

Article

Using Drone Imagery to Reveal How Fire, Vegetation Cover and Landform Shape Thermal Mosaics in Desert Landscapes

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Highlights

What are the main findings?

- Drone-derived thermal mosaics revealed large variation in surface temperatures (up to >45 °C diel range) in the Australian arid zone, highlighting the extreme environments inhabited by Australian fauna raising concerns about further temperature rise under climate change.
- Thermal heterogeneity was strongly shaped by fire history and habitat type, with sand dunes and recently burned areas displaying more fragmented and patchy thermal environments than swales and >50 years unburnt habitats, with recently burned areas also experiencing higher temperatures.

What are the implications of the main findings?

- Thermal drone sensors can detect fine-scale thermal signatures across large areas, useful in identifying thermal refuges created by landform and disturbance regimes.
- Management actions that maintain landscape diversity and a balance of fire ages and unburnt areas are likely to be more effective for conserving thermal refuges than vegetation restoration alone and may ensure critical opportunities for behavioural thermoregulation by dryland fauna during extreme heat events.

Abstract

Extreme heat is an increasing risk for dryland fauna, making it important to understand how landscape features influence thermal conditions. This study used drone-based thermal mapping to measure fine-scale temperature variation across two Australian dryland sites during summer. It examined how landform, fire history, vegetation cover, and grazing affected surface temperatures. Temperatures varied widely, from 6 to 36 °C in the morning to 24–80 °C in the afternoon. Vegetation coverage did not significantly affect surface temperatures. Landform strongly influenced temperature patterns: sand dunes were cooler than swales in the morning but hotter in the afternoon. Dunes also showed more fragmented and patchy thermal environments, likely due to uneven vegetation, steeper slopes, and soil properties. These conditions may offer greater opportunities for animals to regulate body temperature behaviourally. Fire significantly altered thermal landscapes. Recently burned areas were hotter and had more fragmented thermal patches, creating harsher conditions for diurnal species. In contrast, grazing exclusion had minimal effect, though areas without introduced herbivores showed more stable temperatures. Overall, fire and landform shape thermal mosaics by influencing both temperature levels and spatial patterns. Maintaining diverse thermal environments is likely critical for supporting thermoregulation and species survival under increasing heat extremes.



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1. Introduction

Heatwaves are becoming more extreme and frequent in Australia under climate change [1]. Global modelling predicts that heatwaves will become even hotter and longer over the next few decades [2]. Extreme heat events can increase air temperatures to over 50 °C in the arid zone (www.bom.gov.au, accessed on 15 April 2026), with soil surface temperatures exceeding air temperatures and creating inhospitable environments for microbes, plants and animals [3]. Prolonged heatwaves can lead to mass die off events in species such as bats, birds, kangaroos, rodents and koalas [4–7].

More than 70% of Australia lies within the arid and semi-arid zones and these ecosystems will be exposed to heatwaves that are more intense than the most devastating heatwaves yet experienced [1]. Although arid zone species have adapted to living in hot conditions [8], many species are already operating on the edge of their thermal limit [9] and prolonged periods of excessive heat will prevent recovery between bouts of high temperatures. Additionally, although some species can escape high temperatures by seeking underground refuges or adopting nocturnal foraging strategies, many do not utilise underground shelters, are strictly diurnal, or even if nocturnal must still come to the surface to feed at night when minimum temperatures can exceed 35 °C during heatwaves. (www.bom.gov.au, accessed on 15 April 2026). An animal's thermal environment can significantly influence their movement and shelter choice patterns and their ability to withstand the lethal and non-lethal effects of extreme heat. Increasing surface temperatures will also affect the habitat use and activity patterns of fauna and may reduce or change foraging times, alter spatial movement patterns as animals seek thermal refuge and affect rates of predation. For example, heatwaves have been found to increase dingo hunting events on kangaroos [10]. Microhabitat variation can also buffer species from extreme heat; for example, rabbit burrows provide thermal refuge to feral cats in arid Australia, allowing them to avoid otherwise lethal heat stress [11].

Animals can use surface heat refuges for resting and activity both during the day and at night including seeking shade under large trees or thick vegetation cover, and selectively foraging in areas with cooler microclimates. The thermal properties of these refuges and surface temperatures are affected by soil type, topography and vegetation cover and structure [12]. Surface temperatures of bare soil are, in turn, affected by soil conductivity which generally increases with soil moisture and bulk density and is often higher in coarse-textured (sandy) soils than in fine-textured soils at comparable water contents [13]. Soil thermal conductivity influences both soil temperature and the rate at which the soil surface heats and cools. Soils with high thermal conductivity can reach very high temperatures during the day but also cool more rapidly than surrounding areas at night. The cover and structure of vegetation influences surface temperatures through providing shade which reduces incoming radiation and limits evaporative water loss [14]. However, dense vegetation can also reduce turbulent heat exchange and heat loss from radiation, trapping air and slowing cooling times at night when ambient temperature drops [15]. Biotic soil crust and cryptogams can also alter surface and soil temperatures by increasing heat reflectance, and regulating soil moisture content [16]. All of these factors combine to create a thermal mosaic where surface temperatures can vary considerably at a spatial and temporal scale, even within a small area.

Desert ecosystems have been significantly altered since European settlement through overgrazing, extinction of burrowing fauna and changes to fire regimes [17]. Drought, fire and grazing by introduced herbivores and kangaroos are likely to exacerbate the effect of heatwaves by reducing vegetation cover and structure, leading to an increase in soil exposure [18] and surface temperatures [19]. Increasing surface temperatures will increase soil dryness, potentially leading to the death of critical plant species used for shade, moisture or hollows [20]. Understanding how fire and grazing influence the thermal environment will enable effective mitigation techniques to be developed such as maintaining unburnt habitat patches during control burns or reducing grazing pressure from herbivores.

We use drone-based thermal mapping to explore the influence of soil type, fire and herbivore grazing on the thermal environment. Drones with thermal sensors are being increasingly used in conservation and agricultural science as they can be flown at low altitudes, cover large areas and produce high resolution maps with little human safety risk [21,22]. We collected thermal mosaics for multiple plots at two dryland study sites (Arid Recovery and Secret Rocks) in northern South Australia during summer. We recorded surface temperatures in the morning and afternoon time periods to capture extreme temperature fluctuations. At both sites we compared polygon thermal signatures across a fenceline with different grazing regimes to see if the presence of exotic or native herbivores affected the surface thermal environment. We also compared the thermal signature of polygons in different habitat types (sand dunes vs. swales at Arid Recovery and sand dunes vs. sandplains vs. loamy flats at Secret Rocks) and fire ages (2013 burn, 2019 burn and >50 years unburnt). The thermal signatures were compared using a range of metrics including average maximum temperatures, daily temperature range and thermal heterogeneity and structural complexity. Results were used to infer the effects of habitat, grazing and fire history on the surface thermal environment that dryland animals would be exposed to during hot weather.

2. Materials and Methods

2.1. Study Sites

Arid Recovery is a fenced safehaven dedicated to restoring arid ecosystems by reintroducing native species and managing invasive species within a 12,300 ha area (Figure 1). The site is located in arid northern South Australia with an annual average rainfall of 147 mm. The reserve was fully fenced with a 1.8 m high wire netting fence in 2001 designed to exclude feral rabbits, cats and foxes. Inside the fence are two native mammalian herbivores, the reintroduced burrowing bettong (*Bettongia lesueur*) and low densities of native red kangaroos (*Osphranter rufus*). Outside the fence are introduced rabbits (*Oryctolagus cuniculus*) and high densities of red kangaroos. Two main habitat types are evenly distributed on both sides of the fence, clay interdunal swales vegetated by chenopod shrubs (*Atriplex* spp., *Maireana* spp.) and longitudinal orange sand dunes vegetated mainly with *Acacia ligulata* and *Dodonaea viscosa* shrubs.

Secret Rocks is a semi-arid 4000 ha fenced safehaven on the Eastern Eyre Peninsula, South Australia (Figure 2). The site was fenced in 2017 and excludes rabbits, goats, cats and foxes. Herbivores outside the fence include goats (*Capra hircus*), rabbits and high numbers of western grey kangaroos (*Macropus fuliginosus*). Two landsystems are dominant in the area: the Buckleboo land system and the Pinkawillinie land system [23,24]. Dominant habitat types include: longitudinal white sand dunes of deep ancient Molineaux sand (Aeolian) comprised mainly of quartz and supporting low mallee and mixed shrublands; low sandplain of thin layers of Molineaux sand over loam sandy soils and supporting *Triodia* spp. and mallee shrubs; and loamy sandflats overlying clay with tall mallee and mixed woodland. Three fire ages are present in the reserve: a small control burn was

conducted in 2013 (Figure 2), a larger wildfire burnt 1/3 of the safehaven in 2019, and the remaining areas have not been burnt for over 50 years. Annual average rainfall is approximately 270 mm (www.bom.gov.au, accessed on 15 April 2026).

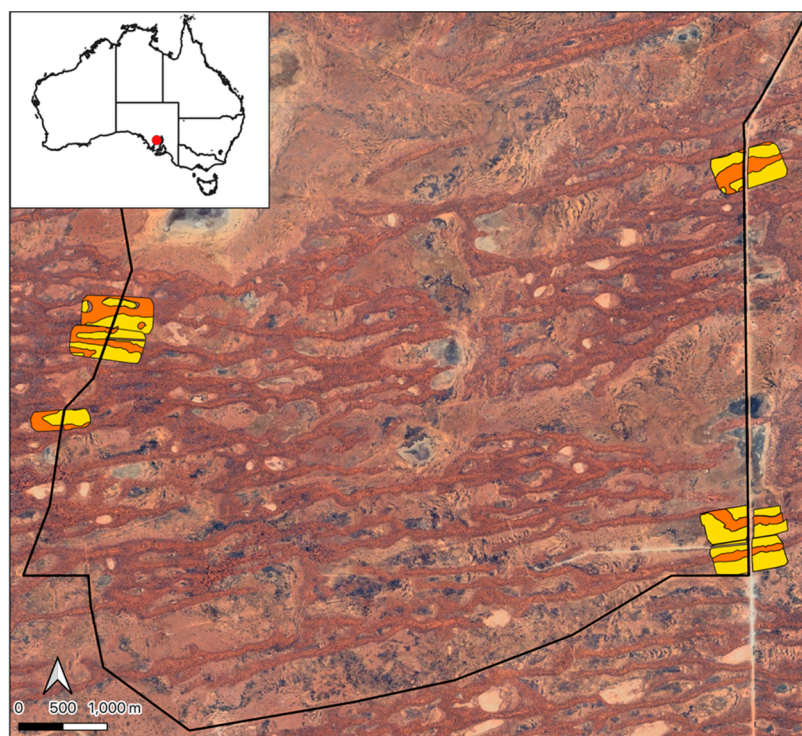


Figure 1. Arid Recovery Reserve showing plots inside and outside the predator-proof fence (black line), and polygons of their habitat types (sand dune: orange, swale: yellow), located within South Australia (red dot, inset), surveyed by drone in February 2023.

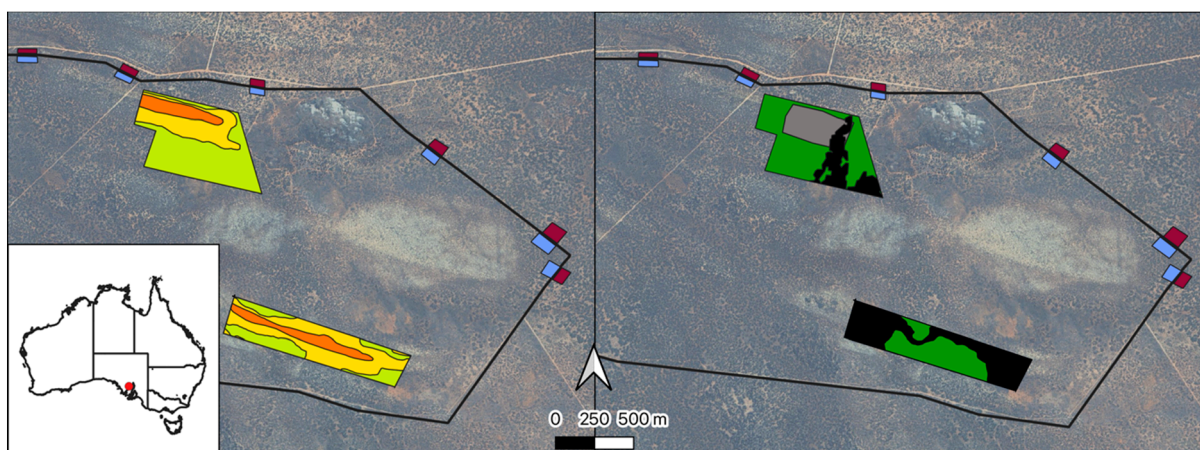


Figure 2. Secret Rocks study site showing the location of the two large inside plots and 6 paired inside/outside plots. Polygons of vegetation types of the large plots are shown on the left (sand dunes: orange, loamy flats: lime green, sandflats: yellow), alongside the inside (blue) and outside (red) plots across the fenceline. Burn history polygons are shown on the right (>50 years unburnt: green, burnt in 2013: grey, burnt in 2019: black), located within South Australia (red dot, inset). All polygon areas were surveyed by drone in February 2023.

2.2. Drone Surveys

During February 2023, we conducted aerial surveys using a DJI Matrice 210 drone equipped with a Zenmuse H20T thermal camera (12MP 1/2.3" CMOS sensor DFOV 82.9 deg wide RGB (Red, Green, Blue) sensor, 640 × 512 px DFOV 40.6 deg radiomet-

ric thermal sensor collecting RJPEG files, SZ DJI Technology Co., Ltd., headquartered in Shenzhen, Guangdong Province, China) over two key locations in the arid zone of South Australia: Arid Recovery and Secret Rocks (Figures 1 and 2). The thermal sensor measured long-wave infrared radiation to derive radiometric surface temperature for each pixel, allowing assessment of spatial variation in surface temperature.

At each site, we flew six paired rectangular plots—six inside the fenced area and six outside. Plots were between 1 and 5 ha and paired across the fence so they were adjacent and in the same habitat type with a 5 m buffer on each side of the fence removed to accommodate the road and fence effects. To prevent temporal changes in surface temperature from biasing measurements as the drone moved across the landscape, we oriented all flight paths to cross the fenceline perpendicularly, maintaining consistent thermal signatures across habitats (Figures 1 and 2). We employed pre-automated transects with 75% front and side overlap at an altitude of 120 m, capturing both thermal and RGB images. At Secret Rocks we flew an additional two large polygons (38 and 30 ha) that incorporated three fire ages (2013, 2019 and >50 years unburnt, covering between 8 and 13 ha of each burn history) and three habitat types (sand dune, sandplain and loamy flats, covering between 6 and 20 ha of each habitat type).

Flights were conducted twice in a 24 h period—once in the morning (start to finish 6.30–10 am) and once in the afternoon (start to finish 1.30–7.30 pm)—to capture the strong diurnal variation in surface temperatures. Sites were surveyed between the 13th and 21st February 2021. We processed the imagery using Agisoft’s dual-sensor workflow (Agisoft MetaShape (v1.4.5)) to produce both thermal and RGB geo-rectified orthomosaics for each site and time period. The resulting spatial resolutions were approximately 11 cm/pixel for thermal mosaics and 3.4 cm/pixel for RGB mosaics. Thermal orthomosaics were converted from raw sensor values to real temperature (°C) by applying a pixel-wise transformation to band 4 (B4—the thermal band), using the formula:

$$\text{Temperature (}^{\circ}\text{C)} = \frac{B4}{100} - 273.15.$$

A constant surface emissivity value of 0.95 (DJI Zenmuse H20T factory default) was assumed for all pixels. Typical emissivity values for natural surfaces, such as vegetation and soils, range from approximately 0.96 to 0.98. Sensitivity analyses indicate that an emissivity uncertainty of 0.02 can introduce temperature errors of approximately 0.5–0.75 °C [25]. However, sensor-related uncertainties (± 2 °C for the H20T) are substantially larger and therefore represent the dominant potential source of error in the measurements.

2.3. Analysis

To quantify temperature differences, we clipped each thermal raster to the relevant polygon boundaries corresponding to burn history, habitat type, and grazing treatment (inside vs. outside the fence). We first generated descriptive statistics for each polygon by calculating median surface temperature and temperature standard deviation for the morning and afternoon flights. We did not conduct formal statistical analyses on these aggregated values because reducing each polygon to a single median or standard deviation substantially limited sample size and statistical power.

For the inferential analyses, we instead adopted a point-based approach. This method preserved fine-scale spatial variation in surface temperatures and ensured robust sample sizes across sites, thereby providing adequate replication for statistical modelling while maintaining spatial representation of thermal conditions. To reduce computational load, we aggregated raster pixels by a factor of 2–8, depending on site size. The larger polygons (Figures 1 and 2) required an aggregation of 8 to allow the raster processing on a standard

computer. Morning rasters were aggregated by retaining the minimum value of neighbouring pixels to preserve the coolest temperatures, whereas afternoon rasters retained the maximum value to capture the hottest conditions. We then extracted all temperature values and their corresponding x - y coordinates into data frames using the raster and terra packages in R [26,27]. As the larger polygons contained very high pixel counts, we subsampled the resulting data frames to reduce processing time, retaining a minimum of 2500 observations for each statistical model.

We collected daily minimum and maximum air temperature data to account for different environmental conditions on sampling days for each polygon. At Arid Recovery we used the gauge 016096 at Roxby Downs (www.bom.gov.au, accessed on 25 June 2026), and at Secret Rocks we used the gauge 018040 at Kimba (www.bom.gov.au, accessed on 25 June 2026).

We used generalised additive models (GAMs) with restricted maximum likelihood (REML) to test for differences in surface temperature between fence location (inside, outside), habitat types, and burn histories, analysing morning and afternoon observations in separate models and including daily minimum temperature for the AM models and daily maximum temperature for the PM models [28,29]. We began by assessing the distribution of the temperature values through the inspection of histograms and confirmed that values were approximately normally distributed; therefore, no transformations were applied. At Arid Recovery we explored temperature differences at different plot pairs in relation to their habitat types and location either inside or outside the reserve (fence treatment). We applied a Gaussian process smooth to the spatial coordinates (x , y) to account for spatial autocorrelation [30,31], i.e., `gam(temperature ~ plot + dailyairtemp + habitat*fence treatment + s(x, y, bs = "gp"), method = "REML")`.

At Secret Rocks we ran two models per morning and afternoon including a Gaussian process smooth: the first to explore differences in temperature at plots inside and outside of the reserve, i.e., `gam(temperature ~ fence treatment + s(x, y, bs = "gp"), method = "REML")` and the second to explore differences in temperature across habitats with different burn histories i.e., `gam(temperature ~ dailyairtemp + burn history * habitat + s(x, y, bs = "gp"), method = "REML")`. The fence treatment model did not include air temperature as all sites were flown on the same day.

To evaluate whether the Gaussian process smooth removed remaining spatial autocorrelation, we inspected Moran's I values and associated p -values [32]. Moran's I p -values ranged between 0.49 and 0.5, confirming residuals exhibited spatial independence. We also generated residual maps by plotting Pearson residuals against their spatial coordinates. Visual inspection showed no systematic spatial structure, supporting the Moran's I results and further indicating that spatial dependence was adequately accounted for in the GAM.

To quantify thermal landscape structure at both Arid Recovery and Secret Rocks, we calculated a suite of landscape-level metrics using the landscape metrics package version 2.1.4 [33]. The landscape metrics package reproduces the calculations developed in the software package FRAGSTATS [34]. Polygons delineating the habitat types, burn histories and presence inside or outside the fenced areas were used as boundaries to limit the morning and afternoon thermal raster data. The thermal rasters were then converted into categorical classes, based on 2 °C intervals, a necessary conversion for the landscape metrics computation. We used a 2 °C interval to match the DJI Zenmuse H20T sensor accuracy of ± 2 °C. Landscape metrics were then calculated at the landscape level for each polygon separately. The resulting metrics quantify thermal heterogeneity and structural complexity within each polygon.

We explored differences in landscape patch metrics using regression models. At Arid Recovery, we tested for effects of habitat type (sand dune vs. swale), fence treatment

(inside vs. outside), and their interaction. This was possible because each polygon in a plot at Arid Recovery represented a single habitat type and was entirely either inside or outside the predator-proof fence. At Secret Rocks, the inside, outside plots had matching habitat types, so we could not compare habitat effects and inside, outside effects in the same model. Further, the polygons within the two large plots identifying burn history and vegetation were not mutually exclusive, i.e., 2019 burn polygon intersected polygons of all three habitat types. Considering the 66 metrics produced by the landscape metrics package, we first removed those of near zero variance [35] and further filtered variables that were highly correlated (>70%), choosing to keep the variable according to ease of interpretation [36], and relevance to thermal values. We ran three separate model types per morning and afternoon and per remaining landscape metric: one testing differences between habitat types (sand dune, sandplain and loamy flats), one testing burn history (>50 years unburnt, 2013 burn, 2019 burn), and one testing fence treatment (inside vs. outside on the paired plots), e.g., `glmmTMB(scaled landscape metric ~ fence treatment)`. We applied the Benjamini–Hochberg *p*-value correction to control for false discovery rates associated with multiple hypothesis testing.

We retained four metrics to explore in detail: contagion index (contag) which measures the extent at which thermal bands are aggregated (or clumped) at the landscape-level, expressed as a percentage; mean Euclidean nearest neighbour distance (enn_mn), the average distance between patches of the same temperature class; mean patch area (area_mn), the average size of thermal zones; and patch density (pd), the number of thermal patches per unit area [34,37]; all metrics are reported in Table S1.

2.4. Vegetation Cover Analysis

We extracted vegetation cover (%) across each of the habitat, fence treatment and burn history polygons at Arid Recovery and Secret Rocks using the online VegMachine version (<https://vegmachine.science-data.qld.gov.au/> accessed on 30 September 2025) tool at the same time as the study (February 2023), using a 10 m monthly composite and extracting total cover (green + non-green cover) [38]. We modelled the relationship between vegetation cover and median temperature (logged) across each polygon to explore the role of vegetation cover in controlling landscape temperature, including AM/PM as a fixed variable and minimum (for AM flights) and maximum daily temperature (for PM flights) on the day of flight, using the package `glmmTMB` version 1.1.9 [39], i.e., `glmmTMB(log(median temperature) ~ vegetation cover*time + scale(dailytemp) + (1|location), data)`.

Finally, as there were expected differences in vegetation cover due to grazing effects inside and outside the fenced reserves, we modelled percent vegetation cover using separate beta-regression models for each site. For both Arid Recovery and Secret Rocks, we fitted a separate `glmmTMB` model with fence treatment as the fixed effect quantifying fence-related differences in vegetation cover within each site, i.e., `glmmTMB(vegetation cover ~ fence treatment*time + dailytemp + (1|Site), family = beta_family())`.

We explored average vegetation cover values across the differing burn histories, but did not model this due to small sample sizes when averaging values across polygons.

3. Results

3.1. Treatment Effects

Surface temperatures varied greatly between the morning and afternoon rasters, ranging from 6 °C to 36 °C in the morning and 24 °C to 80 °C in the afternoon. The highest and lowest temperatures were both observed at the most arid site at Arid Recovery. Variation between temperatures recorded during the morning and afternoon flights was different for each treatment (Figure 3), with the biggest difference in surface temperatures

between AM and PM flights occurring in the 2013 burn area at Secret Rocks where the difference was more than 45 °C (Figure 3a). The 2013 burn polygons also had the lowest standard deviation of temperature in the AM morning and PM afternoon flights suggesting not only the largest change in temperature but a consistency in temperature across the burnt landscape (Figure 3b). Plots inside the fenced reserves at both Arid Recovery and Secret Rocks had lower temporal difference in surface temperatures than outside plots (Figure 3a) suggesting a more temporally thermally homogenous environment inside the fence. When considering the variation in temperatures within treatments, the >50 years unburnt polygon had the highest standard deviation in the afternoon flights at Secret Rocks suggesting sites within this treatment varied in their thermal environment. At both sites, sand dunes had the lowest standard deviation in surface temperature of all the habitat types in the morning, but the highest standard deviation of the habitat types in the afternoon flights (Figure 3b).

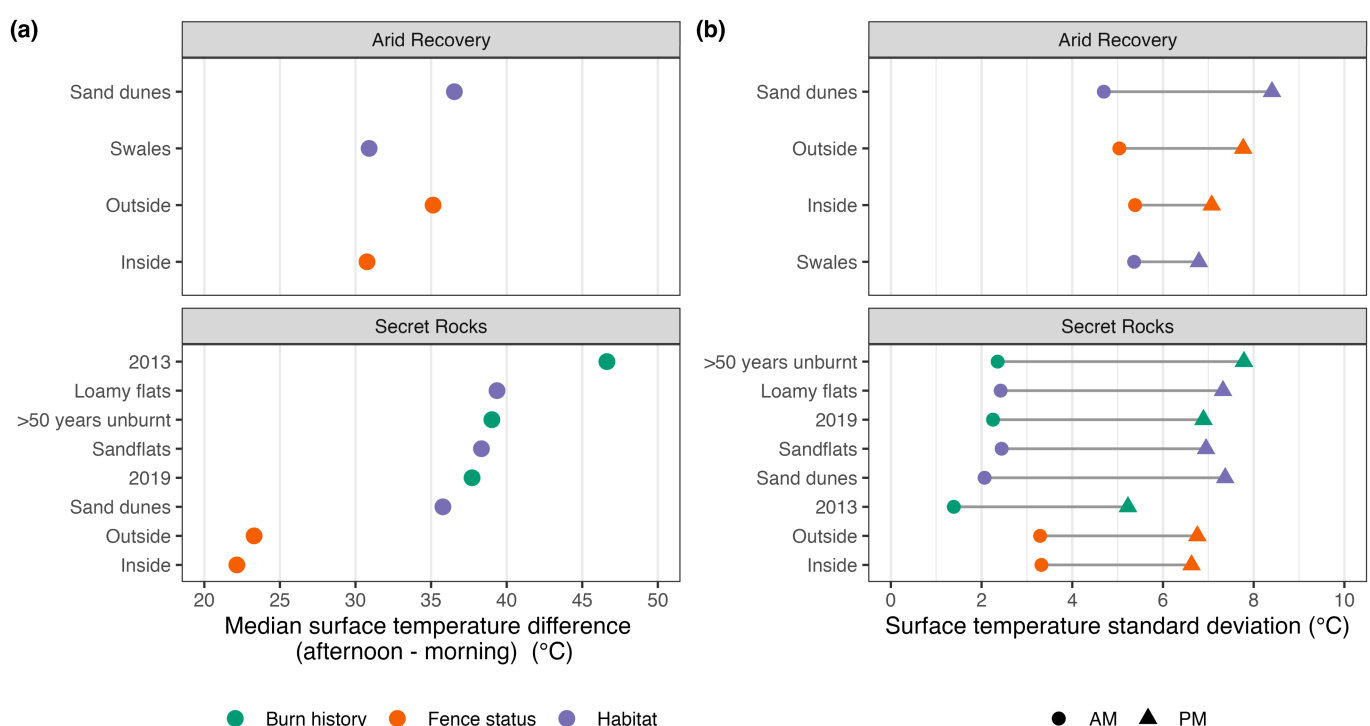


Figure 3. Differences in the median surface temperatures between afternoon and morning (a), and the standard deviation of within site surface temperatures across treatments (b) at Arid Recovery and Secret Rocks.

At Arid Recovery, gam modelling found temperature was significantly higher in swales by approximately 1.3 °C in the morning (Figure 4, Table 1), but by the afternoon swales were significantly cooler than sand dunes by −0.49 °C. A significant interaction effect of landform by time of day showed swales located outside the fence were significantly cooler than swales inside the fence by ~ -0.67 °C in the morning (Figure 4, Table 1). There were no significant differences in surface temperature with the fence treatment.

At Secret Rocks, fire history interacted with habitat to shape thermal conditions. During the morning, a significant interaction showed that sand dune polygons burnt in 2013 were cooler than expected in the morning based on the additive effects of habitat and burn history, indicating a stronger cooling effect of the 2013 fire in dune habitat (Table 1). In the afternoon at Secret Rocks, 2013 burned areas and 2019 burned areas were significantly warmer than >50 years unburnt areas by an average of approximately 2.3 °C and 2.4 °C, respectively (Figure 5).

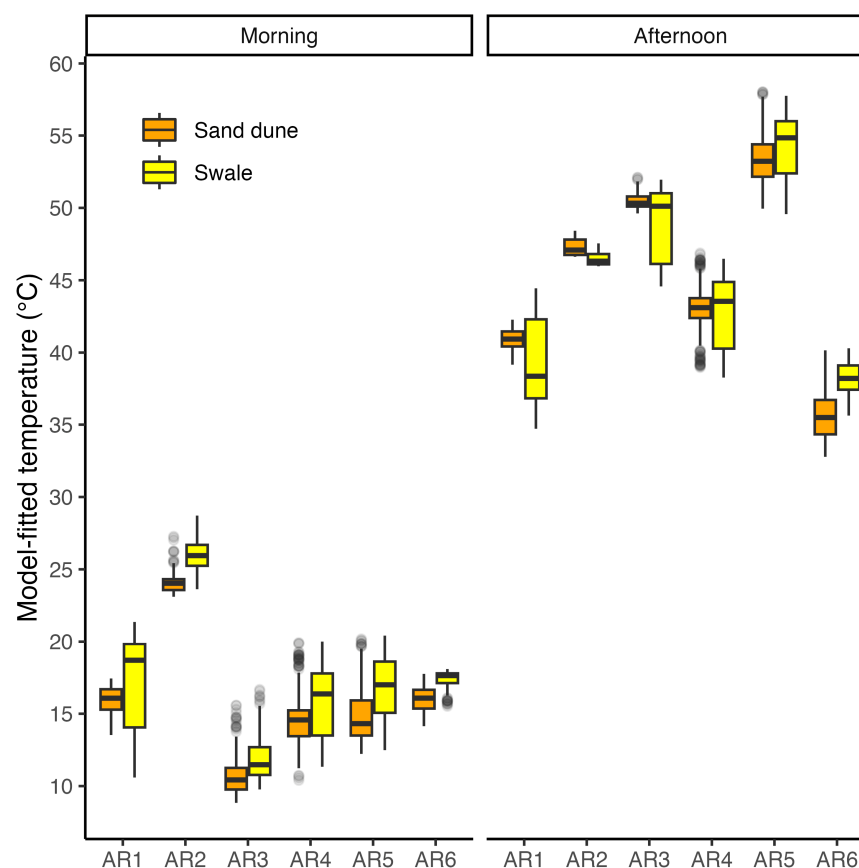


Figure 4. Distribution of model-fitted temperatures from GAMs across plots and habitats for morning and afternoon periods at Arid Recovery field site. Values represent fitted responses at observed plots, incorporating effects of daily minimum and maximum temperatures (for morning, and afternoon flights respectively), habitat type, plot, and spatial structure.

Table 1. Significant results of the GAMs exploring the effect of landform and fire age treatment on surface temperatures collected both morning and afternoon using a drone at Arid Recovery and Secret Rocks field stations.

Site	Time	Model Type	Model Term	Estimate	Std Error	Statistic	<i>p</i> Value
Arid Recovery	Morning	Air temperature	Minimum daily temperature	3.121	0.110	28.326	0.000
		Habitat	Swale	1.337	0.127	10.556	0.000
		Habitat x Fence treatment	Swale:Outside the fence	−0.674	0.186	−3.626	0.000
	Afternoon	Air temperature	Maximum daily temperature	3.974	0.119	33.437	0.000
		Habitat	Swale	−0.487	0.226	−2.153	0.031
		Habitat	Sand dunes	−1.036	0.388	−2.67	0.008
Secret Rocks	Morning	Habitat	Sandflats	−0.846	0.255	−3.318	0.001
		Burn X Habitat	2013 burn:sand dunes	−1.113	0.407	−2.734	0.006
	Afternoon	Burn	2013 burn	2.298	1.055	2.179	0.030
		Burn	2019 burn	2.408	0.940	2.562	0.011

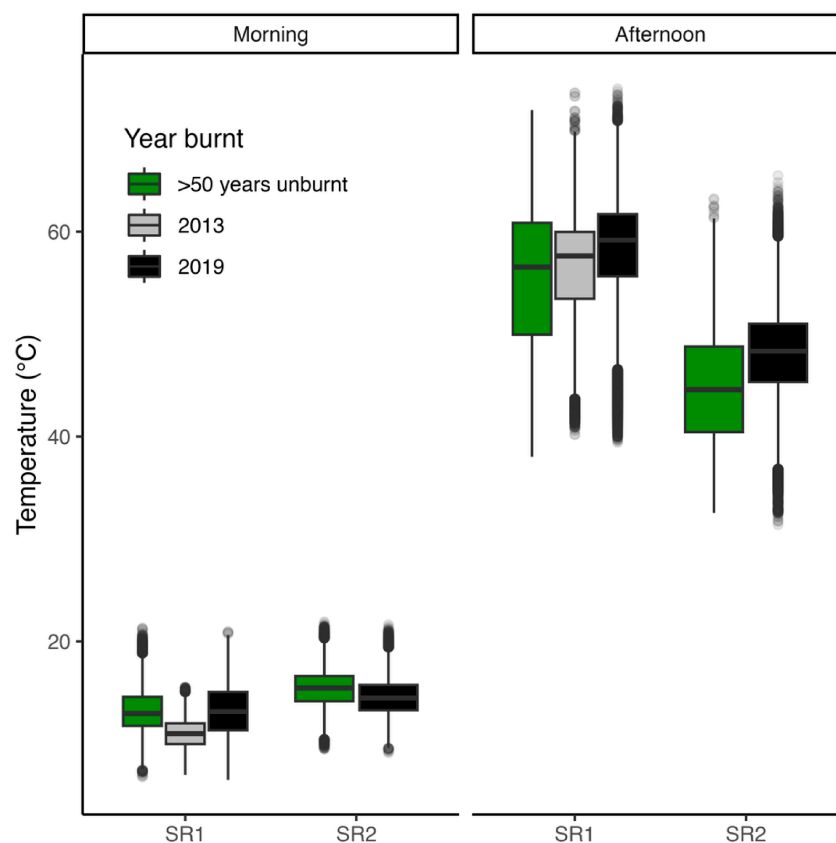


Figure 5. Surface temperature, collected using a drone, differed significantly across different burn histories at the two large plots at Secret Rocks in the morning and afternoon.

Temperatures also varied by habitat at Secret Rocks. Sand dunes and sandflats were both significantly cooler than loamy flats in the afternoon by $\sim 1^\circ\text{C}$. (Table 1, Figure 6).

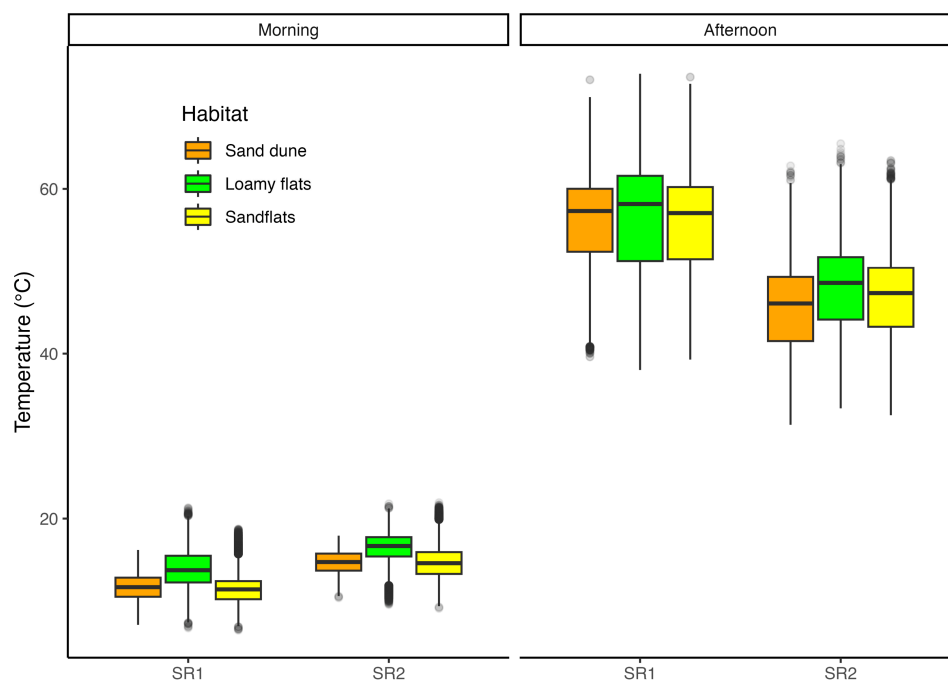


Figure 6. Surface temperature, collected using a drone, differed significantly across different habitats at the two sites at Secret Rocks in the morning and afternoon.

3.2. Patch Metrics

There were no significant differences in patch metrics inside and outside the fences at either Secret Rocks or Arid Recovery. At Arid Recovery we found significant differences in the thermal landscape between sand dunes and swales for mean patch area and patch density (Table 2). The average size of thermal zones on swales were larger, and had fewer thermal patches per unit area compared with sand dunes.

At Secret Rocks there were significant differences amongst patch metrics for all the indices between habitat types. Sandflats and loamy flats had significantly smaller average size of thermal patches and more thermal patches per unit area in comparison to sand dunes (Table 2). Sandflats were significantly more clumped than sand dunes, and loamy flats had greater distances between similar temperature zones (Table 2). Burn histories also significantly affected the patch metrics. The most recently burnt area (2019) had significantly more thermal patches per unit area, and a lower average size of thermal zones than the >50 years unburnt area (Table 2). In the AM, surface temperatures in the 2019 burnt area were significantly less clumped than >50 years unburnt, but in the PM were more clumped than >50 years unburnt (Table 2).

3.3. Vegetation Cover

Vegetation cover was not significantly related to surface temperature (estimate = -0.02 , SE = 0.025 , $z = -2.84$, $p = 0.3$). Temperatures were significantly different between the morning and afternoon (estimate = 0.98 , SE = 0.035 , $z = 27.765$, $p < 0.001$); however, there was no interaction effect ($p = 0.132$).

Vegetation cover differed significantly at Secret Rocks, with ~7% more coverage inside the fence (estimate = -3.57 , SE = 5.83 , $z = -6.13$, $p \leq 0.001$), but no significant differences at Arid Recovery ($p = 0.22$).

The 2019 burnt area had the highest vegetation cover at 69%, followed by >50 years unburnt at 65% and finally the 2013 burn at 50%.

Table 2. Regression model results highlighting significant differences in patch metrics between burn histories and habitat types for the selected metrics of interest.

Metric	Meaning	Site	Term	Time	Adj <i>p</i> Value	Estimate	Std Error	Statistic
Contagion Index (contag)	How clumped or dispersed thermal conditions are across the landscape	Secret Rocks	Sandflats compared to dune	PM	0.002	1.867	0.513	3.64
			2013 burn compared to >50 years unburnt	AM	0.009	1.427	0.469	3.043
			2019 burn compared to >50 years unburnt	PM	0.038	1.48	0.581	2.545
Mean Euclidean Nearest Neighbour Distance (enn_mn)	The average distance between patches of the same temperature class	Secret Rocks	Flats compared to dunes	AM	0.027	1.521	0.58	2.622
Mean Patch Area (area_mn)	Average size of thermal zone	Arid Recovery	Swale compared to dune	PM	0.02	1.219	0.353	3.453
		Secret Rocks	Sandflats compared to dune	AM	0.023	−1.749	0.643	−2.722
			Flats compared to dunes	AM	0.042	−1.281	0.525	−2.44
			2019 burn compared to >50 years unburnt	AM	0	−1.753	0.13	−13.465
		Arid Recovery	Swale compared to dune	PM	0.027	−1.197	0.363	−3.295
Patch Density (pd)	The number of thermal patches per unit area	Secret Rocks	Sandflats compared to dune	AM	0.007	1.882	0.589	3.197
			Flats compared to dunes	AM	0.027	1.262	0.481	2.625
			2019 burn compared to >50 years unburnt	AM	0	1.749	0.202	8.639

4. Discussion

The thermal landscape at our dryland sites was significantly affected by the interacting effects of landform, disturbance history and time of day creating unique thermal signatures and heat mosaics. Changes in solar radiation exerted strong effects on surface temperatures with temperatures ranging by over 45 °C within a plot between morning and afternoon flights. Afternoon surface temperatures reached 80 °C in some plots, well beyond the thermal limits for dryland fauna which would force animals to seek shade or shelter in underground refuges. These extreme diel variations in surface temperatures driven by intense solar radiation are characteristic of dryland environments around the world [40,41].

Diurnal heating had, by far, the strongest effect on surface temperatures, and changes in vegetation cover did not affect surface temperatures at the scale of this study. Likely, the drone sensor resolution and imagery scale could not detect changes in microhabitat normally associated with vegetation cover. Even small reductions in surface temperature can create thermally favourable microhabitats for fauna, because animals are likely to rely on fine-scale microclimates to avoid lethal exposure during extreme heat events. Broader evidence shows that microhabitats can substantially buffer animals from climate extremes, reducing exposure to dangerous temperatures [42–44]. Furthermore, drone-based thermal cameras measure surface temperatures rather than the cooler shaded microclimates that exist within or beneath vegetation. In many dryland and arid systems, these shaded zones can be dramatically cooler than exposed surfaces due to reduced solar radiation and the cooling influence of plant transpiration [42,45]. Accurately quantifying the full thermal refuge potential of vegetation would therefore require coupling drone thermal imagery with temperature loggers placed under vegetation, an approach consistent with studies highlighting the importance of microclimate refuges for predator and prey species in arid ecosystems [11,46]. Such integrated measurements would allow a more complete understanding of how vegetation structure shapes thermal environments for dryland fauna.

Landform significantly influenced thermal signatures, with sand dunes exhibiting greater temporal variation than swales. Afternoon surface temperatures are primarily driven by solar radiation together with the thermal conductance and reflectivity of the plot's surface. Morning flights instead reflect overnight heat retention capacity. Some of the surface temperature variation between landforms is related to soil type (including colour and roughness), which has a significant effect on heat conductance and albedo [14]. Sand is highly conductive compared to other soils when moisture is held constant, and the sand at both locations is mainly comprising silica-quartz which has the highest thermal conductivity among soil minerals [47]. Australian soils often have a higher quartz content than sandy soils globally, contributing to their very high conductivity.

Sandy habitats at Arid Recovery were hotter than swales in the afternoon due to the combination of high solar radiation and high thermal conductance. These environments can become inhospitable to diurnal fauna on the surface during heatwaves, particularly in open areas without shade. Surface temperatures in sandy soils at our site reached as high as 80 °C in the afternoon. Conversely, dry sand loses heat quickly via night-time radiative cooling, meaning sand dunes cool rapidly once the sun sets, resulting in lower morning temperatures in sand dunes than in swales. Sand dunes may therefore provide thermal refugia for nocturnal animals foraging at night. Observations of nocturnal dryland mammals at the arid site indicate that some species use the sandy soils at night to thermoregulate by lying prostrate on the cool dune surfaces and spreading their ventral area over the sand (K. Moseby per obs). At Secret Rocks, sandflats and sand dunes were cooler than loamy flats by approximately 0.8 °C and 1 °C in the morning. These differences may reflect the lower slope, different vegetation structure and soil type of sandflats and sand dunes compared with loamy flats [48].

Sand dunes also exhibited greater thermal spatial heterogeneity than swales, driven by their more clumped vegetation patterns (as measured by the contagion index and patch density) and the fine-scale variation in slope and microtopography, which together generate a wider range of microclimates over short distances. In contrast, swales tended to support larger and more continuous thermal zones, likely reflecting their flatter terrain and the more homogeneous vegetation cover provided by chenopod shrubland communities. These structural differences in the thermal landscape are likely to influence how animals thermoregulate. The greater diversity of thermal environments across sand dunes provides animals with more opportunities to behaviourally thermoregulate by moving between microclimates, whereas the more uniform thermal conditions in swales may constrain such behavioural options. Additionally, sand dunes tend to offer superior substrates for burrowing enabling animals to escape extreme daytime temperatures by retreating into cooler subsurface environments [49].

Fire further modified the thermal environments by altering vegetation structure and increasing surface exposure, consistent with other studies [50,51]. Recently burned areas (2019) exhibited smaller and more fragmented thermal patches and warmer afternoon temperatures compared with >50 years unburnt sites. These environments may therefore present more challenging thermal conditions for diurnal species sensitive to heat extremes. A reduction in vegetation cover and the fragmentation of thermal patches following fire also mean that effective surface heat refuges become fewer and smaller, possibly making it more difficult for animals to locate sufficiently cool microhabitats. Our 2019 burn area was already four years post-fire, with high vegetation cover post burn, suggesting that immediately post-fire thermal environments would be even more extreme.

The temperature differences between the varying habitat types and fire ages measured were less than 2.5 °C. Understanding the ecological implications of these differences requires further study. However, many desert animals are already operating on the edge of their physiological thermal limits [52] with narrow thermal safety margins [53]. Extreme heat events rather than average temperatures cause catastrophic die offs in many species [54] and under these conditions even a few degrees can be the difference between survival or mortality. We suggest that future research could look at how animals use different habitats and fire ages under extreme heat conditions using GPS tracking data layered over thermal drone imagery. The magnitude of temperature difference is also one aspect of thermal exposure, but consideration should also be given to the distribution and heterogeneity of thermal patches.

We expected that grazing exclusion within fenced reserves would lead to greater vegetation cover and structural complexity which could buffer temperature extremes through shading and reduced surface exposure leading to thermal benefits. Vegetation cover was significantly higher inside the fence at Secret Rocks but despite these vegetation differences we did not detect significant thermal differences between inside and outside sites. This may indicate that soil and landform characteristics exert a stronger influence on surface temperatures than vegetation structure in this system or that the presence of cryptogams and soil crust at our plots also significantly influences surface temperatures. At the time of our study, the Secret Rocks fence had only been established for 5 years, with rabbits removed and kangaroos controlled for only two. These changes may simply be too recent to have produced measurable effects on vegetation structure or thermal environments. While the temperature differences observed here were relatively small, grazing-driven changes in vegetation structure influence soil exposure [18] and are likely to influence the spatial distribution of thermal microhabitats available to animals. A comparison across a stronger grazing gradient—particularly in systems with large herbivores—would likely

reveal clearer thermal effects through increased bare ground, reduced shade, and altered vegetation structure.

At Arid Recovery we did not detect vegetation differences despite introduced herbivores such as rabbits being removed from inside the reserve for over 20 years. However, the native burrowing bettong, a browsing threatened marsupial, was reintroduced in 2000. This species reached high levels inside the reserve, possibly preventing substantial increases in vegetation cover [55,56] and reducing the expected contrast between inside and outside areas. Alternatively, vegetation changes may be too subtle to detect in thermal data or may only emerge following major rainfall events that stimulate plant growth. We did find inside plots showed lower temporal variation between morning and afternoon flights, suggesting a more thermally homogeneous environment. Additionally, outside swale sites were cooler in the morning compared with inside sites. These differences could be due to subtle effects of changes in leaf litter or changes in topography from increased foraging pits dug by reintroduced animals. More research is needed to understand the subtle drivers of thermal environments in arid areas, including expanding the study to a greater temporal time period to capture the effects of climatic variation on land surface temperatures.

A limitation of our study is that drone-based thermal imagery measures surface temperatures rather than the operative temperatures experienced by animals. Many species move under or within vegetation, use shaded microsites, or retreat into burrows—microhabitats that are not detected by drone-mounted thermal cameras—making it difficult to fully capture the range of thermal conditions available to dryland fauna. Nonetheless, surface thermal patterns provide a valuable proxy for spatial variation in potential thermal microhabitats, and can help identify locations where more intensive measurements (e.g., temperature loggers placed under vegetation or underground) are warranted. In addition, combining drone thermal imagery with high-resolution landscape metrics and spatial GAMs offers a robust framework for analysing thermal landscapes at ecologically relevant scales [28,57]. The use of Gaussian process smooths removed spatial autocorrelation, improving the reliability of inferences about the drivers of thermal variation [28]. The application of a constant emissivity value across all habitats may affect absolute temperature estimates, as emissivity differs across soil types and vegetation, although the application of a constant value across all landscapes means the spatial comparisons are robust, and introduced error is minimal in comparison to sensor introduced error at ± 2 °C for the H20T.

A further limitation relates to the analysis of fire history at Secret Rocks. The burn age classes (2013 prescribed burn and 2019 wildfire) are each represented by a single fire event, with little spatial replication. As a result, observed differences among burn classes may be confounded with other spatially structured factors such as pre-existing vegetation composition, soil properties, or topography. Consequently, effects attributed to fire age should be interpreted cautiously and considered exploratory rather than definitive. Although each burn category covered relatively large spatial areas (approximately 8–13 ha) and likely encompassed some within-category heterogeneity, this variation does not substitute for true replication across independent fire events. Therefore, we interpret fire effects as part of an integrated disturbance–landform–vegetation complex that shapes thermal environments, rather than as an isolated driver. Experimental manipulations or replicated fire histories across comparable habitat types would be required to more definitively partition these influences.

We found that thermal environments in dryland landscapes are shaped by strong diurnal temperature variation and a combination of landform, vegetation cover and disturbance history. Landform influenced the temporal variability and spatial heterogeneity of surface temperatures, while fire increased afternoon temperatures, and altered the distribution and size of thermal patches across the landscape. Grazing effects were weak in our study but reduced temporal variation in temperature. Fine-scale spatial and temporal thermal

heterogeneity can be critically important for animals inhabiting arid environments, where surface temperatures frequently exceed physiological tolerance limits during the day. Such variability influences the availability of microsites for behavioural thermoregulation as well as the location of thermal refugia. Climate change is expected to increase both average temperatures and the frequency of extreme heat events in dryland regions and thus predicting how arid ecosystems may respond to increasing temperatures under climate change will become increasingly important [58,59]. Management actions that prioritise landform diversity (and in doing so, incorporate diversity in soil types and topography), and promote heterogeneous fire mosaics, therefore play an important role in sustaining thermally diverse habitats and supporting the persistence of fauna in warming dryland ecosystems.

5. Conclusions

This study demonstrates that thermal landscapes in arid environments are shaped primarily by strong diel temperature variation and the interacting effects of landform and fire history. Using high-resolution UAV thermal imagery, we detected substantial spatial and temporal heterogeneity in surface temperatures, with differences exceeding 45 °C within individual sites over a single day. Landform emerged as a key driver of thermal dynamics. Sand dunes exhibited greater temporal variability and higher thermal heterogeneity than swales, providing a broader range of potential microclimates. Fire further modified thermal structure, with recently burned areas displaying warmer and more fragmented thermal environments. In contrast, grazing exclusion had limited detectable influence on surface temperature patterns despite some differences in vegetation cover. Vegetation cover alone was not a strong predictor of surface temperature at the spatial resolution examined, suggesting that soil properties, topography, and disturbance history play a more dominant role in shaping surface thermal conditions in these systems. Importantly, our findings highlight that thermal heterogeneity—not just absolute temperature—may be critical for supporting behavioural thermoregulation in arid-zone fauna. Overall, UAV-derived thermal mapping provides a powerful tool for quantifying thermal environments across large landscapes. Maintaining landscape heterogeneity, including diverse landforms and fire mosaics, is likely to be essential for preserving thermal refuges and supporting biodiversity resilience under increasing climate extremes.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/drones10070519/s1>, Table S1: All model results from the landscape metrics modelling.

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