

# Traprock KBA, Queensland

## BirdLife Australia Key Biodiversity Area (KBA) Change Detection Report, July 2015 – July 2023

Prepared for [BirdLife Australia](#) by [Michael Dear](#), May 2024

### Links

[Traprock QLD BirdLife Factsheet](#)

### Glossary

*Mean*: the average of a set of numbers.

*Normalised Difference Vegetation Index (NDVI)*: The NDVI is a common remote sensing index used for the assessment of vegetation cover and vigour. The NDVI has values in the range of -1 to 1. Values below 0 are generally associated with deep water. Values above 0.8 are associated with dense forest.

*Normalised Burn Ratio (NBR)*: The NBR is used primarily for assessment of fire extent and severity. It is also a useful indicator of healthy vegetation and bare ground.

*Masked*: Pixels that were excluded from the dataset due to a lack of data e.g. cloud cover

*Random Forest*: A machine learning algorithm often used for land cover classification.

### Key Points

- The Traprock KBA covers an area of 64226 ha.
- A substantial area of land ( $\approx 743$  ha) has been cleared, most likely due to the recent construction of the MacIntyre Wind Farm.
- Re-growth of woody vegetation has decreased the proportion of the KBA covered by grass from 28% in 2015 to 22% in 2023.

### Method

A bi-temporal pair of Landsat 8 satellite images for the dates 29/7/2015 and 19/7/2023 was obtained from [Digital Earth Australia's](#) Open Data. Each  $30m \times 30m = 900m^2$  in the study area was represented by one pixel in the dataset. The dataset included the red, green, blue, near-infrared, shortwave infrared 1, and shortwave infrared 2 bands, plus the NDVI and NBR indices. A classification with the classes Bare, Grass, Medium Wooded, and Dense Wooded was established. Colour-composite and NDVI images were used to develop training and test sets for each of the two dates. A random forest classification was used to classify the datasets for each date. The model was trained on 1116 samples and tested on 279 samples in each class for each

time step. This represented an 80:20 split of the candidate sample dataset. Post-classification analysis was applied to the two classifications to establish various change statistics.

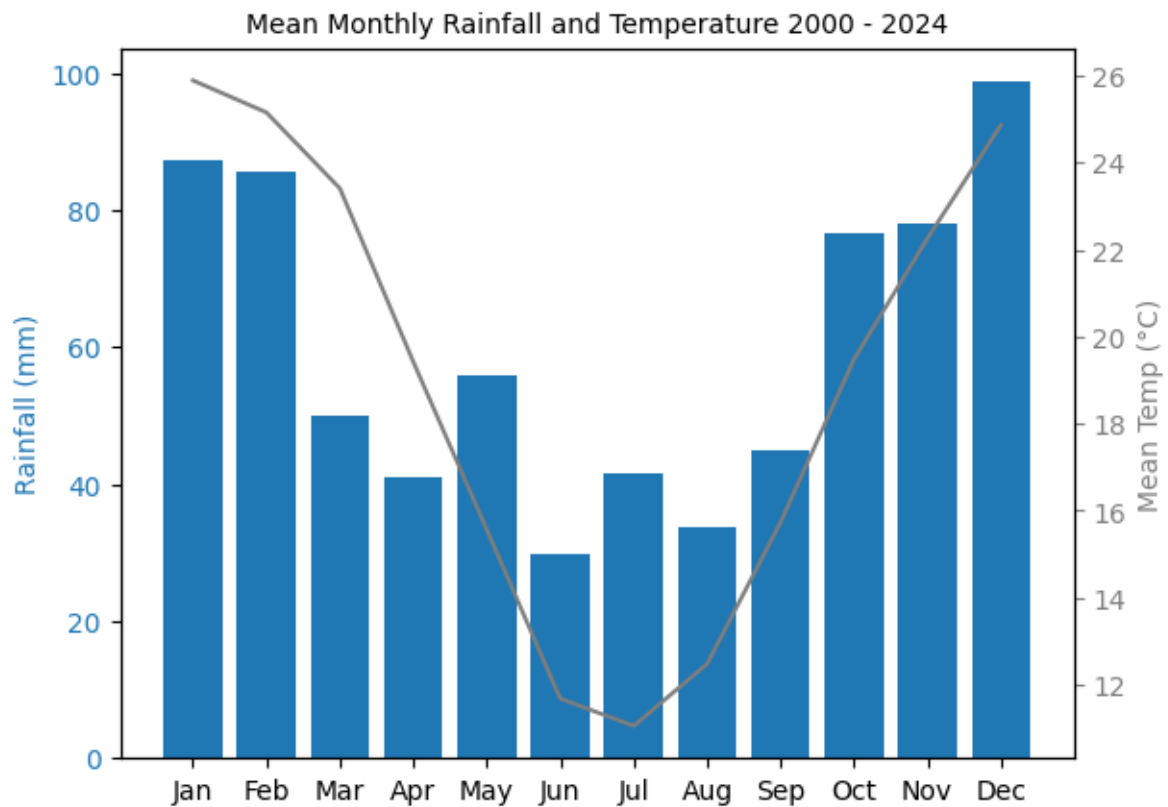
## Site

The Traprock KBA is in southern Queensland, at latitude  $-28.38^{\circ}S$  and longitude  $151.5908^{\circ}E$ . The KBA covers 64226 ha, with land uses including grazing, forestry, and wind farming.

## Long-term Monthly Rainfall and Mean Temperature

The monthly rainfall for the period 200 – 2024 was obtained from the Bureau of Meteorology (BoM) automatic weather station (AWS) at Glenelg (AWS#: 041034) and the monthly mean maximum and minimum temperatures from the Texas Post Office weather station (AWS#: 041100). The maximum and minimum temperatures for each month were averaged to produce a mean average monthly temperature variable. The plot of rainfall and temperature (Figure 1) indicates that there is a strong seasonality in the KBA, with a cool, drier conditions in winter, and warmer, wetter conditions in late spring and summer.

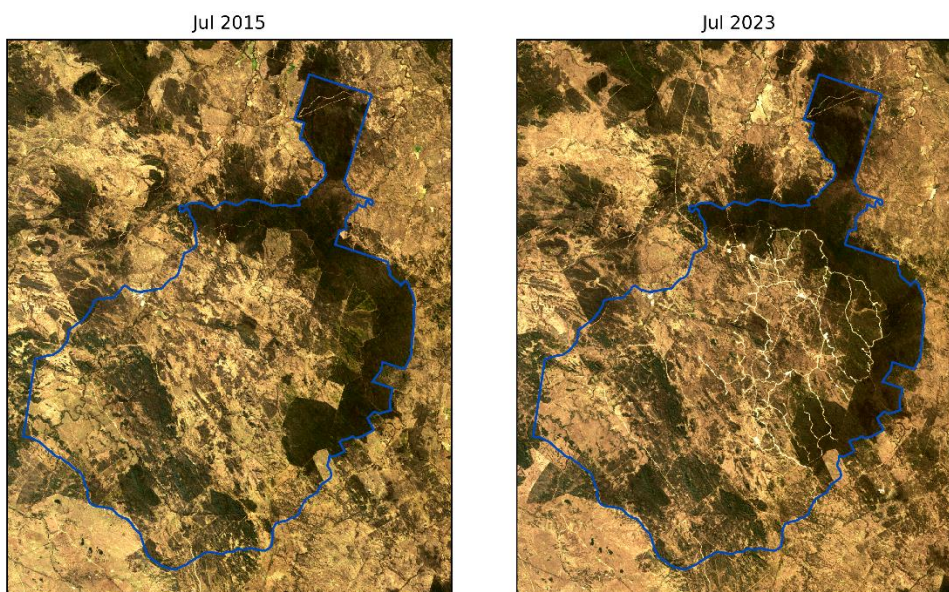
Figure 1  
Long-term Monthly Rainfall and Mean Temperature.



### True colour (RGB) Plots

The plots in Figure 2 show a true-colour representation of the KBA and its surrounds. The KBA boundary is shown in blue. The network of roads associated with the wind farm is a prominent feature of the July 2023 image.

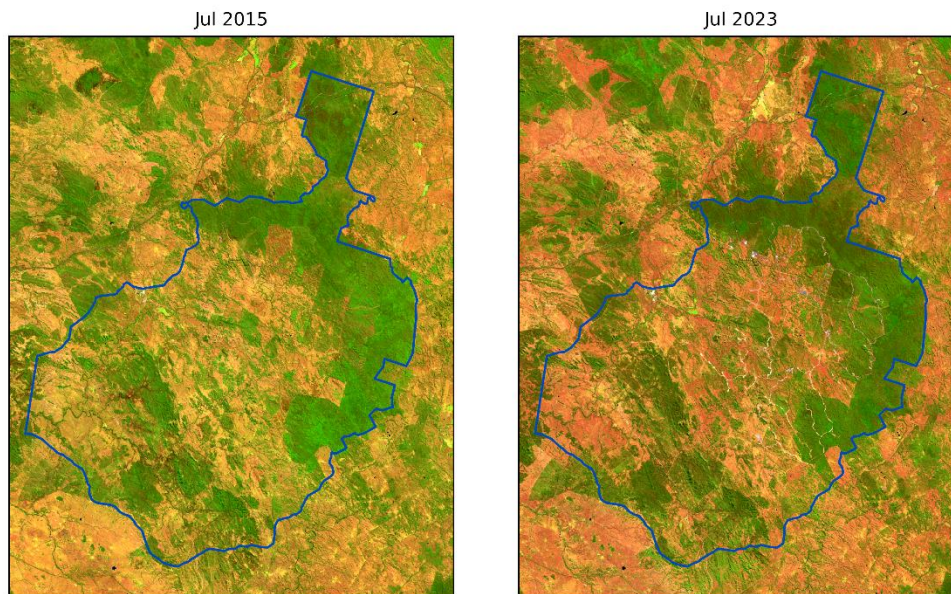
Figure 2  
True colour (RGB) Plots.



## Shortwave Infrared 1, Near Infrared, Red Plots

The plots in Figure 3 show denser, woody vegetation as green, drier grassy vegetation as light brown and orange, and bare ground including unsealed roads as white.

*Figure 3*  
*Shortwave Infrared 1, Near Infrared, Red Plots.*



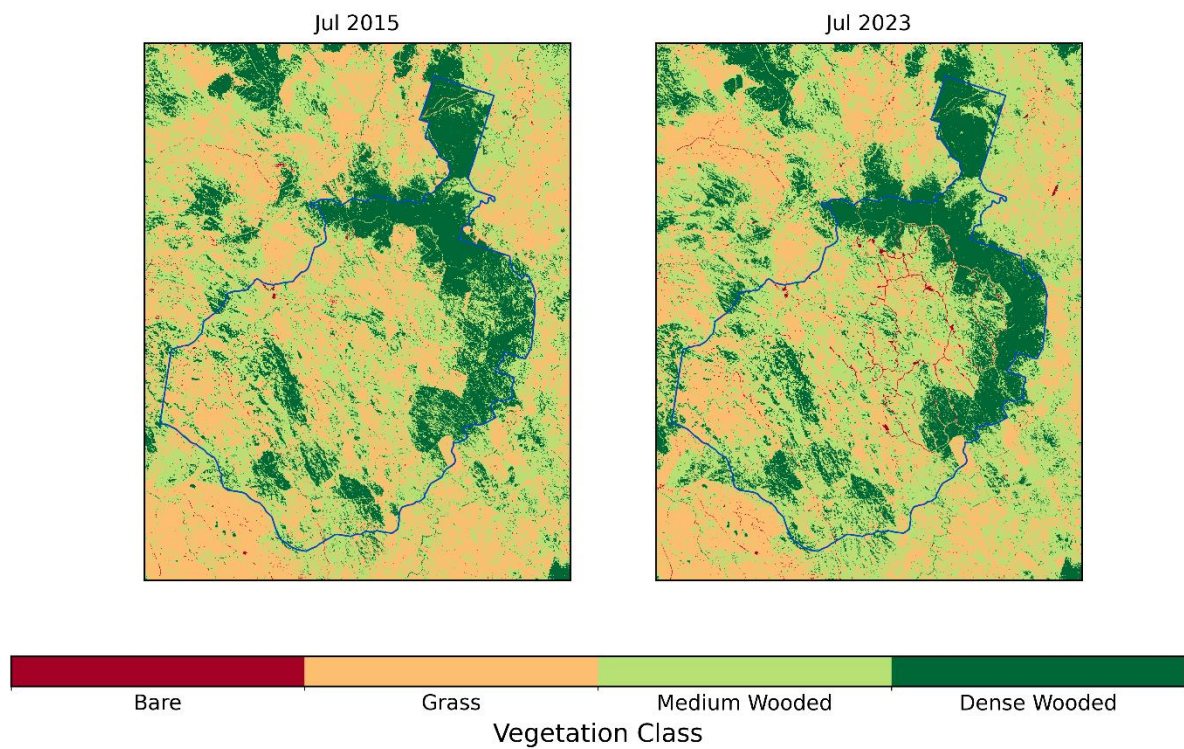
## Land Cover Classification

### Random Forest Classification Plots

The random forest classification plots (Figure 4) highlight the extent of the wind farm construction (red). Close inspection also indicates areas in which woody vegetation has replaced grassy vegetation. This process is evident in the middle of the KBA and around the periphery of the densely wooded area in the northeast of the KBA.

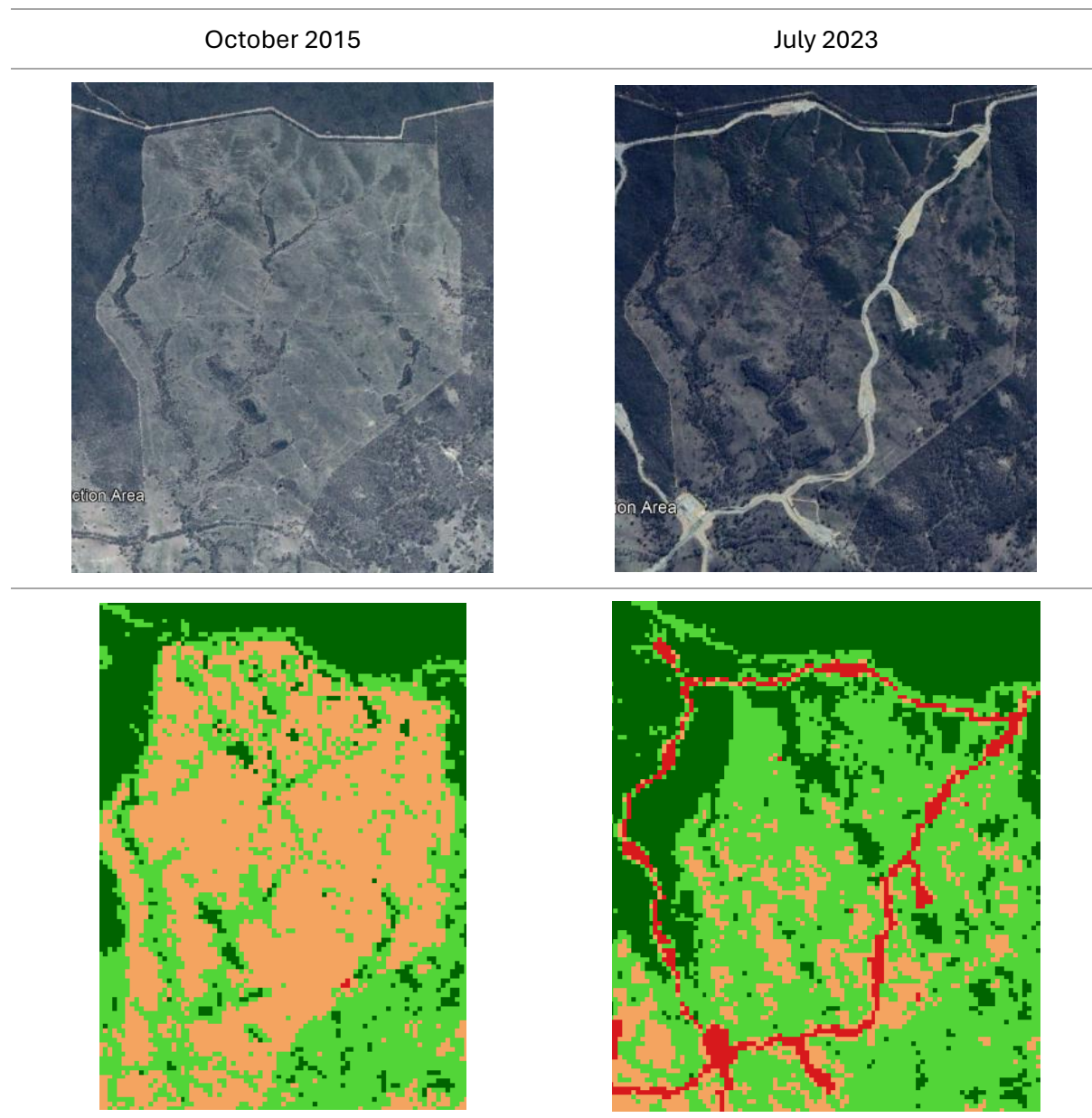


Figure 4  
Random Forest classification plots.



The images in Figure 5 demonstrate the accuracy of the classification. The top row are images from Google Earth, and the bottom row are the associated random forest classification. The regrowth is evident in the July 2023 image and is well identified in the associated classification.

Figure 5  
Comparison of an area showing regrowth.



## Model Accuracy

The overall accuracy of each random forest classification was high (Table 1), indicating the usefulness of the method for classifying land cover in the KBA.

Table 1  
Overall accuracy (correct classification) for each time step.

Accuracy	
<b>Jul 2015</b>	97.4%
<b>Jul 2023</b>	97.5%

From the confusion matrices (Table 2 and Table 3) it can be observed that the Medium Wooded class has the least accurate classification, being confused with both the Grass and Dense Wooded classes in 2015, and the Dense Wooded class in 2023. Dense Wooded was confused to an extent with Medium Wooded at each time step.

Table 2  
Confusion matrix for Jul 2015.

	Bare	Grass	Medium Wooded	Dense Wooded
Bare	279	0	0	0
Grass	0	276	3	0
Medium Wooded	0	9	259	11
Dense Wooded	0	0	6	273

Table 3  
Confusion matrix for Jul 2024.

	Bare	Grass	Medium Wooded	Dense Wooded
Bare	279	0	0	0
Grass	0	277	2	0
Medium Wooded	0	0	262	17
Dense Wooded	0	0	9	270

## Class Change

The increase in the Bare, decrease in the Grass and increase in the Medium Wooded classes is evident from the results in Table 4. Table 5 indicates that the Bare class increased by 426% from 2015 to 2023, whereas Grass decreased by 22%.

Table 4  
Area (ha) of the KBA per class.

	Bare	Grass	Medium Wooded	Dense Wooded	Total
Jul 2015	174.15	18114.84	26154.72	19784.16	64227.87
Jul 2023	916.65	14089.50	28890.45	20331.27	64227.87

Table 5  
Total change (ha) and percentage change in each class.

	<b>Jul 2015</b>	<b>Jul 2023</b>	<b>Jul 2023-Jul 2015</b>	<b>Change_ %</b>
<b>Bare</b>	174.15	916.65	742.50	426.4
<b>Grass</b>	18114.84	14089.50	-4025.34	-22.2
<b>Medium Wooded</b>	26154.72	28890.45	2735.73	10.5
<b>Dense Wooded</b>	19784.16	20331.27	547.11	2.8

The class change matrices in Table 6 and Table 7 suggest that 454 ha of land previously classified as Grass became Bare by 2023, whereas 5790 ha became Medium Wooded. By comparison, 272 ha of Medium Wooded became Bare, 2145 ha became Grass, and 3461 became Dense Wooded. Manual inspection of the classifications overlaid on Google Earth imagery using QGIS indicates that the movement from Medium Wooded to Bare is most likely due to clearing for the wind farm, whereas movement from Medium Wooded to Grass was due in part to land clearing. Figure 6 shows an example of land clearing.

Table 6  
Class change matrix (ha).

		<b>Jul 2023</b>			
		<b>Bare</b>	<b>Grass</b>	<b>Medium Wooded</b>	<b>Dense Wooded</b>
<b>Jul 2015</b>	<b>Bare</b>	92.16	59.31	14.76	7.92
	<b>Grass</b>	454.32	11791.98	5789.61	78.93
	<b>Medium Wooded</b>	272.07	2144.79	20276.64	3461.22
	<b>Dense Wooded</b>	98.10	93.42	2809.44	16783.20



Table 7  
Class change matrix (%).

		Jul 2023			
		Bare	Grass	Medium Wooded	Dense Wooded
Jul 2015	Bare	52.9	34.1	8.5	4.5
	Grass	2.5	65.1	32.0	0.4
	Medium Wooded	1.0	8.2	77.5	13.2
	Dense Wooded	0.5	0.5	14.2	84.8

Figure 6  
Random Forest classifications and true colour (Google Earth) images of land clearing.

