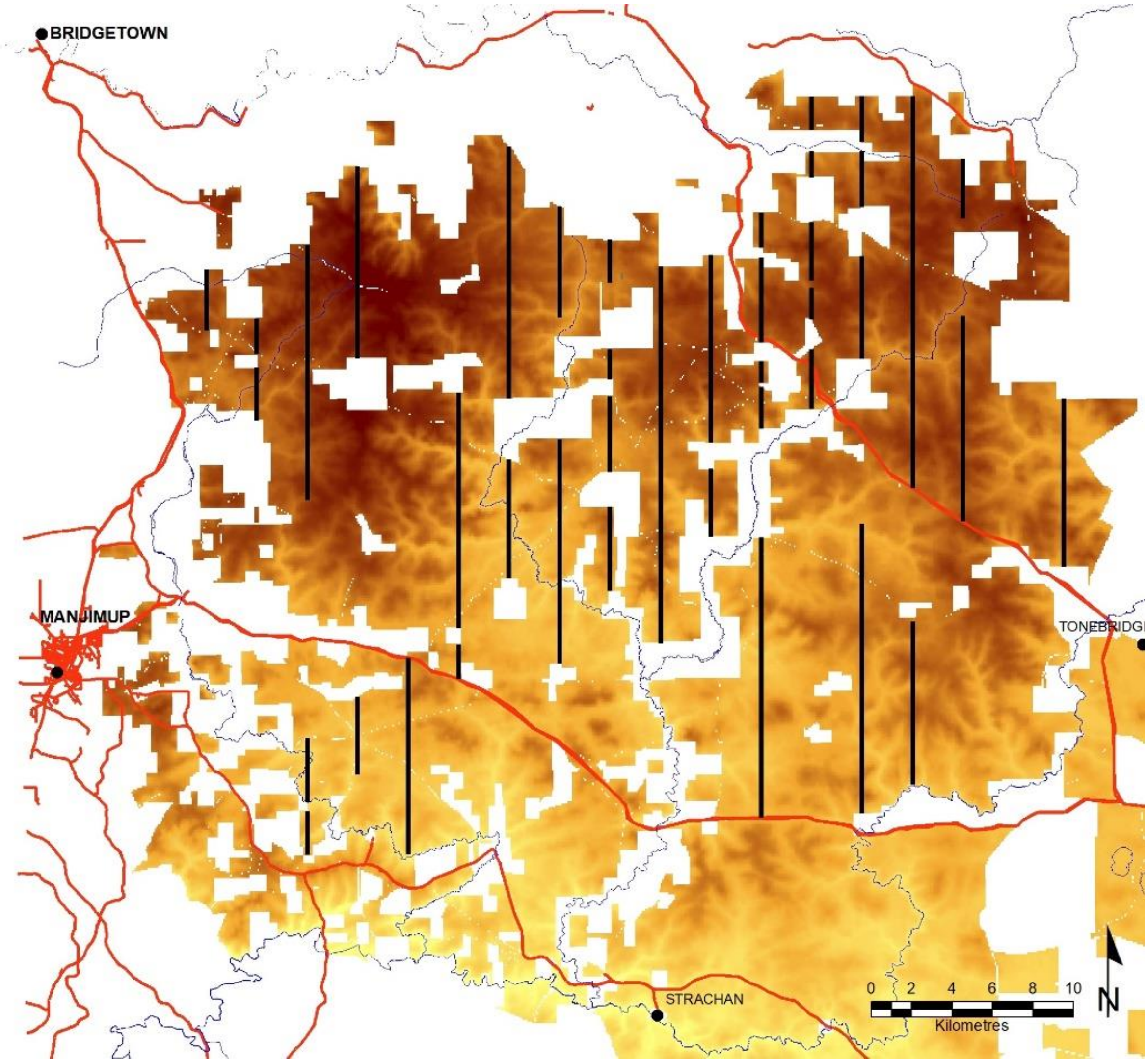
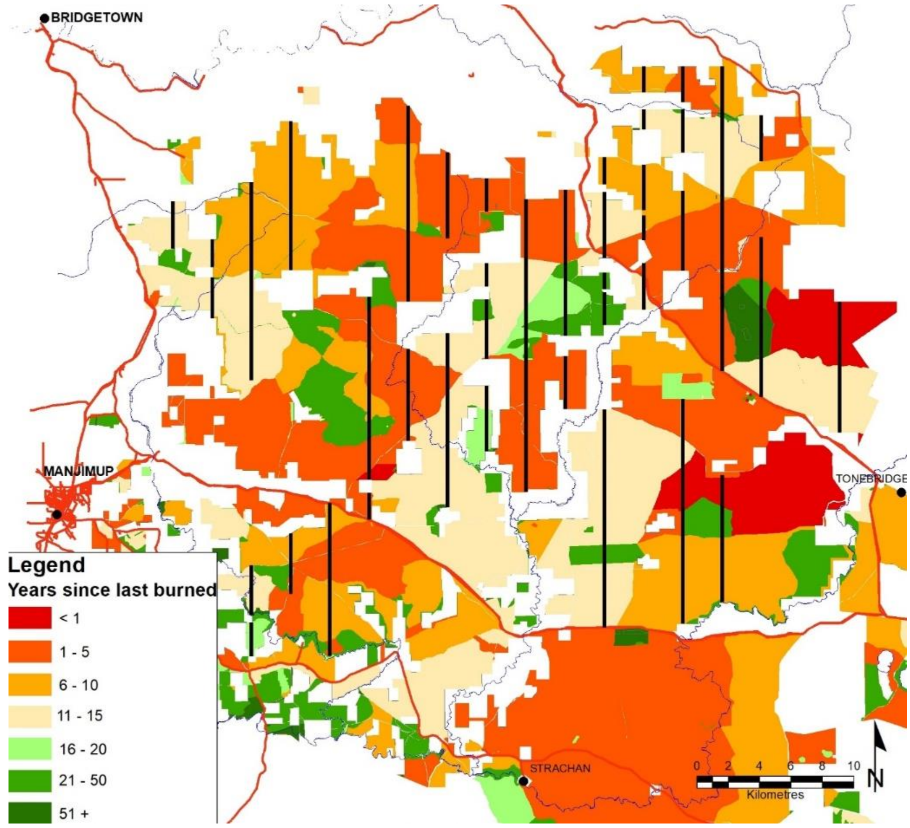
Appendices

Appendix 1 Spatial covariates explored in relation to ngwayir density surface models based on 2019 and 2022 data.

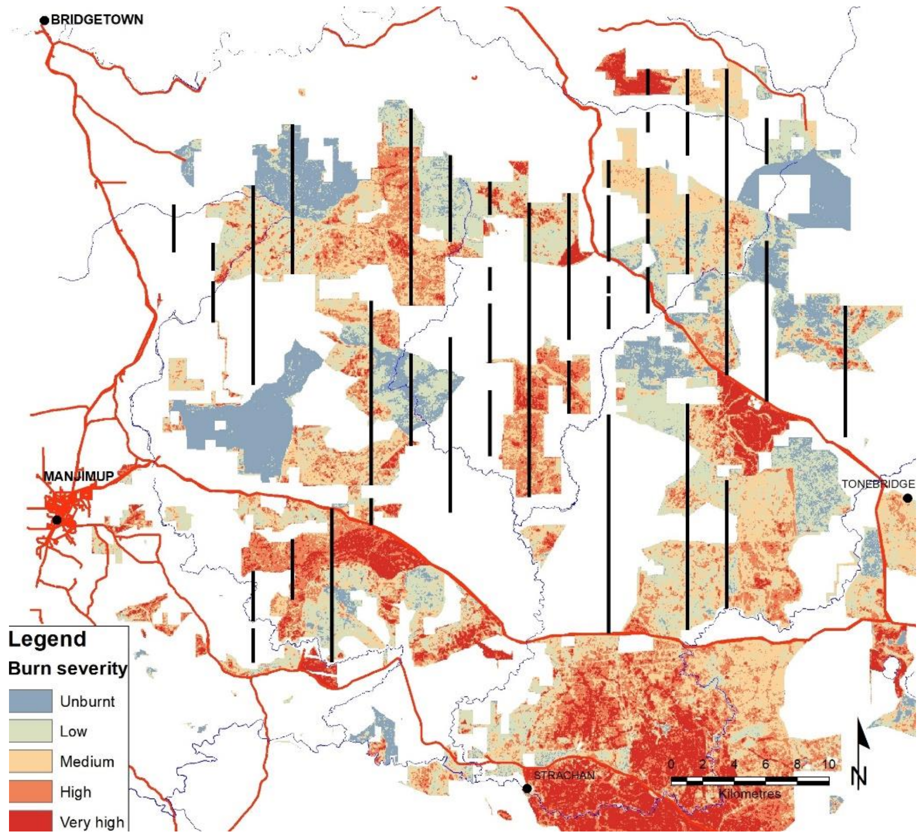
2019



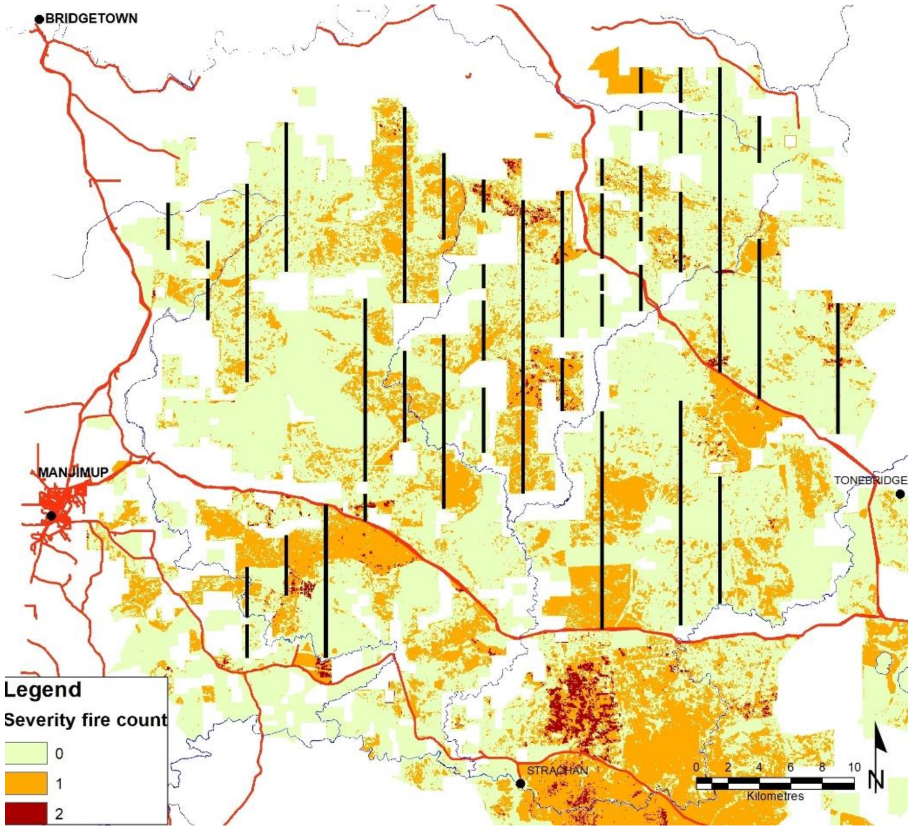
Elevation (2019). Darker colours indicate higher elevation.



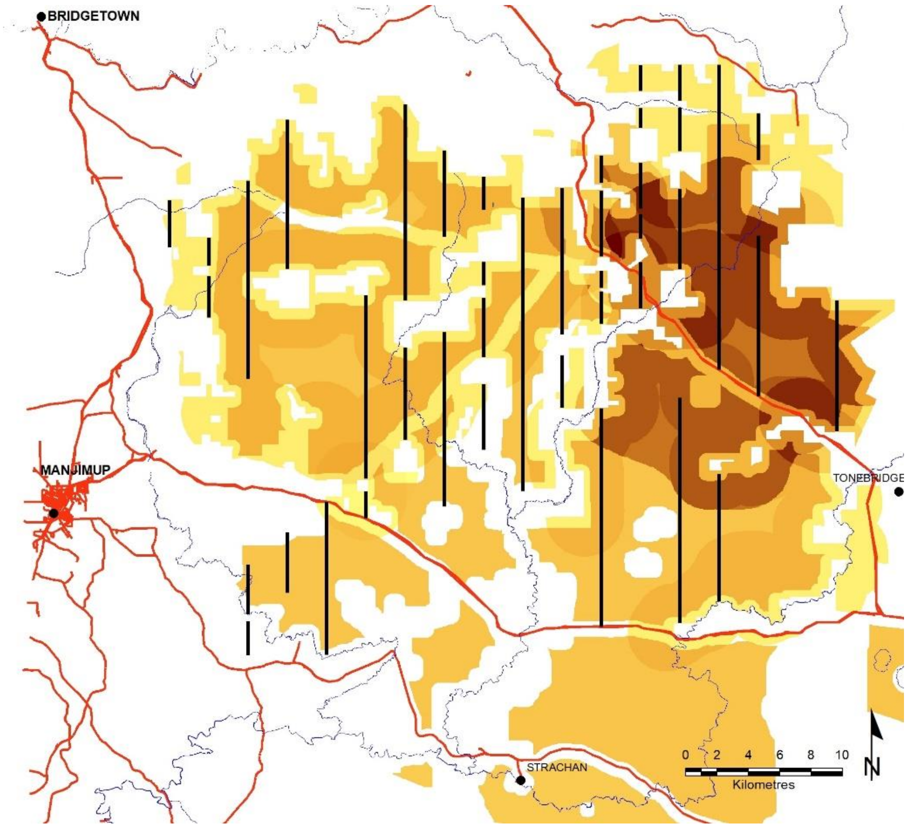
Fire age (2019).



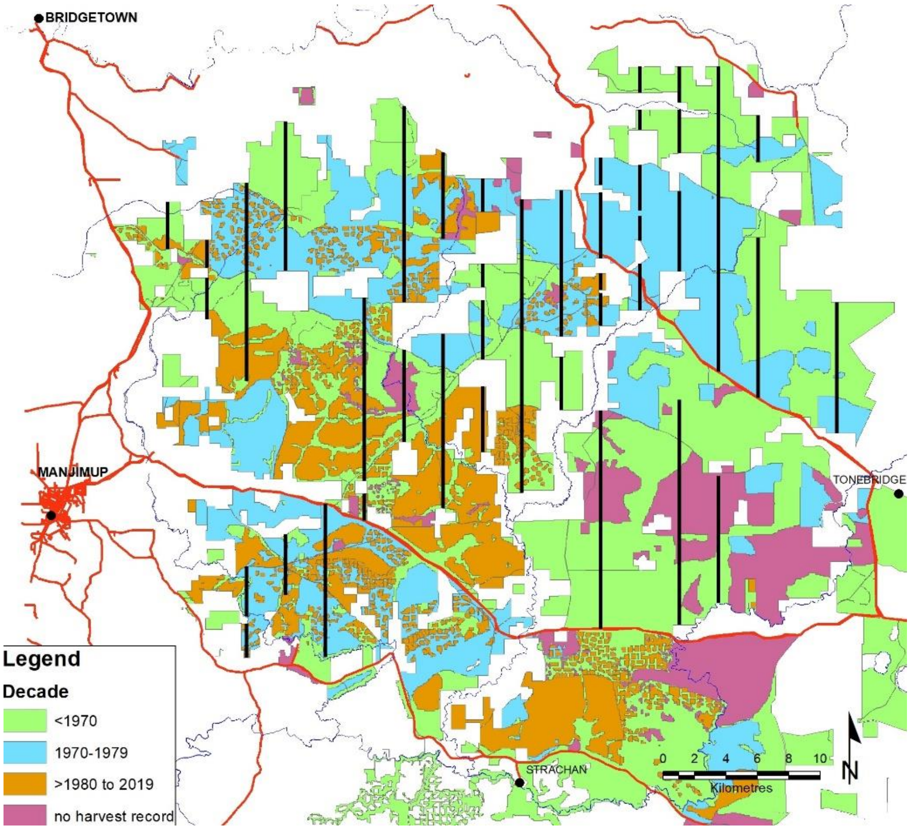
Burn severity over the last 10 years (2019)



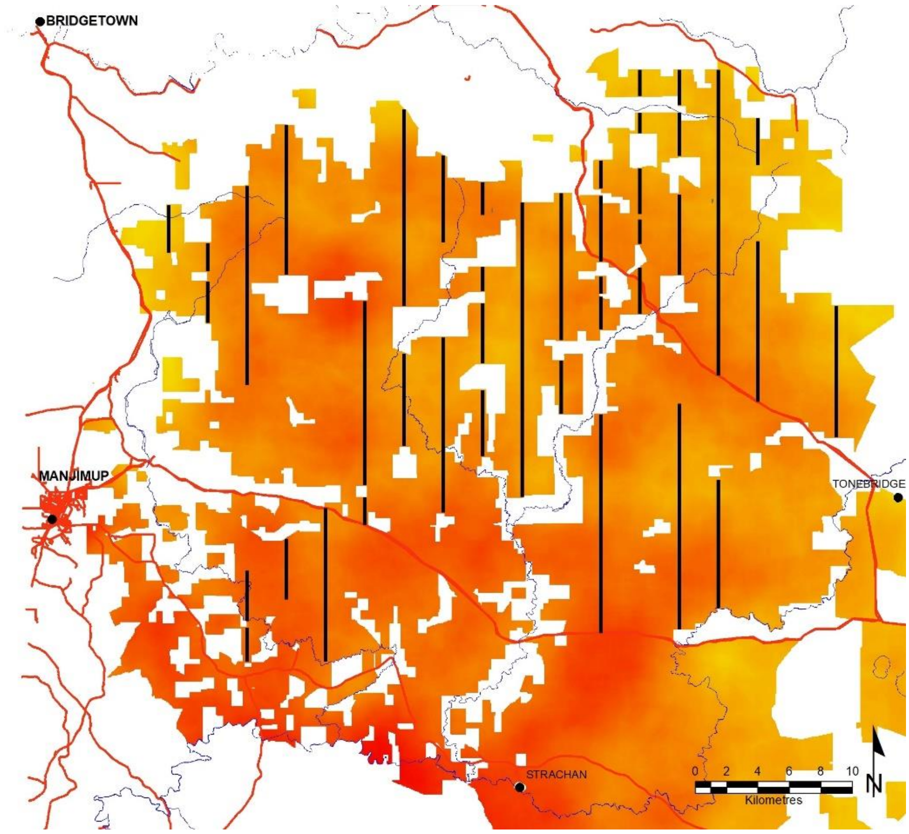
Severe fire count over the last 20 years (2019).



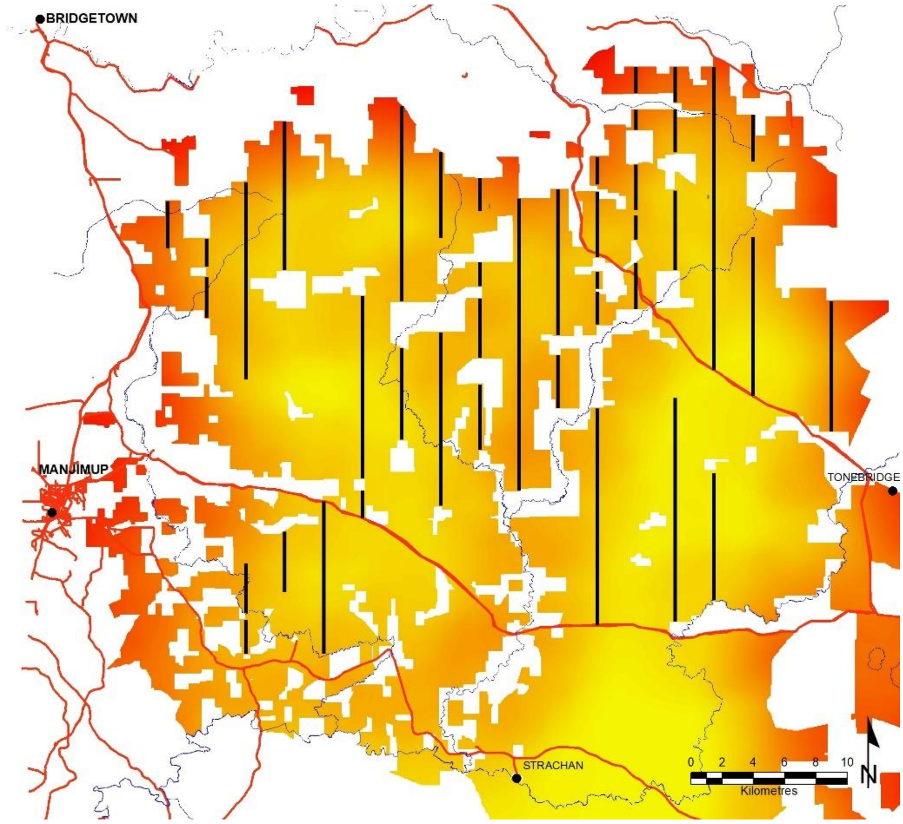
Fox Baiting intensity (2019). Darker colours indicate higher intensity.



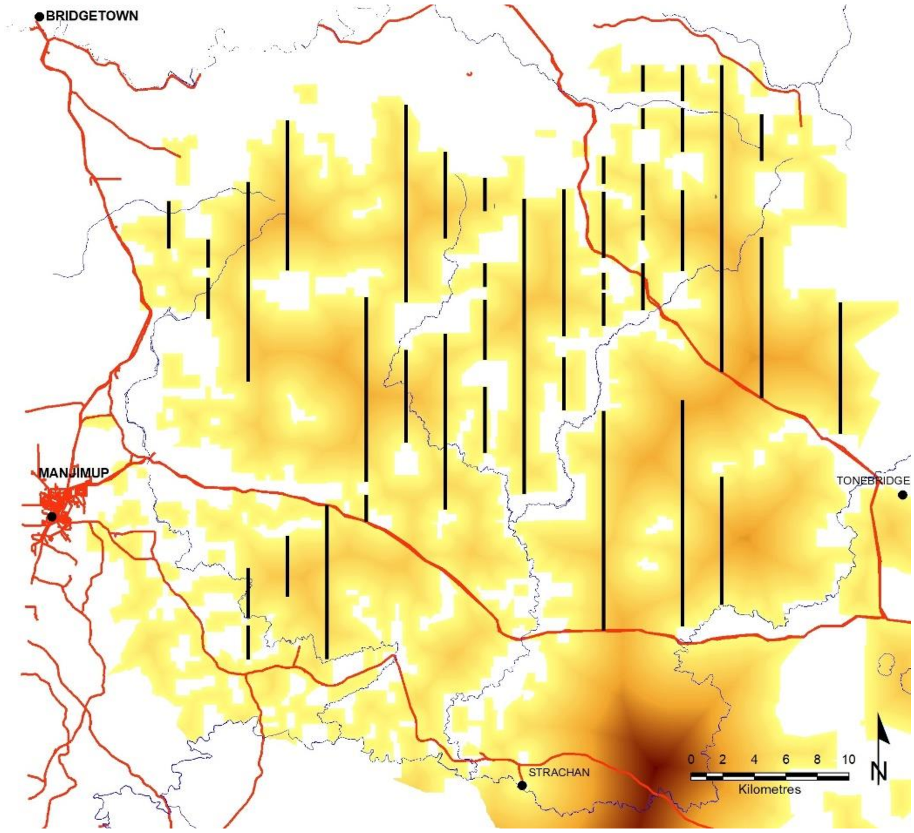
Timber harvesting period (2019).



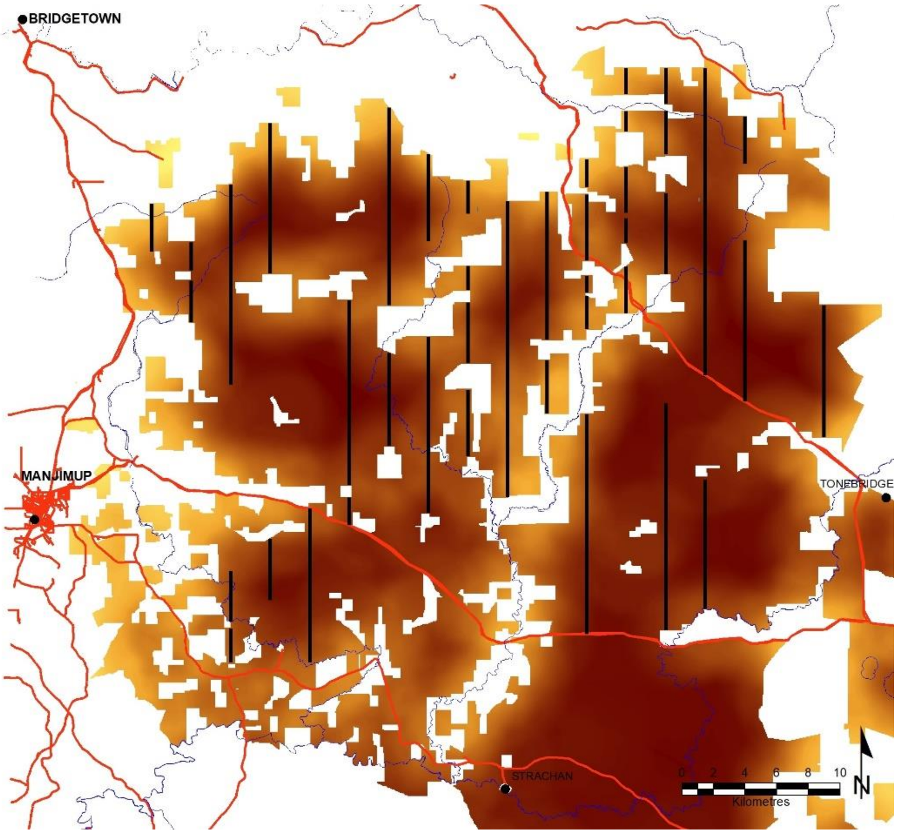
Road density (2019). Darker colours indicate higher density.



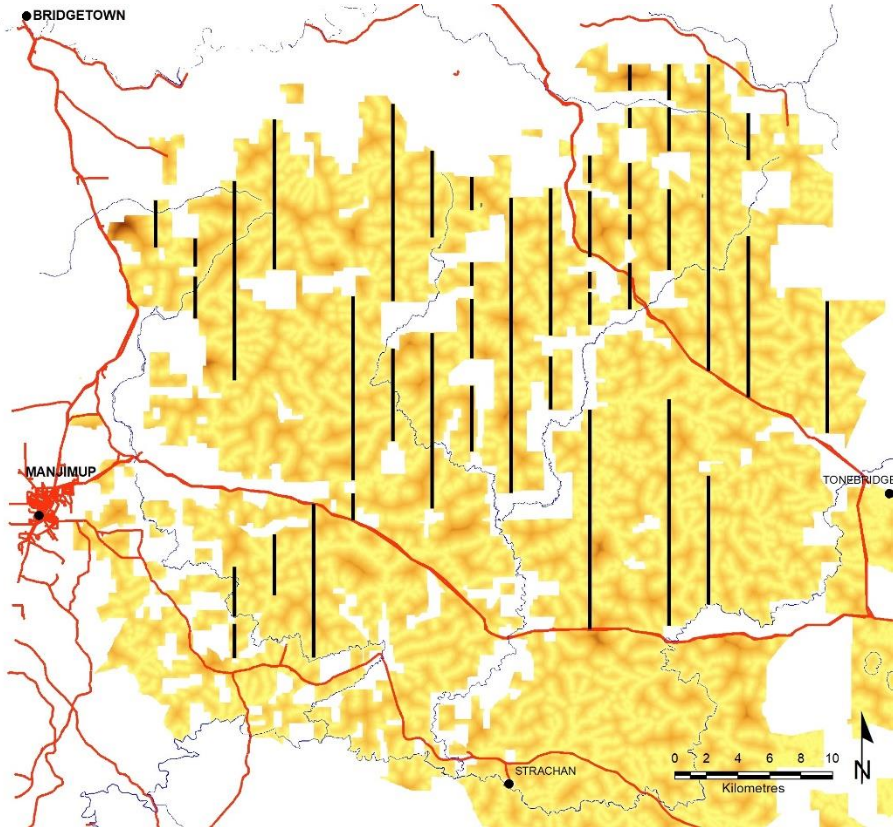
Agriculture proportion within 5 km (2019). Darker colours indicate higher proportion.



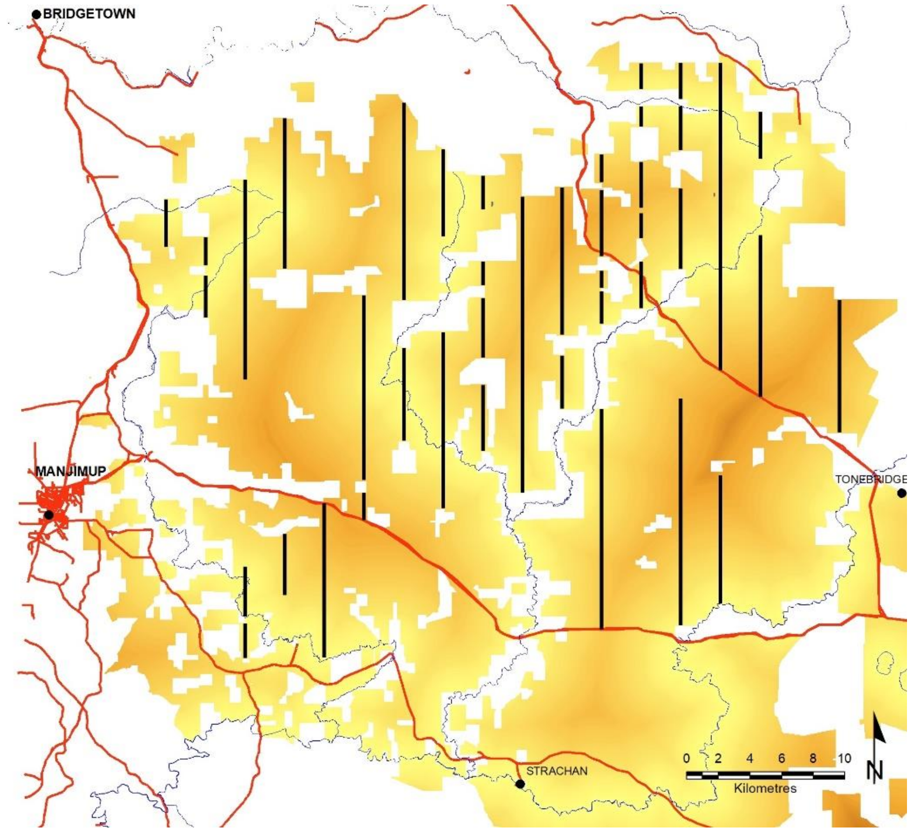
Proximity to agriculture (2019). Darker colours indicate further away.



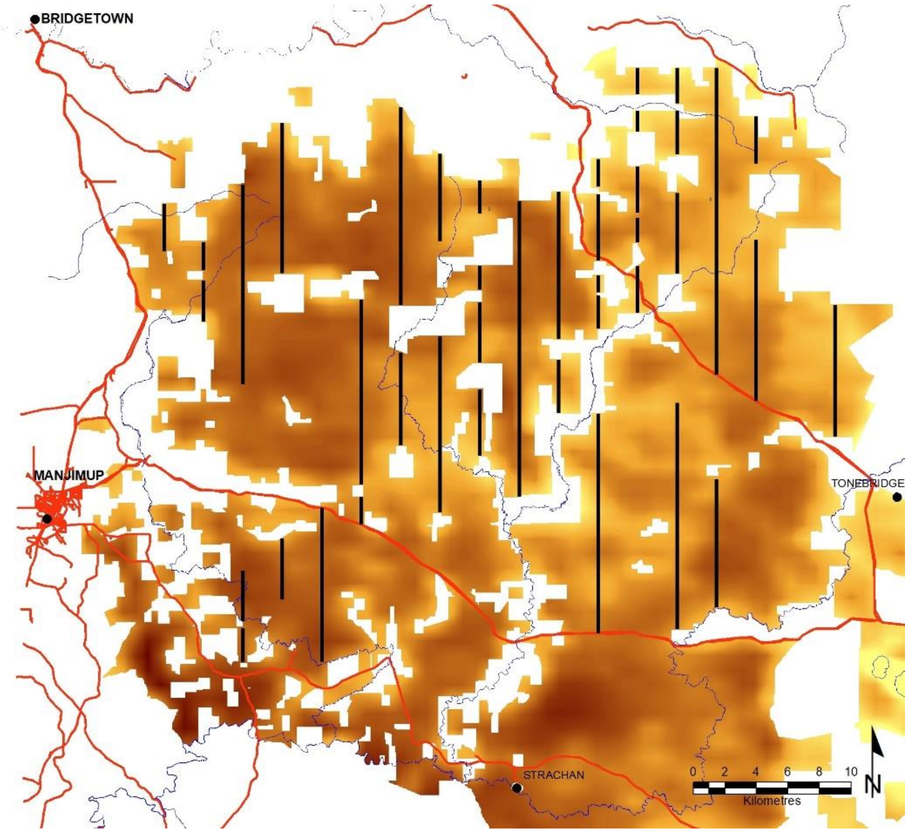
Remnant Vegetation proportion (2019). Darker colours indicate higher proportion.



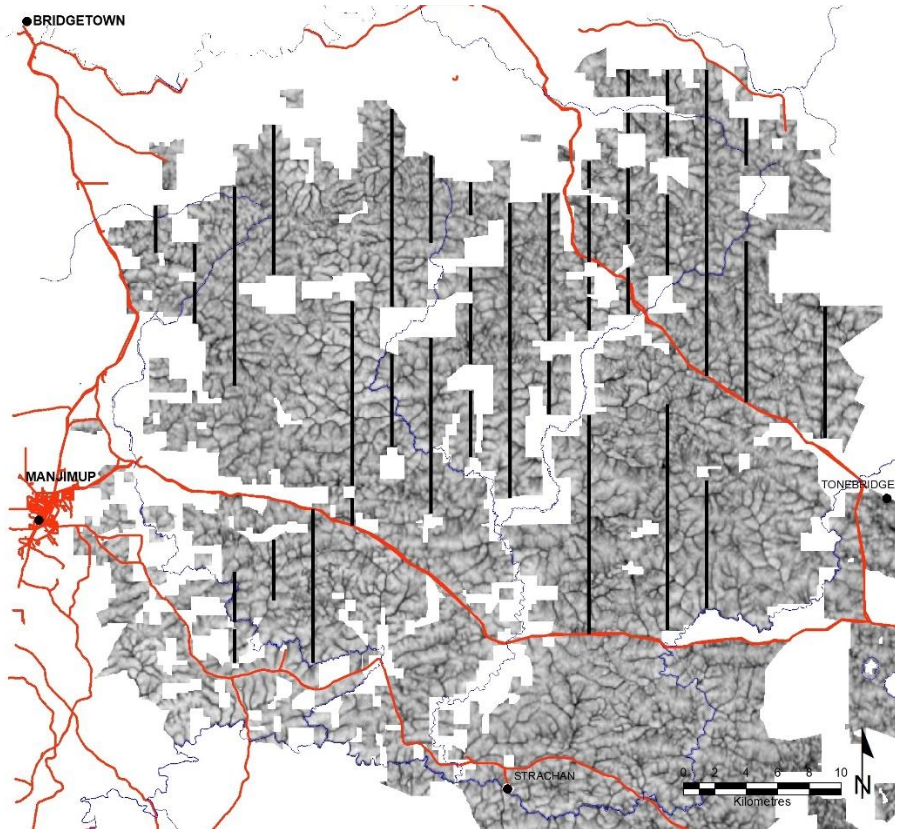
Distance to all surface water features (2019). Darker colours indicate further away.



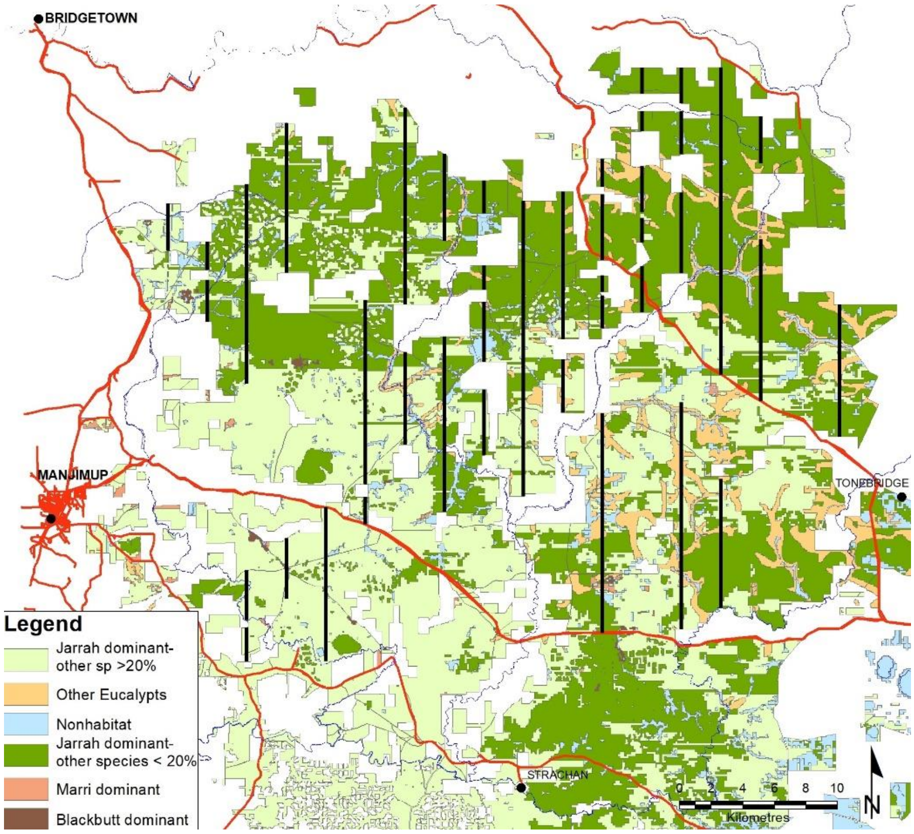
Distance to major surface water features (2019). Darker colours indicate further away.



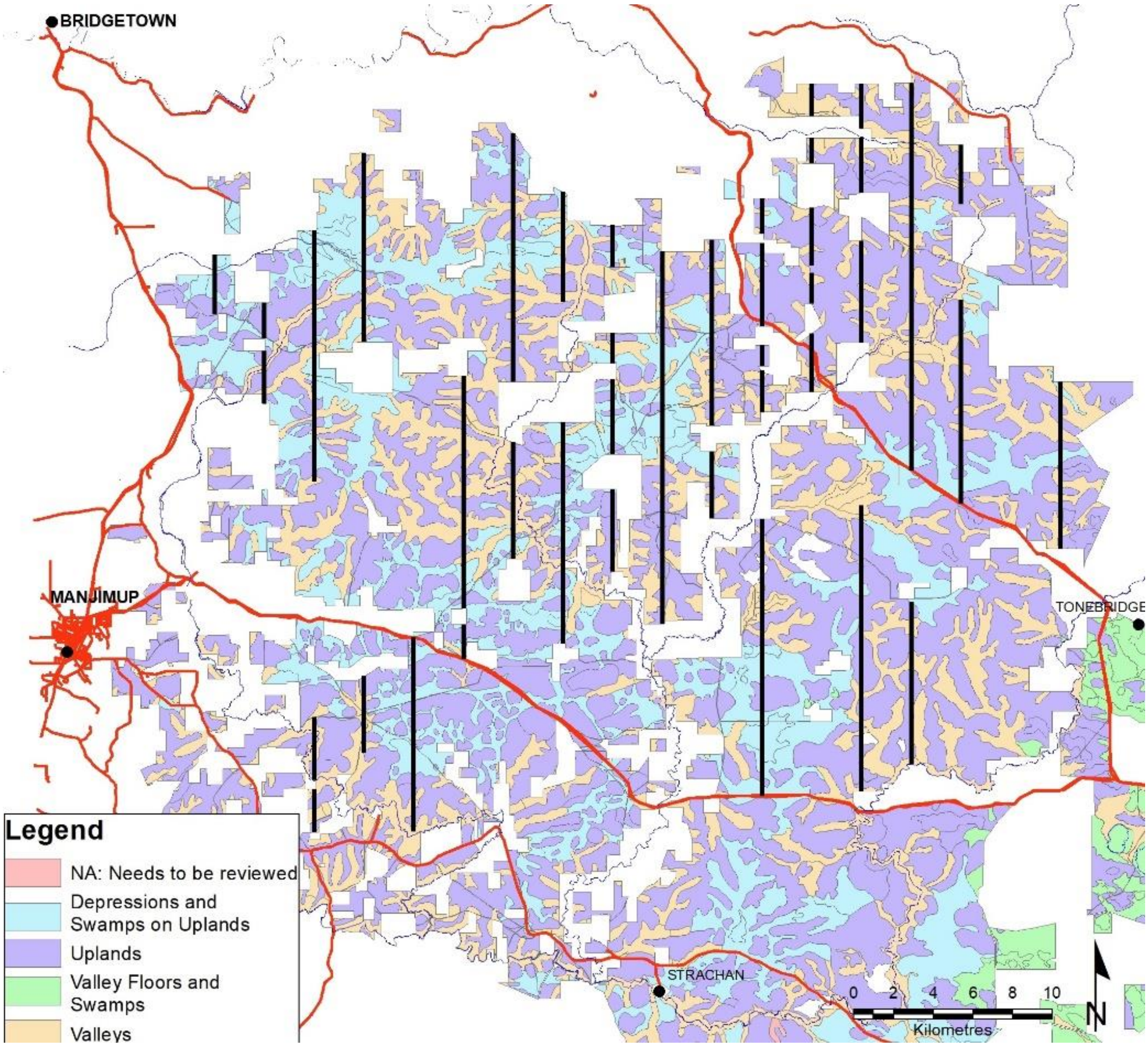
Primary productivity (2019). Darker colours indicate higher productivity.



Site wetness (2019). Darker colours indicate wetter.

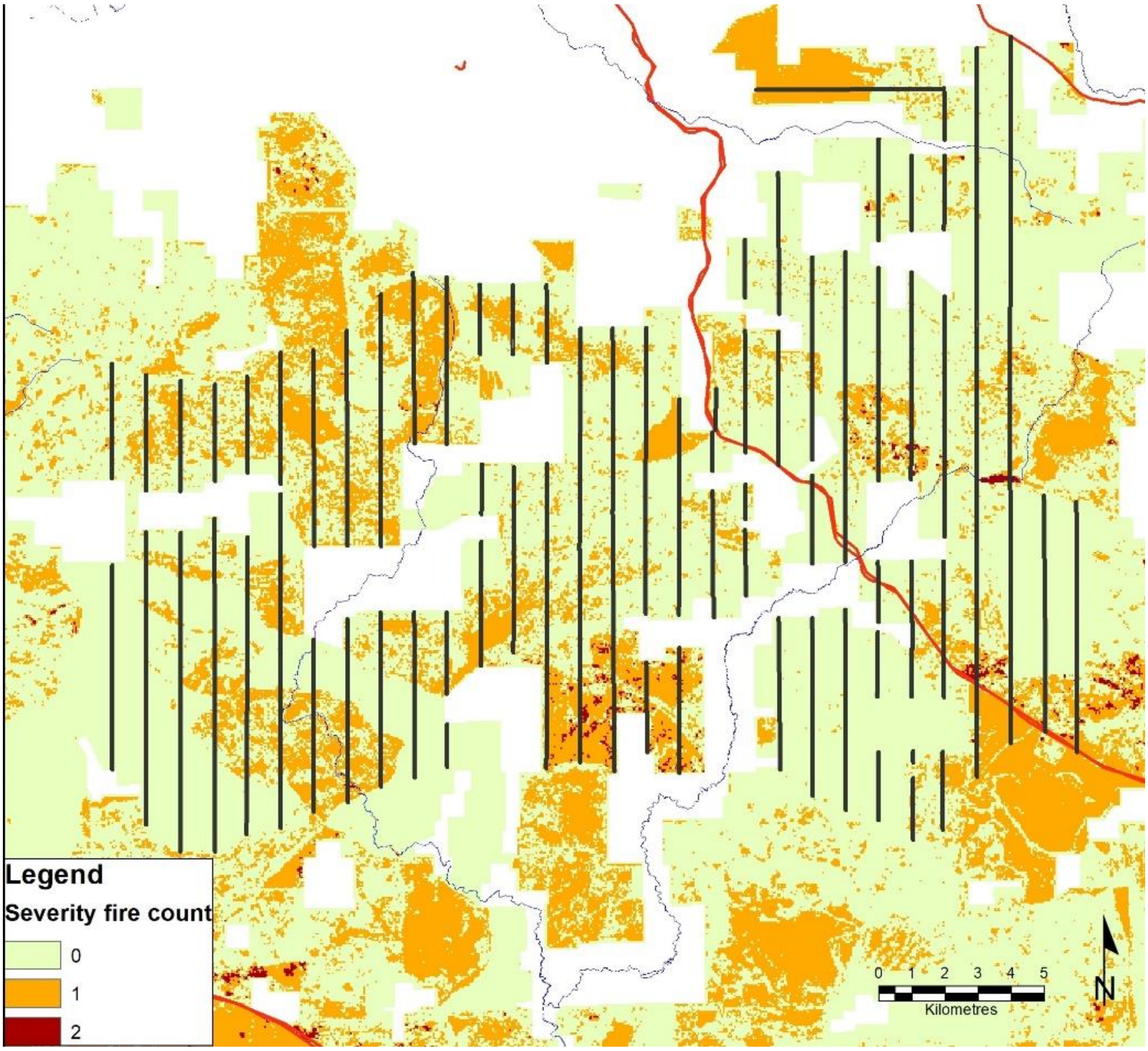


Forest type (2019).

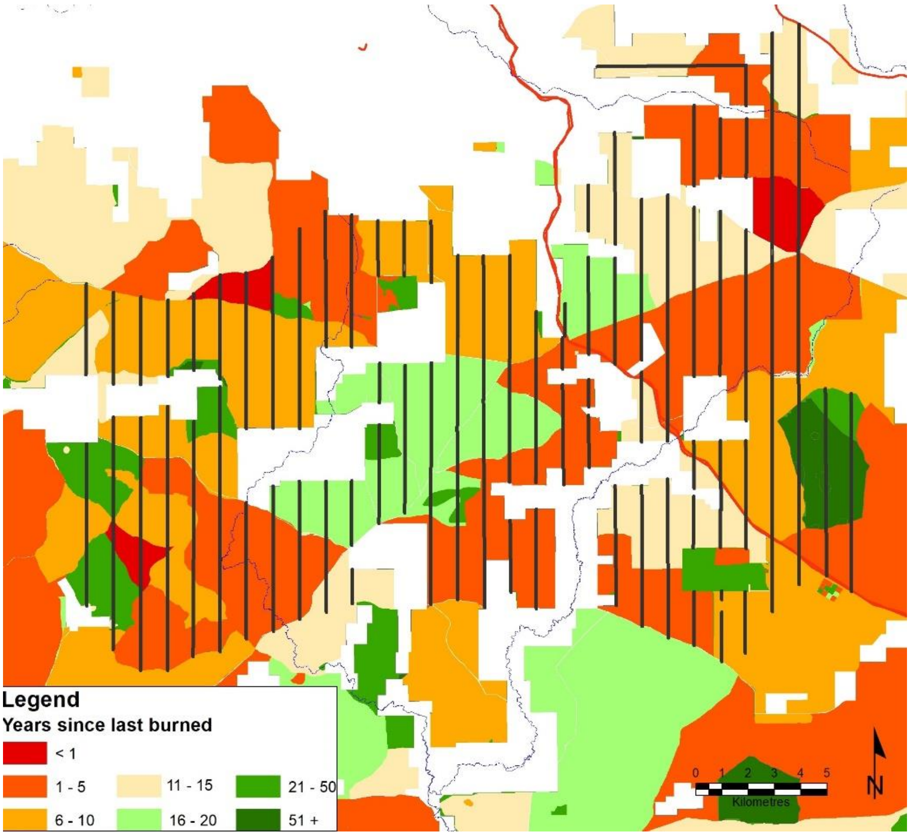


Landscape position (2019).

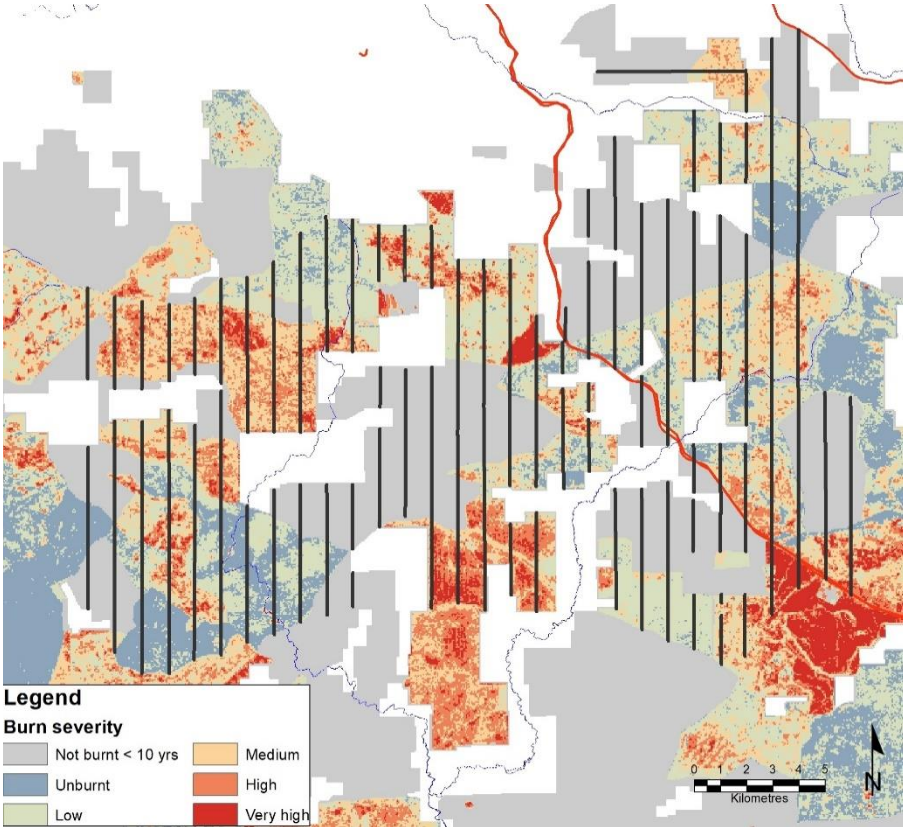
2022



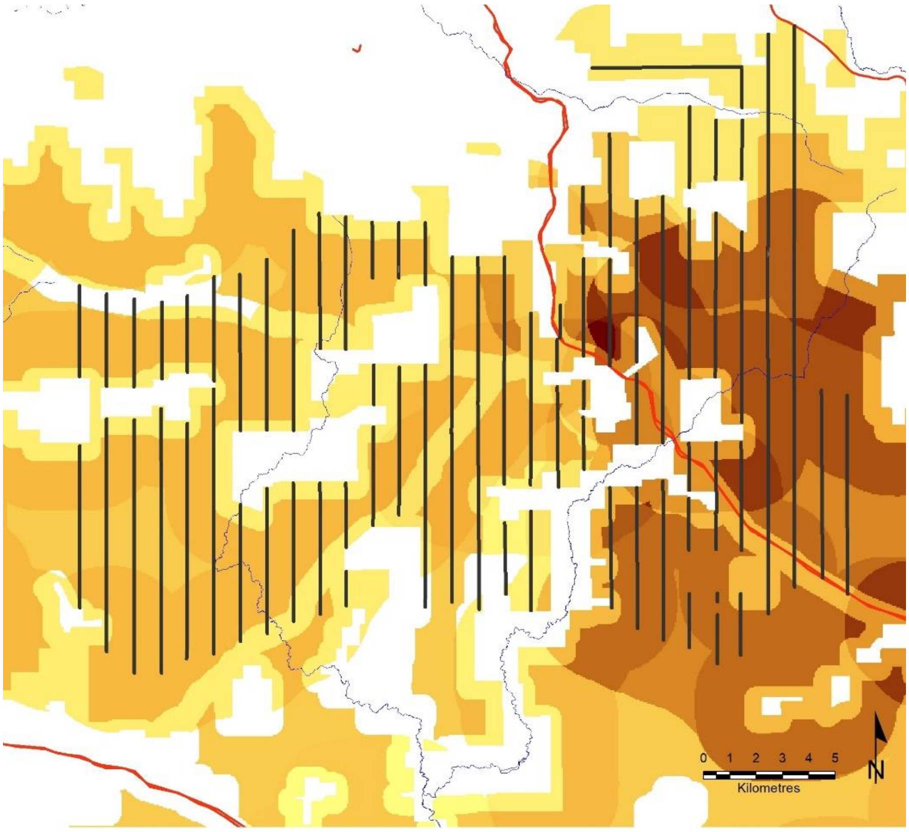
Severe fire count over the last 20 years (2022).



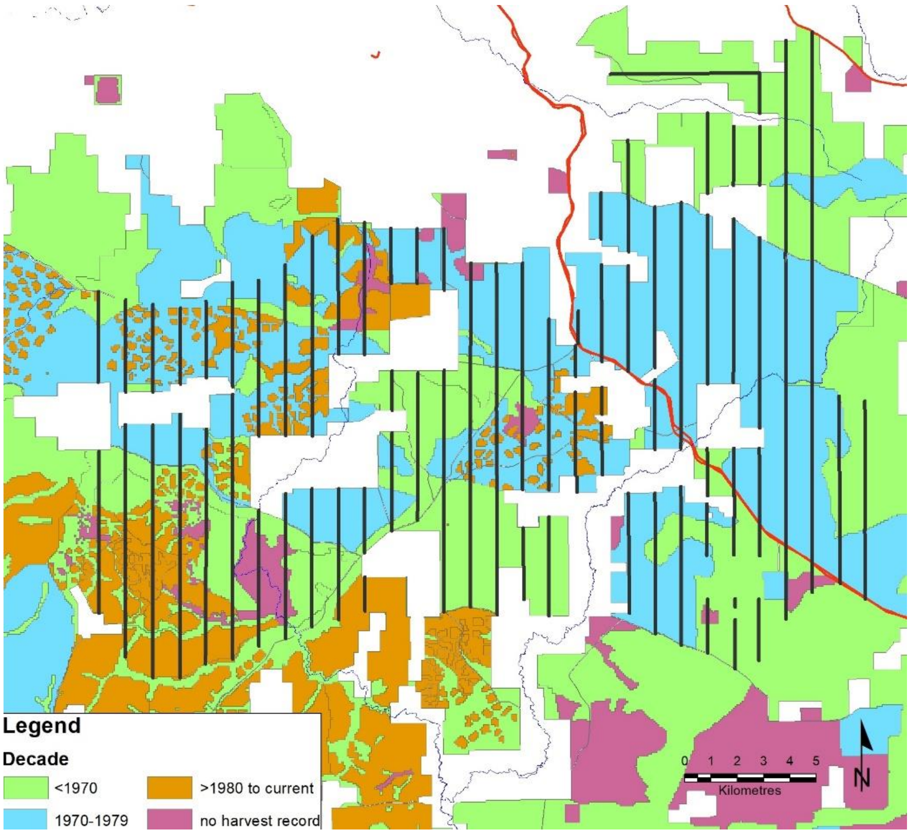
Fire age (2022).



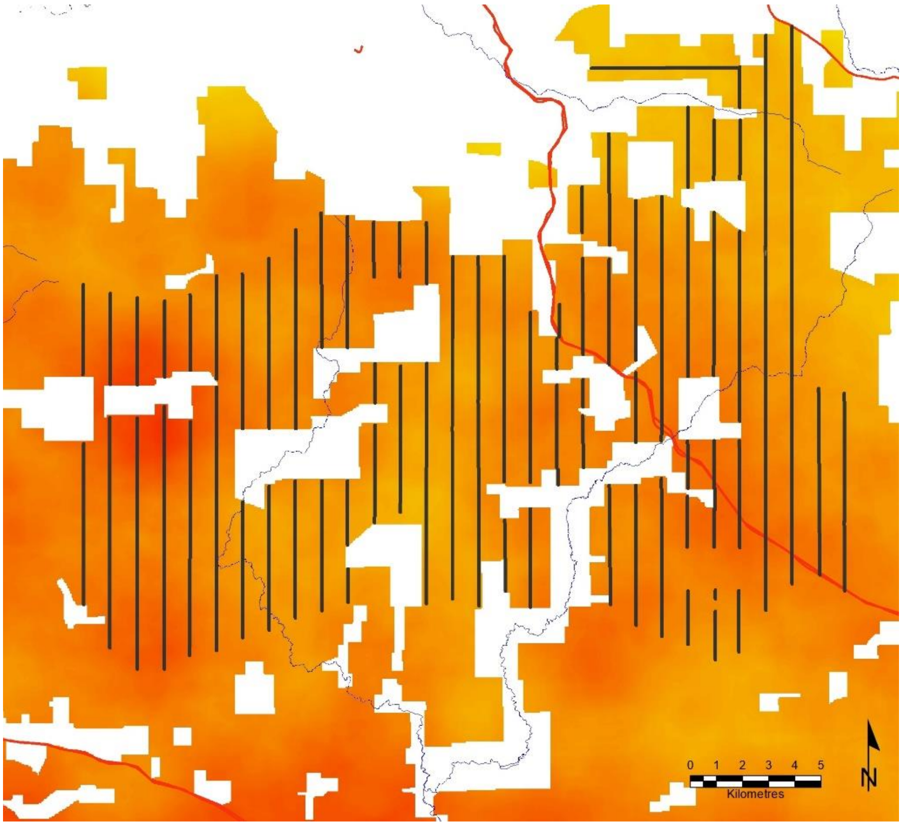
Burn severity over the last 10 years (2022)



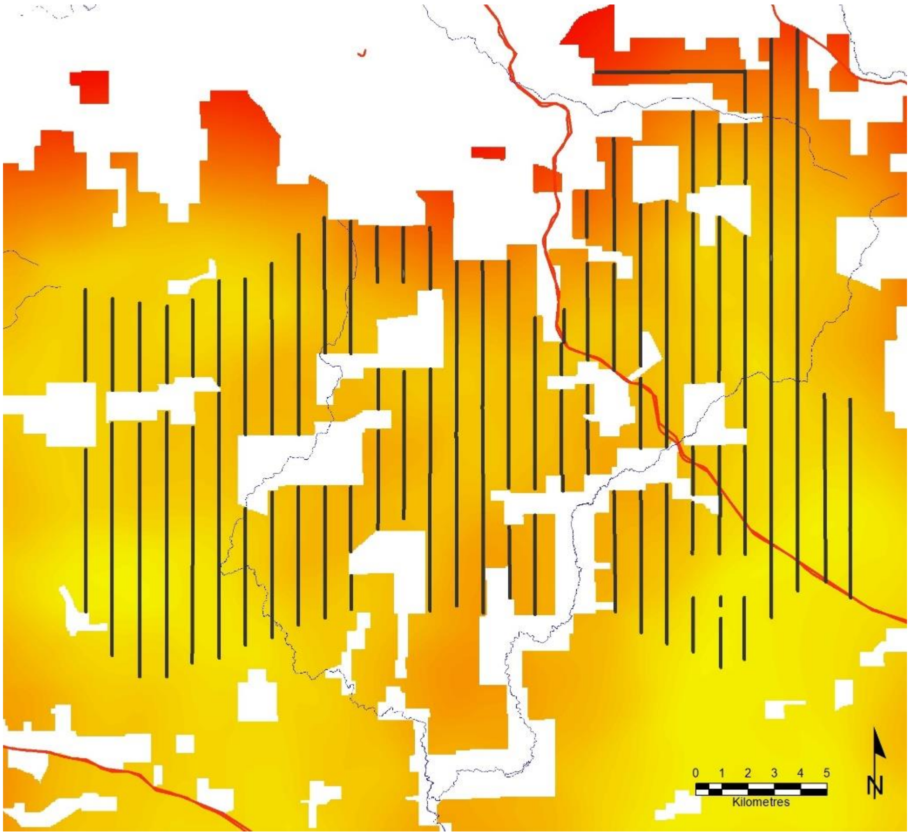
Fox Baiting intensity (2022). Darker colours indicate higher intensity.



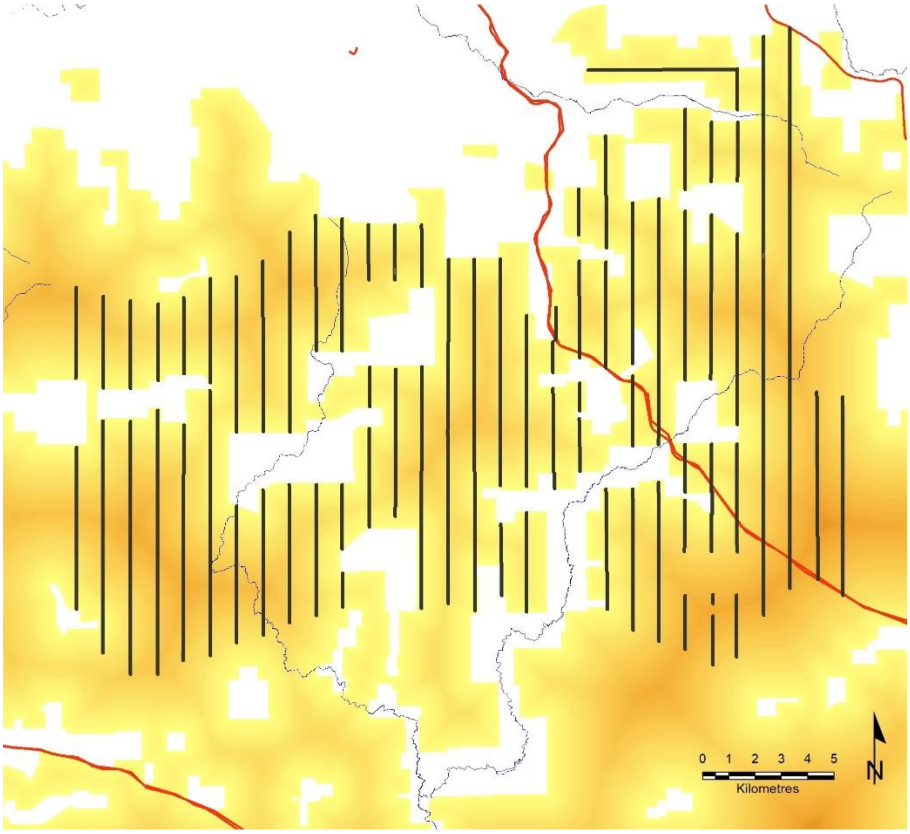
Timber harvesting period (2022).



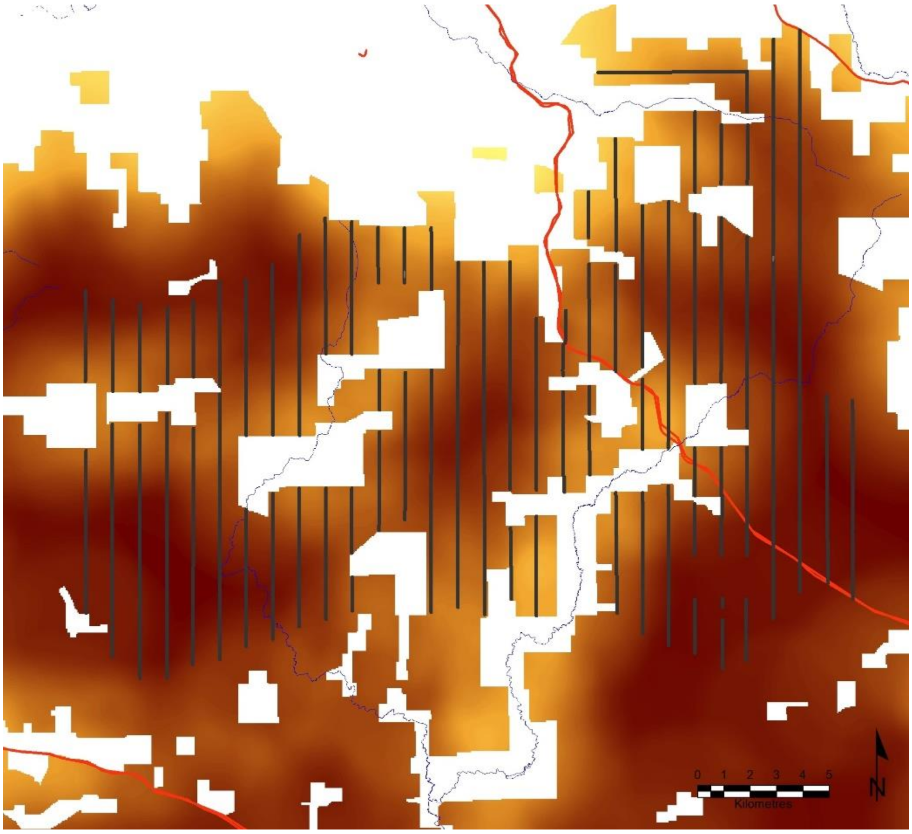
Road density (2022). Darker colours indicate higher density.



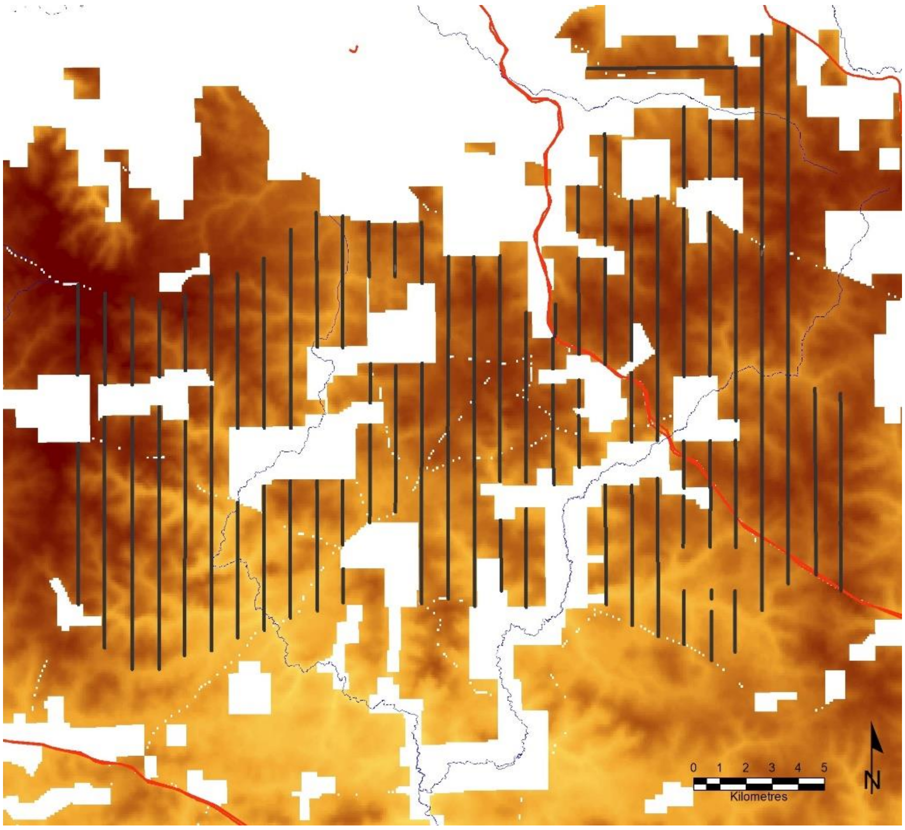
Agriculture proportion within 5 km (2022). Darker colours indicate higher proportion.



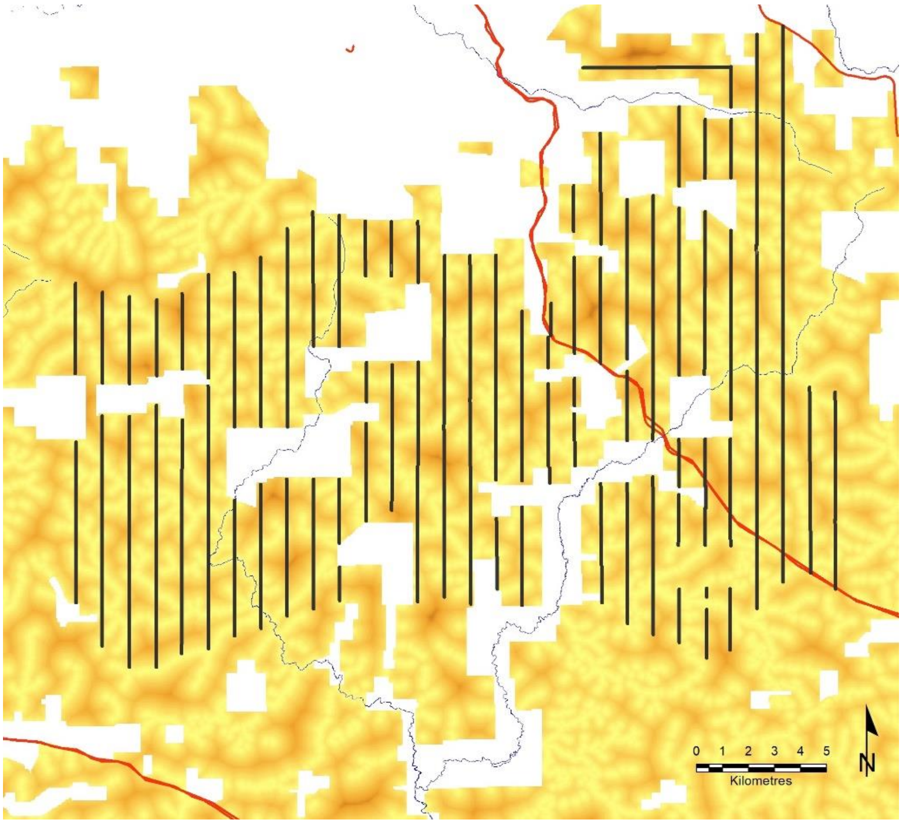
Agriculture proximity (2022). Darker colours indicate further away.



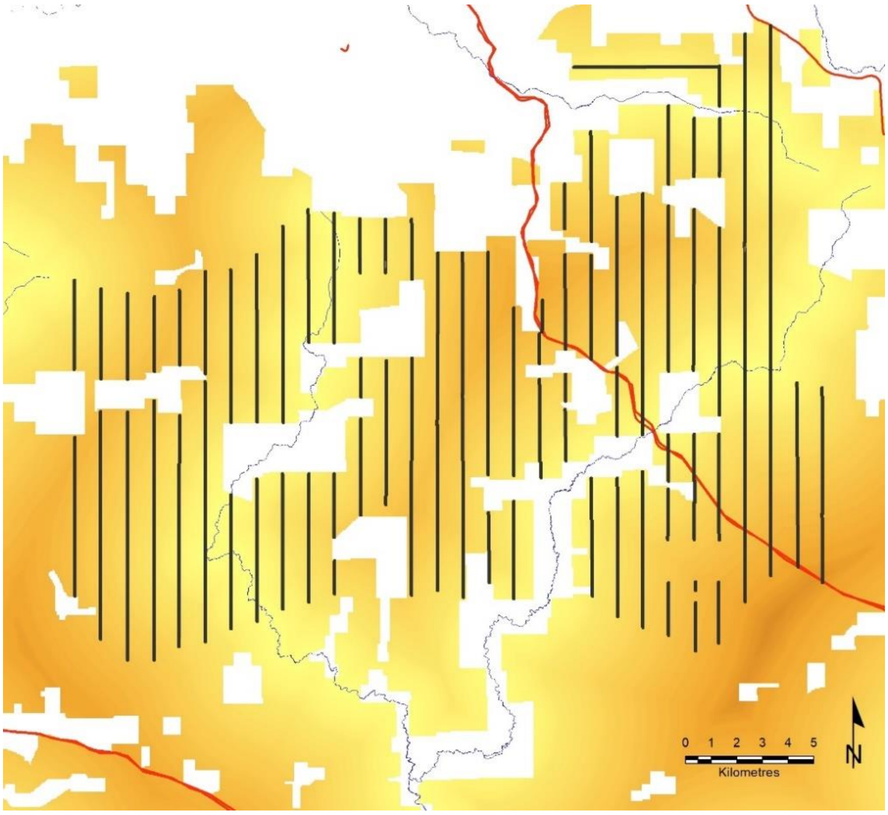
Remnant Vegetation proportion (2022). Darker colours indicate higher proportion.



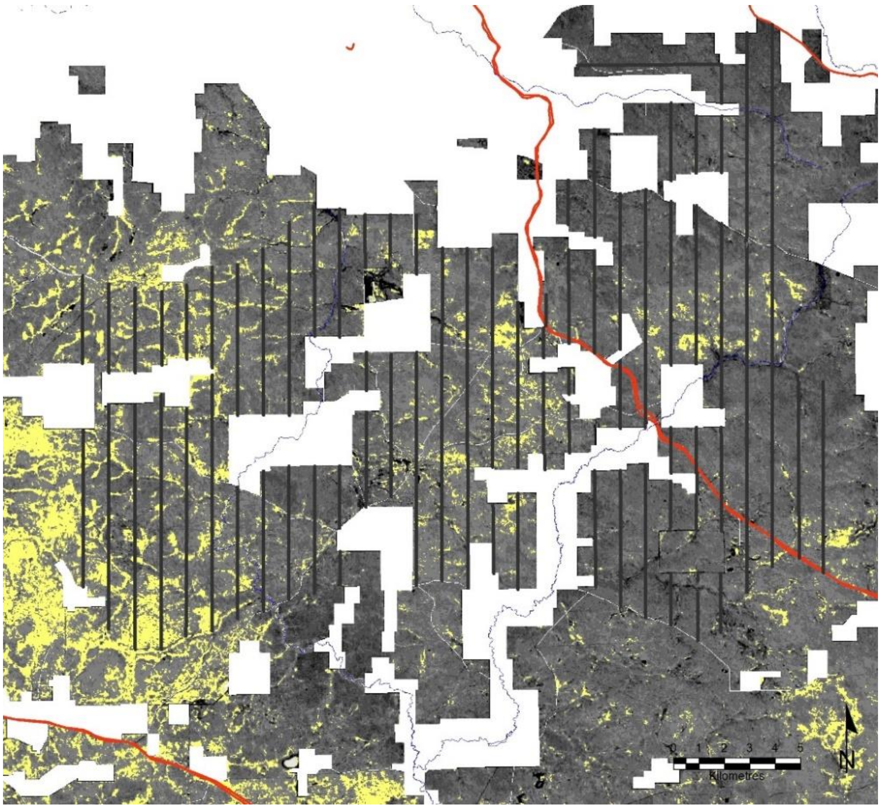
Elevation (2022). Darker colours indicate higher elevation.



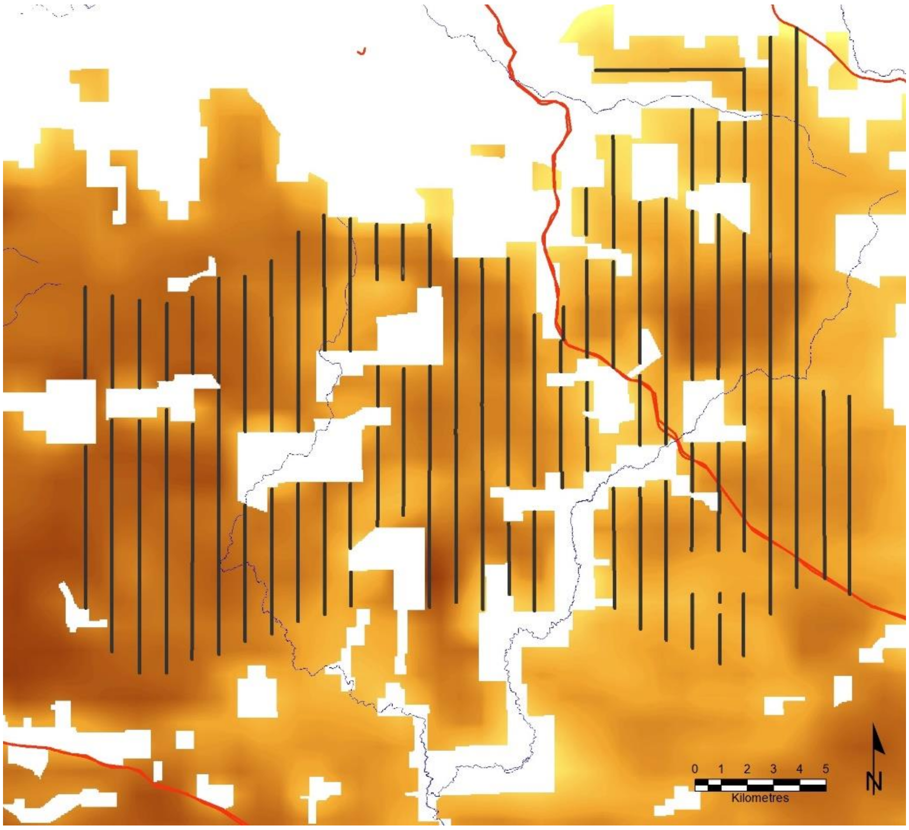
Distance to all surface water features (2022). Darker colours indicate further away.



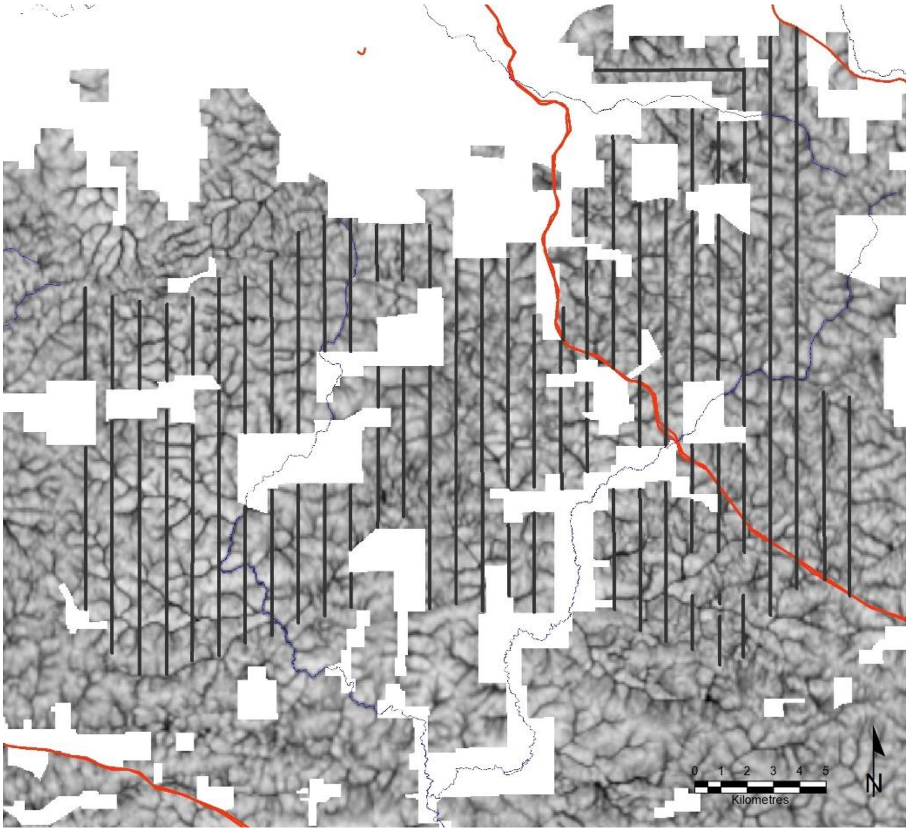
Distance to major surface water features (2022). Darker colours indicate further away.



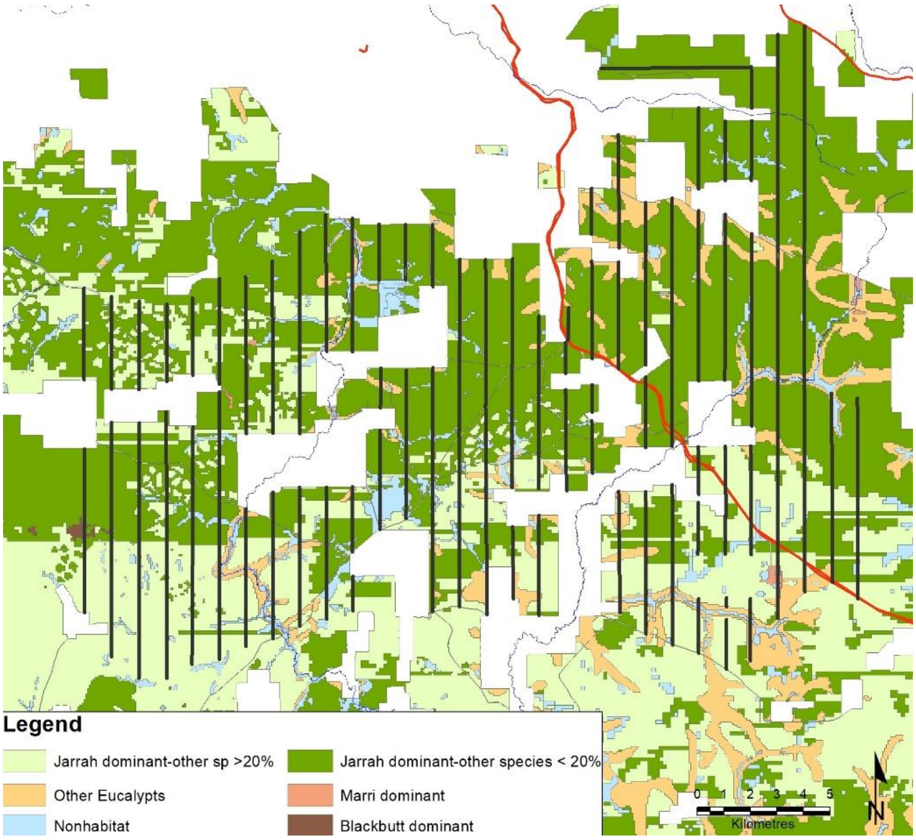
Vegetation density (2022). Values 4 &5 (corresponding to vegetation densities consistent with thickets and riparian vegetation) are highlighted yellow.



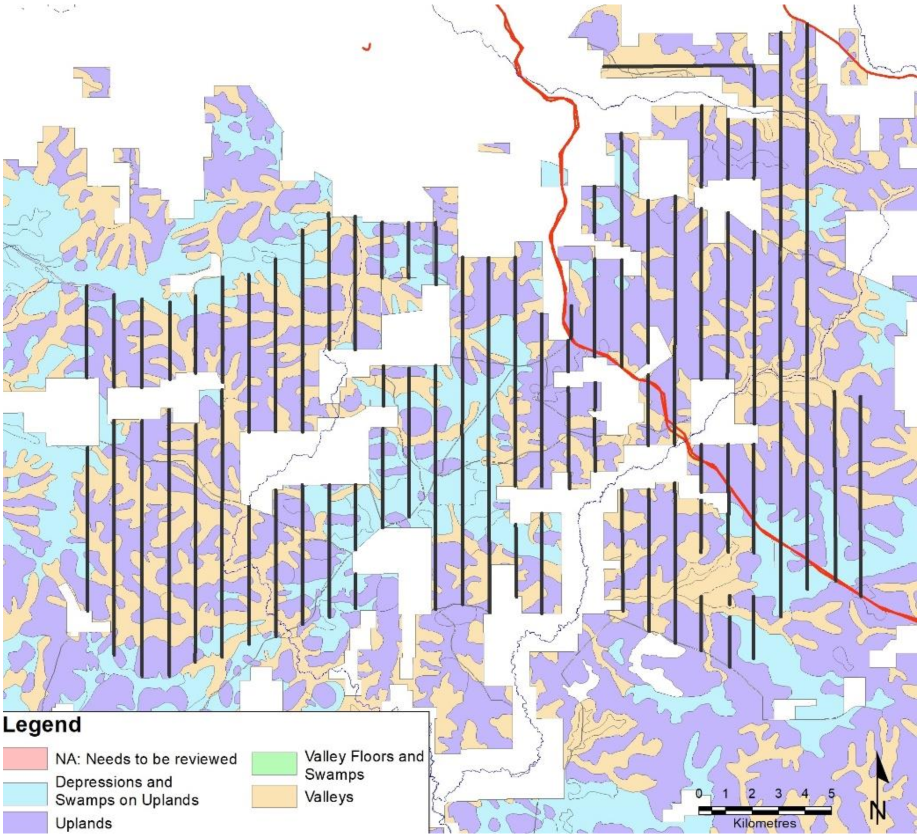
Primary productivity (2022). Darker colours indicate higher productivity.



Site wetness (2022). Darker colours indicate wetter.

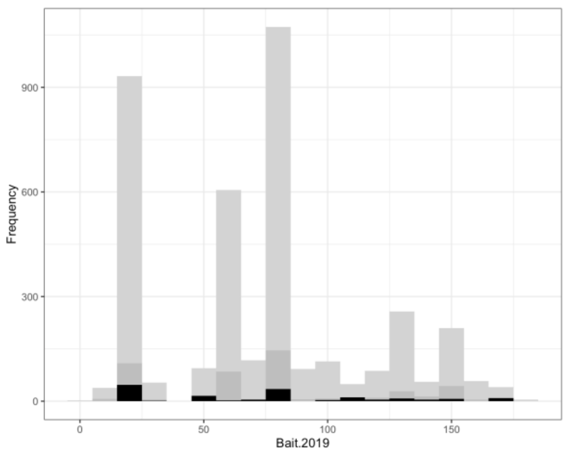
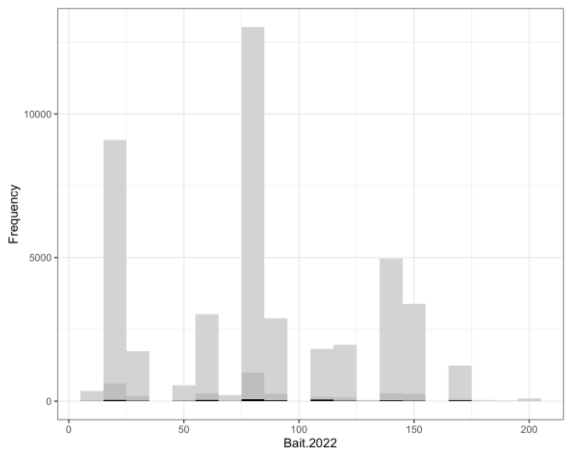
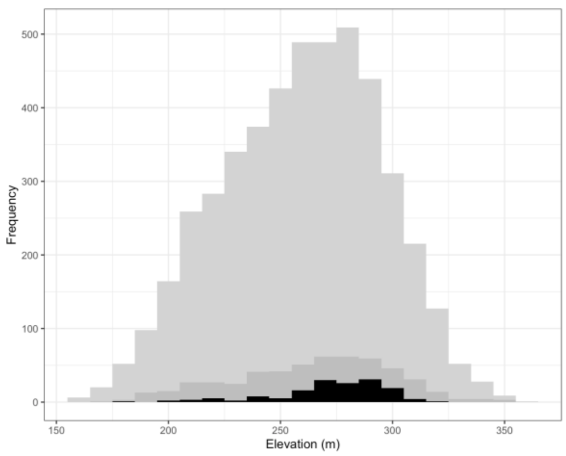
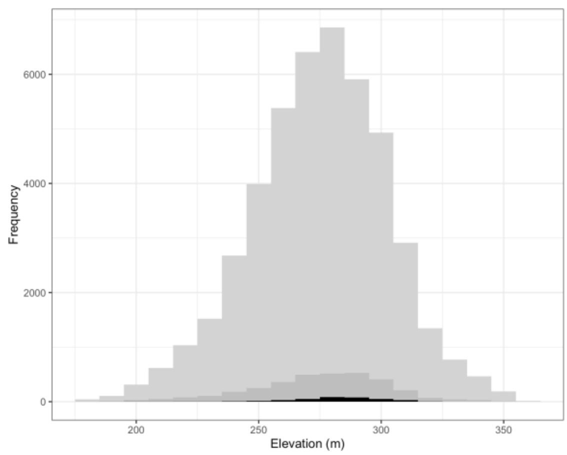


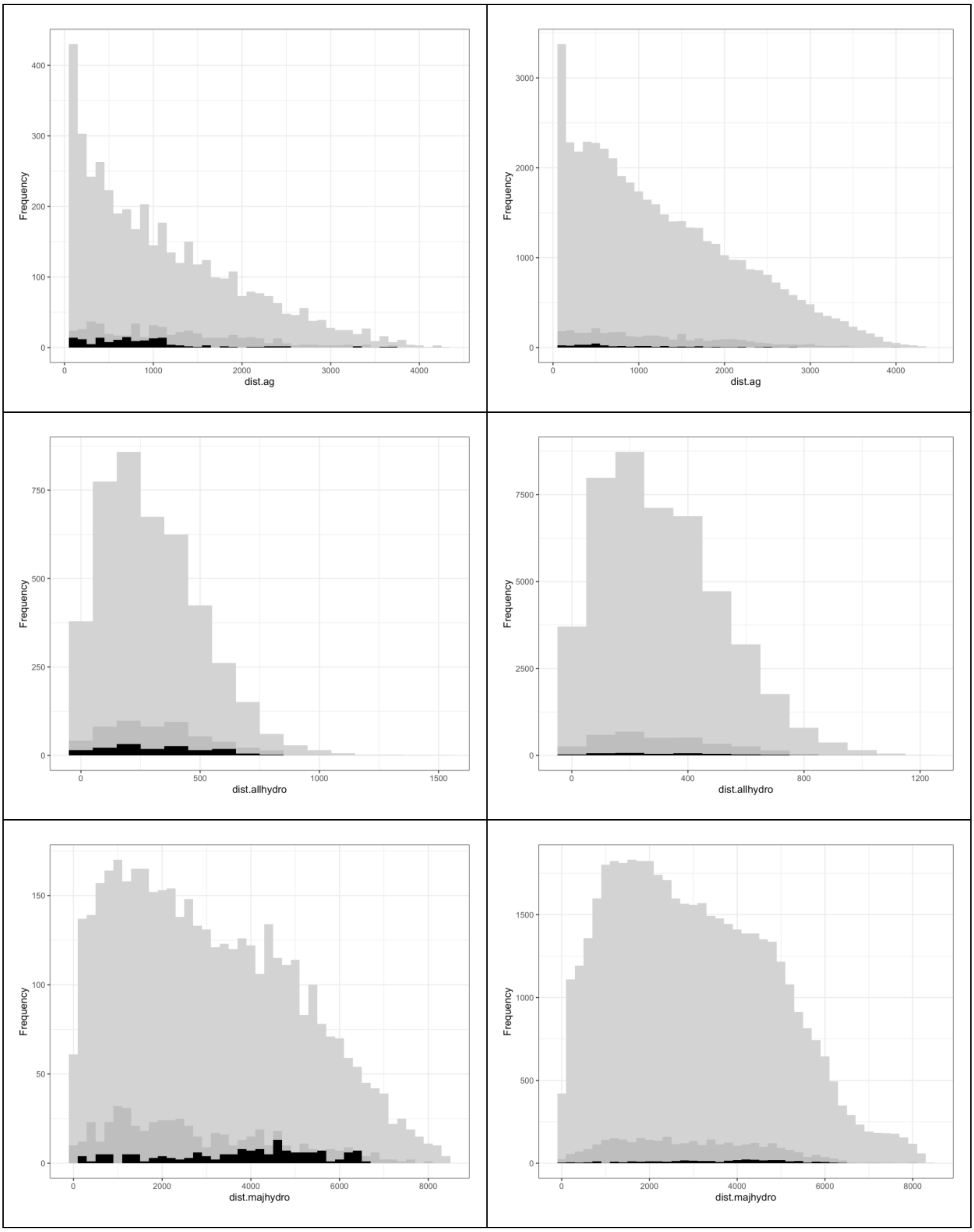
Forest type (2022).



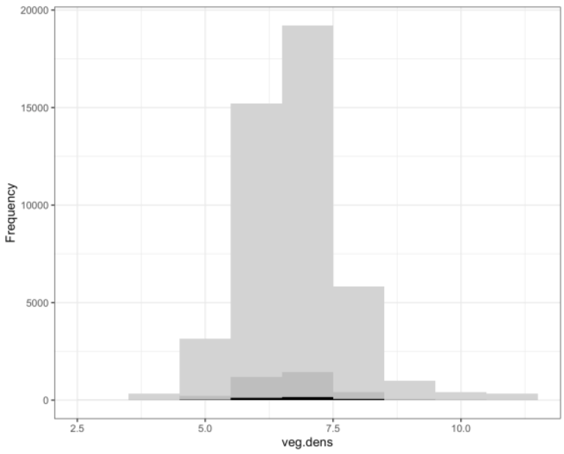
Landscape position (2022).

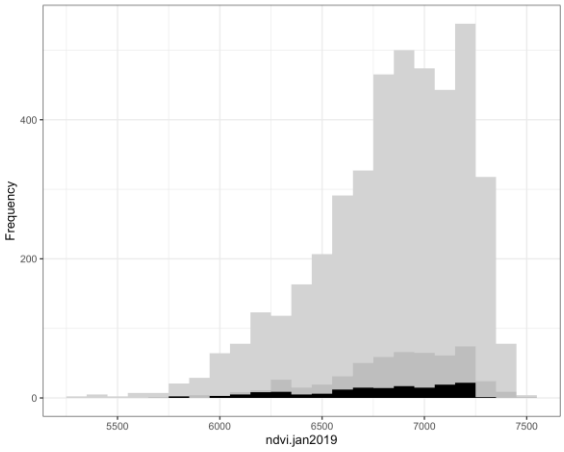
Appendix 2 Frequency histograms of the spatial covariates explored in relation to ngwayir density surface models based on 2019 and 2022 data, comparing the available covariate space in the prediction grid (light grey), to what was sampled (dark grey), and what detected ngwayir (black).

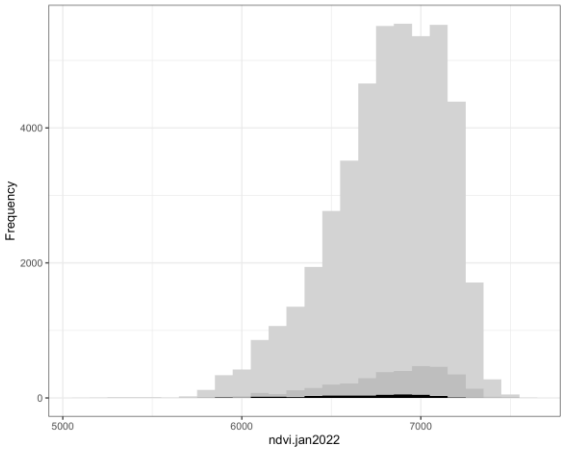
2019	**2022**
	
	

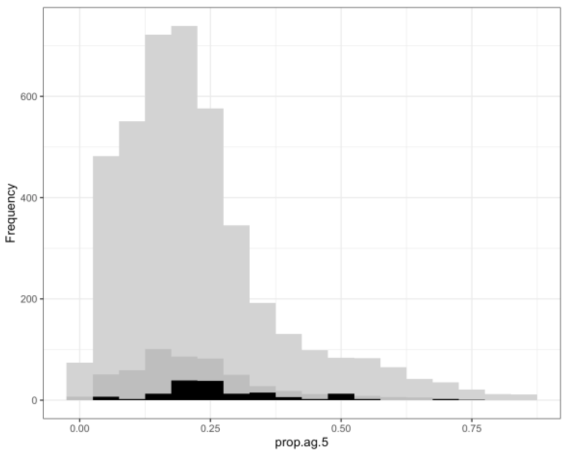

Frequency
dist.ag
Frequency
dist.ag
Frequency
dist.allhydro
Frequency
dist.allhydro
Frequency
dist.majhydro
Frequency
dist.majhydro

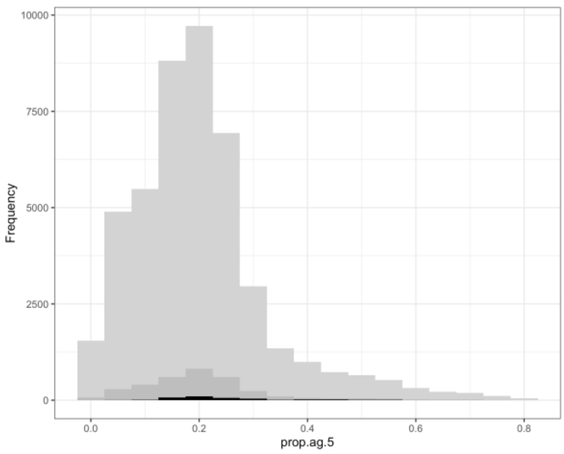
veg.dens was not analysed for 2019.

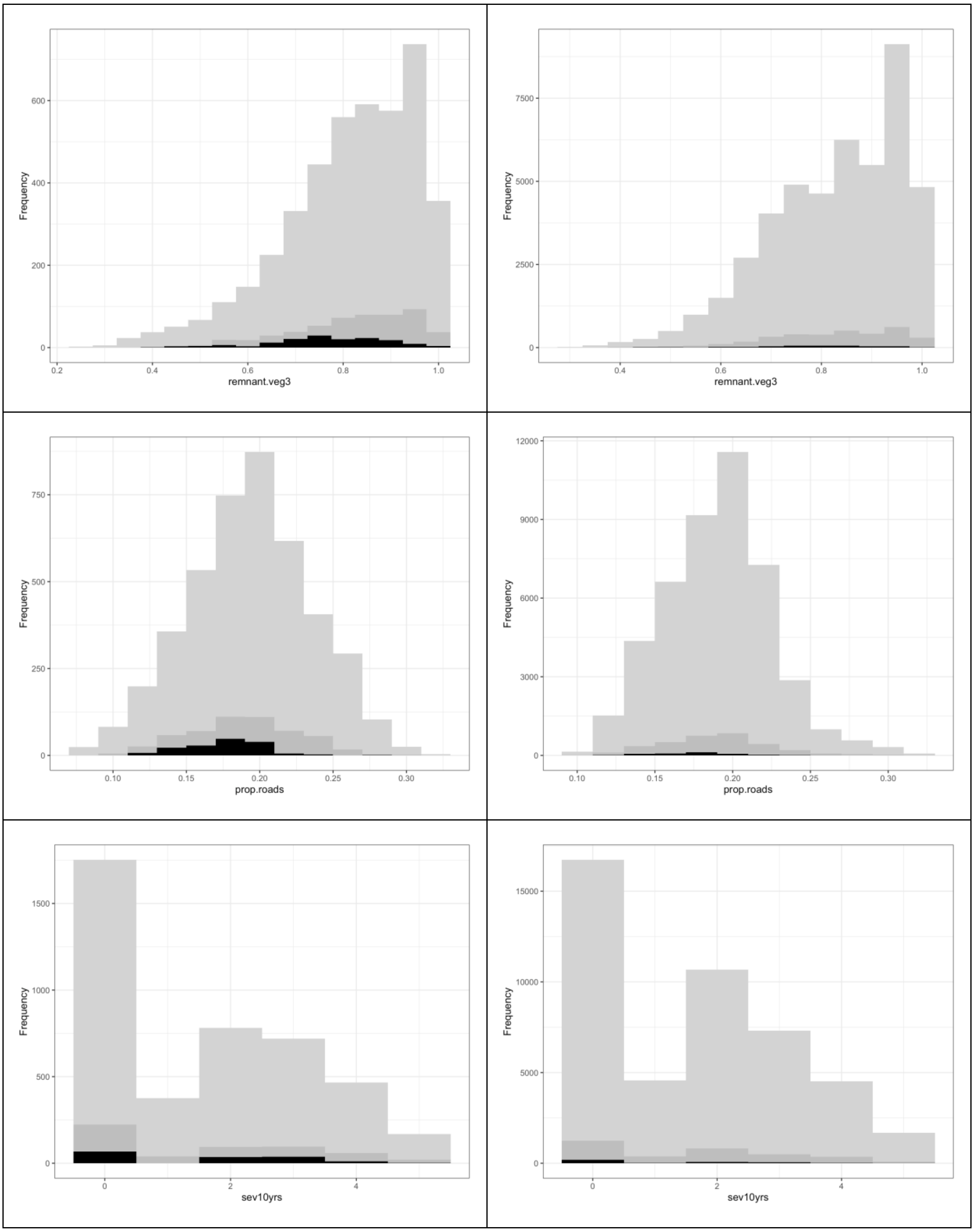


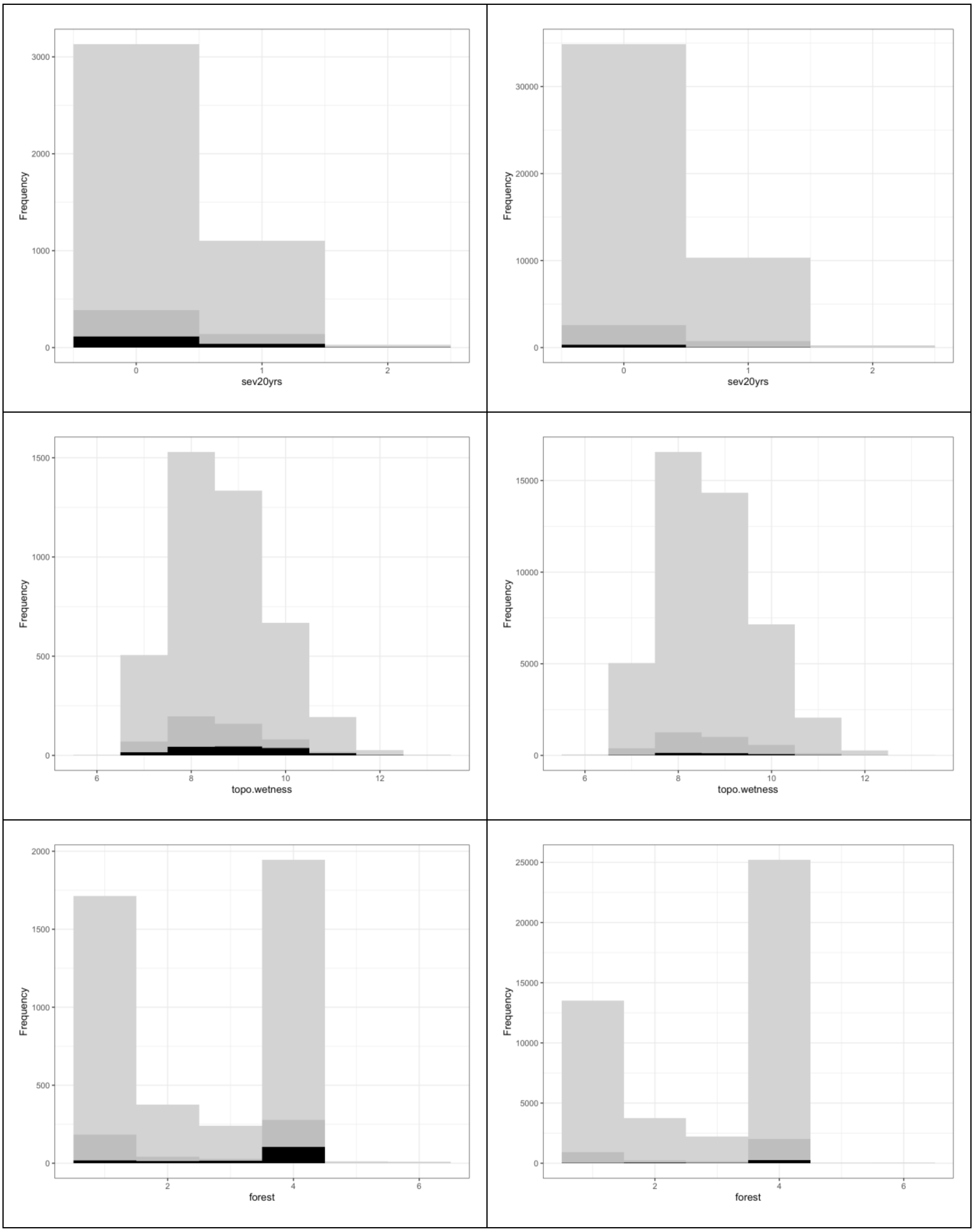


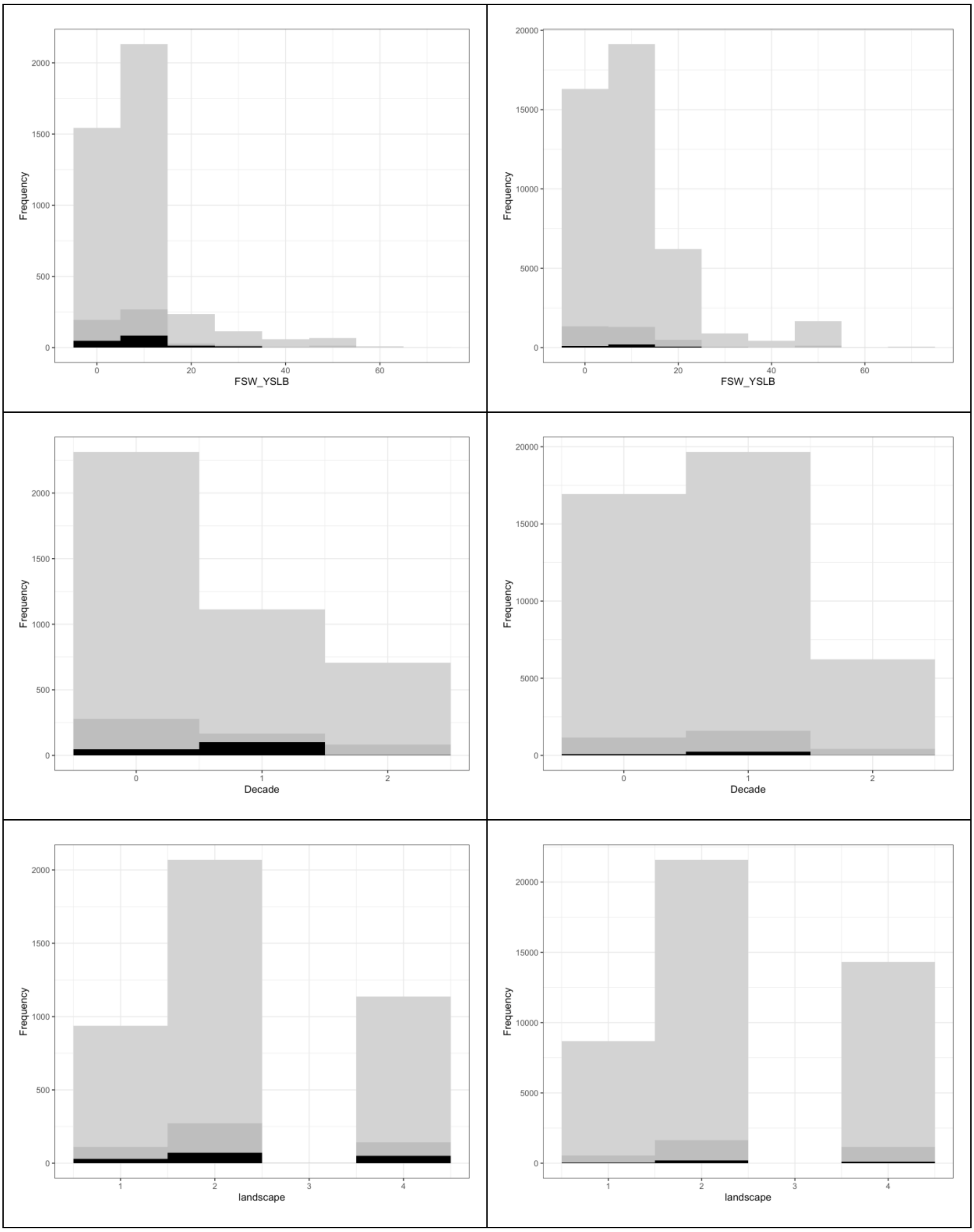







Frequency
remnant.veg3
Frequency
remnant.veg3
Frequency
prop.roads
Frequency
prop.roads
Frequency
sev10yrs
Frequency
sev10yrs


Frequency
sev20yrs
Frequency
sev20yrs
Frequency
topo.wetness
Frequency
topo.wetness
Frequency
forest
Frequency
forest


Frequency
2000
1500
1000
500
0
0
20
40
60
FSW_YSLB
Frequency
20000
15000
10000
5000
0
0
20
40
60
FSW_YSLB
Frequency
2000
1500
1000
500
0
0
1
2
Decade
Frequency
20000
15000
10000
5000
0
0
1
2
Decade
Frequency
2000
1500
1000
500
0
1
2
3
4
landscape
Frequency
20000
15000
10000
5000
0
1
2
3
4
landscape