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Distribution characteristics of the free-roaming dog population of the western area of Tongatapu, Kingdom of Tonga: Developing a GIS for biosecurity and animal welfare projects

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Abstract

The free-roaming dog population of Tongatapu, Kingdom of Tonga, is a ubiquitous, well-known and persistent feature of the island. Information on the quantity, condition and spatial distribution characteristics of these dogs is needed for projects aimed at improving biosecurity conditions in different impacted sectors of society, while addressing the management of an animal associated with humans. Health and safety of the human population, agriculture and biodiversity are directly affected by the presence of free-roaming dogs in Tongan communities. A survey conducted over western Tongatapu recorded locations of free-roaming dogs sighted when driving along the roads of 12 towns and villages. Locations were recorded using an iPad and the mobile application Collector for ArcGIS. A total of 1152 dogs was recorded, mostly within villages and residential roads. Patterns of spatial distribution of dog locations were described using kernel density, hotspot analysis, and cluster and outlier analysis tools available in ArcGIS Pro. Using the species distribution modelling algorithms Maxent and random forest (RF), the suitability of the entire island for free-roaming dogs was determined using as input the dog locations and environmental variables consisting of population, land use and road types. Results of both algorithms show that roads and residential areas consistently show the highest probability of free-roaming dog presence. The RF algorithm also produced maps that show predictions of the values of other variables collected during the survey, including body-condition scores, age group and sex types over the entire island. Overall, the maps produced and the database created contribute a baseline biosecurity knowledge-base supporting rational decision-making and governance for the island.

Keywords

Stray dogs, Tonga, free-roaming dogs, animal welfare, Tongatapu

Introduction

Free-roaming dogs are consistently present in the streets of the Kingdom of Tonga, particularly in the main island of Tongatapu (World Nomads 2019; O'Sullivan 2018; Penny 2009) Their obvious territorial behaviour, high numbers, and a need for vigilance in their presence are cited in guides, tourist-related literature and anecdotal reports (Asleson et al. 2011). A survey of students from the region showed 60% of the respondents from Tonga reported dogs as a neighborhood nuisance, compared to 40% from Fiji, 30% in Aotearoa / New Zealand, and less than 20% in Australia (Utter et al. 2008). Research in Madagascar found that communities in conservation areas indicated improvements in daily living if free-roaming dogs were absent (Kshirsagar et al. 2020).

The threat to biosecurity, agriculture and livestock in Tonga is exemplified where, together with pigs and goats, free-roaming dogs were held responsible for the destruction of crops and replanting efforts in Tongatapu (Department of Environment 2002). Stray dogs severely impacted an international aid effort that sought to introduce livestock, with the dogs reported preying on birthing sheep (Ministry of Agriculture, Food and Forests 2014). The lack of any research on the impact of free-roaming dogs on Tongan farm biosecurity required a look at dog-related impacts such as those in China, where intensive pig-farming was impacted due to the prevalence of the highly contagious pseudorabies or Aujesky's disease, associated with the presence of stray dogs and cats (Xia et al. 2018). Stray dogs on poultry farms in Egypt were identified to present considerable risk, serving as transport vectors of fowl mites that cause parasitic diseases outbreaks, resulting in significant financial losses (Abouelenien et al. 2020). Also in Egypt, significant risk was determined from stray dogs scavenging carcasses of poultry affected by avian influenza, identifying the lack of compliance with biosecurity measures for both home and farm-based operations (Negro-Calduch et al. 2013). Access of dogs to pork and faeces from pigs infected with the African swine flu is reported as a major biosecurity risk along the pig value-chain in Uganda (Dione et al. 2016).

In terms of impacts to biodiversity, dogs, cats and pigs were identified as major threats to the endemic Malau or Polynesian megapode (*Megapodius pritchardii*), categorised as a critically endangered species by the International Union for Conservation of Nature (IUCN) (Ministry of Agriculture, Food and Forests 2014). In India, dogs were reported to attack 80 species, including 31 on the IUCN Red List of threatened species and four on the Critically Endangered List (Home et al. 2018), Globally, dogs have contributed to 11 recorded extinctions and threaten 188 species (Doherty et al. 2017). Considering the impacts of dogs on small, isolated island communities or countries, relevant information for effective interventions and management plans is necessary.

In terms of human health and with no formal related work in Tonga, research elsewhere showed that 42% of dogs studied in East and Southeast Asia had exposure to ectoparasites reported to serve as vectors for zoonotic pathogens that may be harmful to humans (Colella et al. 2020). In Nepal, 40% of dogs had ectoparasites, while 73% had endoparasites and 12% had haemoprotozoans (Massei et al. 2017). Pigs, cattle and dogs were identified as the three top species with leptospirosis among 14 host species in the Pacific Islands (Guernier et al. 2018). In Northern Italy, the presence of campylobacter in 17% of tested dogs led to the recommendation to improve biosecurity measures in dog shelters, which were found to have the highest infection rates (Giacomelli et al. 2015). While there was a negative presence of leptospirosis in Tongatapu dogs, the consistent presence of endoparasites and the potential for associated diseases was seen to present a health risk, particularly for children (Naden 2020).

As dogs are a preferred companion animal, the welfare of the population cannot be ignored, particularly in Tonga, where permanent veterinary services are not readily available except for annual or bi-annual veterinary clinics conducted by the organisation South Pacific Animal Welfare, with veterinarians and veterinary nurses coming from Aotearoa / New Zealand and Australia (Moger 2019; Tulloch 2019). Hence it is necessary to conduct projects such as vaccinations, desexing and animal-population controls, all of which require an estimate of the dog population to determine needed resources (Belo et al. 2015).

Dog estimation methods include the use of questionnaires sent by post or mail (AVMA 2012), door-to-door interviews (Butler et al. 2004; Butler & Bingham 2000) and direct observation (Hudson et al. 2018). Other efforts have used telephone surveys, which were found to be more applicable in urban areas with sufficient telecommunication infrastructure. Door-to-door surveys were also observed to be suited for rural areas (Ortega-Pacheco et al. 2007). Aerial photography has also been used, and has the advantages of image availability for post-survey analysis and access to sites inaccessible to people (Aiyedun & Olugasa 2012). Other studies have used dog counts in association with a parameter such as human density (Slater et al. 2008), household number (Atuman et al. 2014; Butler & Bingham 2000) and road length (Childs et al. 1998). In a study in São Paulo, Brazil, communities were stratified based on population size and living conditions prior to surveys for dog and cat presence (Alves et al. 2005).

The long-term effectivity of biosecurity and animal management projects require monitoring and evaluation of impacts based on an initial estimate of dog population. The dog population data also provides information for planning and decision making (German et al. 2006; Totton et al. 2010). Related work to determine estimates of dog populations for project information requirements and monitoring include efforts for rabies vaccination in Namibia (Athingo et al. 2020), spatial analysis of stray dogs in Albuquerque, New Mexico, USA (Brock 2018), distribution patterns of rabid dogs in Bali, Indonesia (Melyantono et al. 2021), spatial analysis of rabies in Tunisia (Ben Hassine et al. 2021), and identifying hotspots of zoonotic parasite transmission through dog–human contact in Chile (Alegría-Morán et al. 2021).

A description of the spatial distribution of free-roaming dogs is seen as a crucial first step in addressing their presence in human communities (Dias et al. 2013). Using ArcMap (v10.2) as the main Geographic Information Systems (GIS) platform provides several analytical tools that map and produce visualisations depicting spatial relationships within the data and with the environmental factors of the area. Results of standard geostatistical analysis such as hotspots and clustering provide visual evidence of the significance of relationships between the dog location data and existing environmental variables (Montajes et al. 2021). Checks for spatial autocorrelation, multi-collinearity, and other characteristics of locations that may affect the analysis and model robustness provide confidence in the results of geostatistical analysis (Miller 2012).

The objective of this study was to estimate the free-roaming dog population of the Kolovai district of the island of Tongatapu. A desexing project proposed by South Pacific Animal Welfare (SPAW) (Moger 2019) covering the area of the Kolovai district, on the north-western side of the island, needed dog population information and the spatial distribution of the dogs to develop plans, evaluate the project, and support work contributing to the effective management of the dog population. This study seeks to contribute to a strengthened and improved biosecurity system in a scarcely studied and unique island setting.

Materials and Methods

Initial pilot survey

An exploratory survey was conducted in December 2017 to investigate local conditions and determine appropriate approaches for the spatial-distribution research. Initial plans to conduct a stratified random area dog-count based on hotspots or coldspots of housing density were replaced by a road-based approached deemed to be more pragmatic, safe and suitable for the observed dogs roaming around in the six areas visited. Dog counts per length of different roads was determined as the most suitable parameter to use in population estimates. The mode of the dog location survey was decided to be best conducted using a car, for safety reasons. The best time of day was also determined, as well as distance from the road of a sighting, to count a dog location. Photographs of sighted dogs and video records of travel along the roads surveyed proved particularly useful in post-survey data confirmation and assessment of records.

Dog location survey

Direct counts of dogs on and along roads, based on related work (Childs et al. 1998; Hiby & Hiby 2017), covered villages of the Kolovai district of Tongatapu in October 2019. Based on wildlife sampling techniques in ecological studies using transects, this method was comparable to sight-resight methods recommended by the World Society for the Protection of Animals (WSPA) (AVMA 2012), where sighted animals were marked and recounted once sighted again, with the population estimated using the Chapman method (Cleaton 2017; Meunier et al. 2019). A major advantage was simplicity and ease in conducting repeat surveys (Hiby & Hiby 2017). Since all the roads were included, a random sampling of transect lines was not necessary (Belo et al. 2015).

Survey preparation included the development of data input forms and maps in ArcGIS Online to facilitate data gathering. The software Collector for ArcGIS was installed on an iPad and maps covering the area were downloaded for offline use. Included as layers in the maps were administrative areas, roads, residential areas and residential buildings available from ArcGIS Online sources (https://data.humdata.org/dataset/tonga-administrative-level-0-1-2-3-boundary-polygons;

Figure 1. Areas covered by the survey in October 2019.

https://data.humdata.org/dataset/hotosm_ton_roads). For the location survey, the data included fields for entering the sex of dogs, age classification (categorised into juvenile, adult and old, subjectively judged during the survey), and a body-condition scoring field using the standard nine-point dog condition scale (German et al. 2006; Laflamme 1997). This body-condition score was a critical monitoring variable for the development of a database of the dog population and serves as a reference database for follow-up animal welfare projects. The database created also allowed the storage of pictures associated with each point location, allowing the confirmation of sex, age and body scores recorded in the field. Twelve villages were identified for coverage, ten in Kolovai district and two in Nukunuku district. In the Tonga Census of 2016 (Tonga Statistics Department 2017), the villages of Fahefa and Ha‘autu were separate, but they are treated as one area in this study as they are adjacent and covered by one residential area (Figure 1).

Survey using Collector for ArcGIS

The ideal time period for the survey was early in the morning (7–9am) and late in the afternoon (4–6pm), when dogs were out on the roads and readily seen. In between these periods, when temperatures were hotter, most dogs were under cars or tended to shelter in the shade, making it difficult to spot or locate them. A car was used for the survey for safety reasons, based on previous experience with some aggressive dogs. Car windows had to be closed in a few instances, when dogs were aggressive.

All roads in the survey areas were covered at a speed between 10 and 15 km/hr. As most dogs had access to the road, with mainly open gates or absence of fences, all sighted dogs were recorded in the Collector for ArcGIS app (Collector). Photographs of dogs were taken, serving as a reference to confirm the sex, age (categorised as juvenile, adult and old) and body condition scores.

Processing of data using ArcGIS Pro

Most of the recorded co-ordinates were near or on the road. This nature of dog locations facilitated calculating the number of dogs per road length and removed the requirement to measure distance from the road, which would require more complicated distance functions (Childs et al. 1998). After each survey day, data collected was synced with the ArcGIS Online account to the geodatabase. The results of the survey for number of dogs per road length (in kilometres), humans per dog, and numbers per area (in hectares) were determined for comparison with related dog population surveys (Downes et al. 2013; Hambolu et al. 2014; Kato et al. 2003; Ortega-Pacheco et al. 2007; Rinzin et al. 2016; Totton et al. 2010). The calculated parameters were also compared using the Kruskal-Wallis statistic to test for independence of numerical data. Body score data was tested for relationships with the categories of sex (male and female) and age groups (juvenile, adult and old) using the Chi-squared test for independence of categorical or non-numerical data (Usui et al. 2016)

Kernel density distribution in ArcGIS Pro (ESRI 2018b) was used to visualise the dog intensity locations over the area, together with spatial statistics tool Hotspot Analysis, which uses the Getis-Ord Gi* statistic that indicates locations where there is a clustering of high or low values (ESRI n.d.; 2021b; Getis & Ord 1992; 2010), and the Cluster and Outlier Analysis (Anselin's Local Moran's I) tool, which indicates spatial outliers and similarity of values of neighbouring locations (Anselin 1995; ESRI 2018a). These tools provide valuable information on the spatial characteristics of the distribution, such as the identification of areas to focus attention and where to allocate more resources, and identifying areas for further investigations and determining accessibility (Elith & Leathwick 2009; Raxworthy et al. 2007).

Species distribution modelling for Tongatapu Island

Dog location data was converted into formats suitable for the selected SDM algorithms, which require geographical locations and relevant environmental variables. To address spatial auto-correlation commonly found in species locations, the area surveyed was subdivided into uniformly sized hexagons with dog counts summarised within each hexagon. The centroids of each hexagon with dog presence were used as the occurrence data input to the SDM programs (Brown et al. 2017). This reduction of occurrences using a regularly sized grid prevents over-fitting of the model and reduces inflation of model performance measures (Boria et al. 2014; Syfert et al. 2013).

Environmental variables and their categories used for modelling consist of the population for each village in 2016 (Tonga Statistics Department 2017), the land cover and roads (HDX n.d.). A mean human population of 1132 was found among the 66 villages of Tongatapu with Kolofo'ou, Kolomotu'a and Ma'ufanga, which make up the capital Nuku'alofa, showing the highest three population sizes at 8247, 7586, and 7382 respectively. For the land-use layer, the five highest categories were farmland (74.71%), residential (14.25%), orchard (8.97%), industrial (0.38%) and quarry (0.31%). Road types and their percentages in terms of overall length included tracks (45.80%), residential (22.96%), unclassified (11.73%), tertiary (8.96%), secondary (4.28%) and primary (3.06%) (Figure 2). These variables were downloaded as shapefiles and converted into raster formats for the modelling.

To check cross-correlation among the variables, the SDMToolbox 0.9 (Brown et al. 2017) was used, with a Pearson correlation coefficient value of less than or equal to 0.7 set to determine the variables to include in the model (Hannah et al. 2019). The variance inflation factor (VIF) of less than 7.5 determined whether multi-collinearity existed in the model (Benitez et al. 2021; Dormann et al. 2013; ESRI 2019; González-Maya et al. 2016).

Species distribution modelling (SDM) predicts the suitability of an area based on the location of a species and selected relevant environmental variables (Araújo

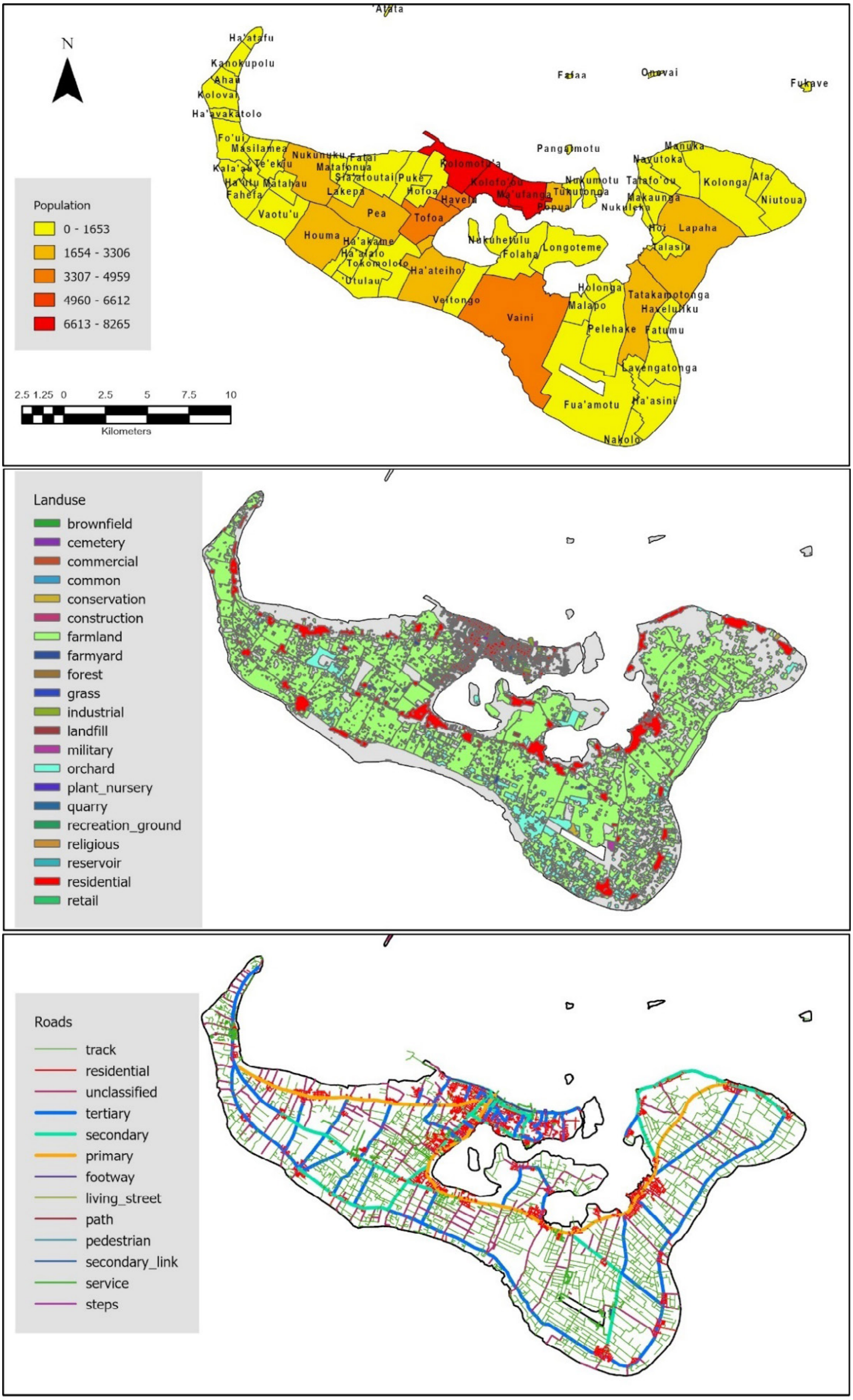

Figure 2. Variables used for modelling (top: population 2016; centre: land use; bottom: road types).

& Guisan 2006; Elith & Leathwick 2009; Sinclair et al. 2018; Villero et al. 2017; Zurell et al. 2020). SDM builds models and maps depicting areas where the species are most likely to be present, or areas of suitability for the species. The maps provide information on where to focus limited resources in mitigating impacts of the free-roaming dogs, not only on the area where the dogs were located, but in other areas with available environmental variables employed by the model. For many species, socioeconomic data was used as an environmental variable, particularly for areas where settlements or human influence has a significant effect on the distribution of the species (Gallardo & Aldridge 2013; Kapitza et al. 2021; Żmihorski et al. 2020). Model results include measures of variable importance and significance for fine-tuning and evaluating model performance to determine whether further iterations are required. Similar geostatistical studies on stray cat and dog distributions were conducted in different areas and projected to other geographical locations or time periods (Aguilar et al. 2015; Downes et al. 2011; MacLeod et al. 2020). Related work on the spatial distribution modelling of dogs focused on diseases or pathogens associated with their location (Hudson et al. 2018; Melyantono et al. 2021) and distribution in a certain city or region (Yen et al. 2019.

The SDM tools used were Maxent (Phillips et al. 2017; Phillips & Dudík 2008) and random forest (RF) (Breiman 2001) as implemented in ArcGIS Pro v2.6 (ESRI 2021). These machine learning approaches develop suitability models from presence data and environmental rasters. Maxent is a presence-only modelling tool resulting in maps depicting the suitability of the entire island to the species. The Area under the Curve (AUC) of the receiving operator characteristic (ROC) resulting from the Maxent model was used to evaluate model performance (Elith et al. 2011; Phillips & Dudík 2008). RF was likewise used to predict suitability, and had the additional capability of predicting the values of the other variables recorded during the surveys, including the categorical variables of sex, body condition, age group and the continuous variable population for 2016. Results of the RF model were assessed using F1 scores, and the Matthews correlation coefficient (MCC). Sensitivity and accuracy with MCC values provide robust checks of model performance (Chicco et al. 2021; Matthews 1975).

Results

Dog counts and location

Seven survey sessions resulted in 1152 dogs sighted on the roads travelled and areas covered. Data validation, correction and entry of additional data, including body condition, age group and sex, was conducted in ArcGIS Online from the data collected with Collector, with an example screenshot shown in Figure 3.

Spatial distribution of free-roaming dogs

The survey covered 338 roads, mostly within residential areas, with dogs recorded when sighted from the car on both sides of the road (Table 1). Except for the main road, Hihifo, which traverses towns from Ha'atafu to Nuku'alofa, the rest of the mainly residential roads are unpaved, with varying degrees of maintenance. Most are passable except during rain, when some may be flooded or too muddy to be accessed. In several cases, new settlements were under development and the roads present were not yet reflected or present in the database and map used. The highest densites in terms of dogs/hectares were in Ahau, Foui, Te'ekiu and Matahau, while Nukunuku and Ha'avakatolo showed the lowest density values. In terms of humans/dogs, Kolovai, Matahau, and Te'ekiu had the lowest figures, while Masilamea had the highest, followed by Nukunuku. For the dogs/km values, Kanokupolu and Te'ekiu had the highest values, while Kolovai and Nukunuku the lowest values (Table 1).

The dog locations recorded show high densities concentrated in the centres of Kolovai, Foui, Matahau and Te'ekiu, with a more spread-out or lower density at Nukunuku (Figure 3). Hotspot analysis with the Getis-Ord Gi* statistic shows significant hotspots in Kolovai, Foui and Te'ekiu while a coldspot is shown in Nukunuku. CLOA shows high–high clusters together with low–high outliers in Kolovai, Foui and Te'ekiu. Nukunuku's distribution is quite different from the other sites, with a combination of low–low clusters and high–low outliers. The rest of the sites do not show any significant hotspots/coldspots or clustering/outlier characteristics.

In terms of the recorded body scores, out of the 1152 dogs counted in the residential areas, 391 locations had recorded body score data using the standard 1–9 scoring system, and 201 dogs had their sex identified (54.7% females, 45.3% males). Distribution classification according to age showed that 83.6% were adults, 10.9% were juveniles and 5.3% were old dogs.

For all the dogs with body condition recorded,

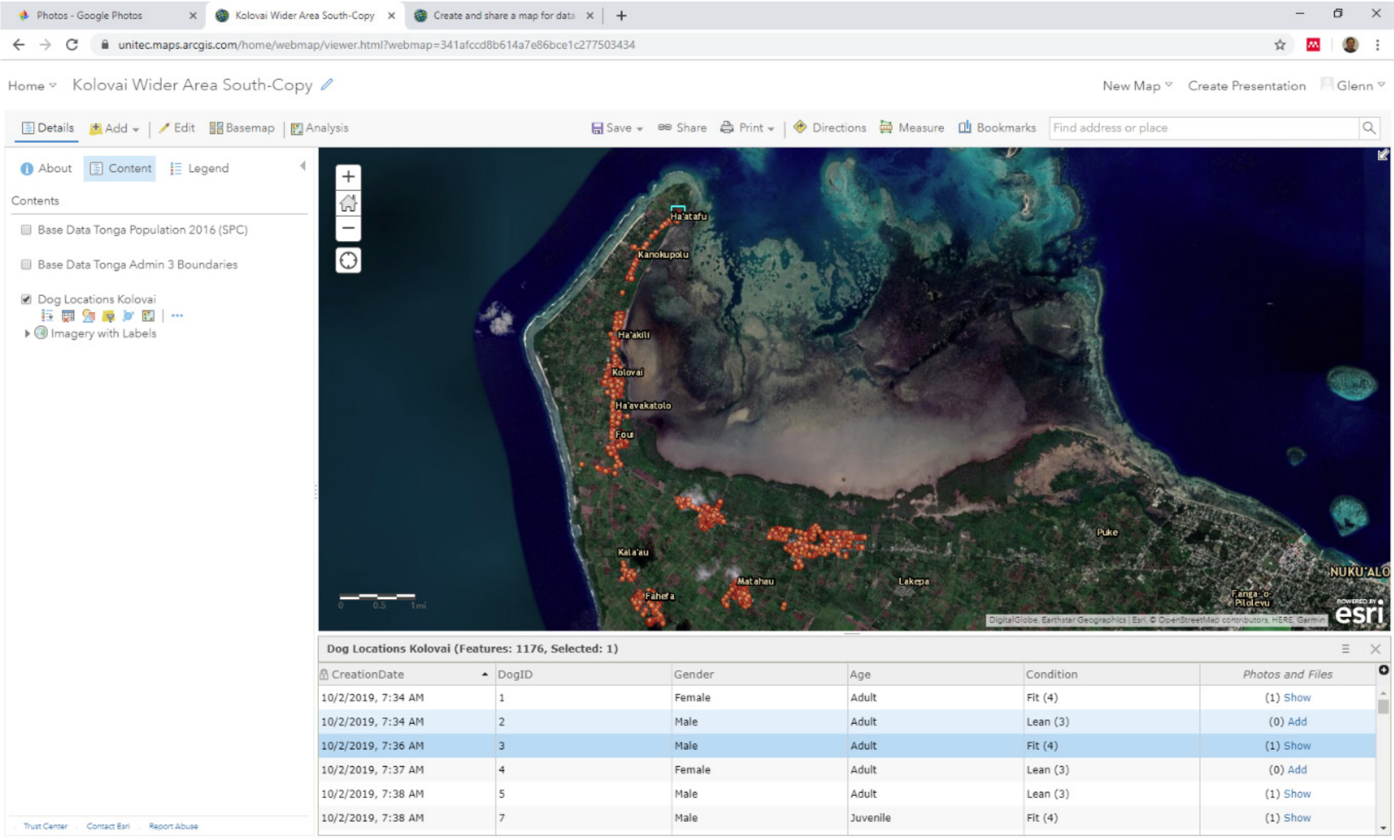

Figure 3. Results of data collection in ArcGIS Online.

Table 1. Dog count ratios were calculated for each town/village.

Town/ village	Dog count	Road length (km)	Area (ha)	Households	Population	Households/ dogs	Humans/ dogs	Dogs/ km	Dogs/ ha
Ahau	72	3.214	11.621	61	386	0.84	5.46	22.41	6.20
Fahefa	111	4.769	27.856	111	684	1.01	6.21	23.07	3.99
Foui	116	3.240	21.025	106	657	0.93	5.76	35.18	5.45
Ha'atafu	31	1.042	6.684	47	269	1.52	8.68	29.75	4.64
Ha'avakatolo	32	1.440	12.719	40	195	1.25	6.09	22.22	2.52
Kala'au	26	1.097	5.594	26	152	1.00	6.71	23.69	4.82
Kanokupolu	52	1.272	10.320	68	339	1.31	6.38	40.87	5.04
Kolovai	158	7.247	36.026	118	618	0.75	3.91	21.80	4.39
Masilamea	30	1.505	7.398	34	229	1.13	7.37	19.93	4.06
Matahau	122	3.579	20.672	105	570	0.85	4.72	34.37	5.95
Nukunuku	278	16.166	91.405	371	1989	1.33	7.23	17.20	3.04
Te'ekiu	124	3.333	20.537	104	578	0.83	4.52	37.81	6.14
Overall	1152	47.905	271.857	1191	6,666	1.03	5.78	24.05	4.24

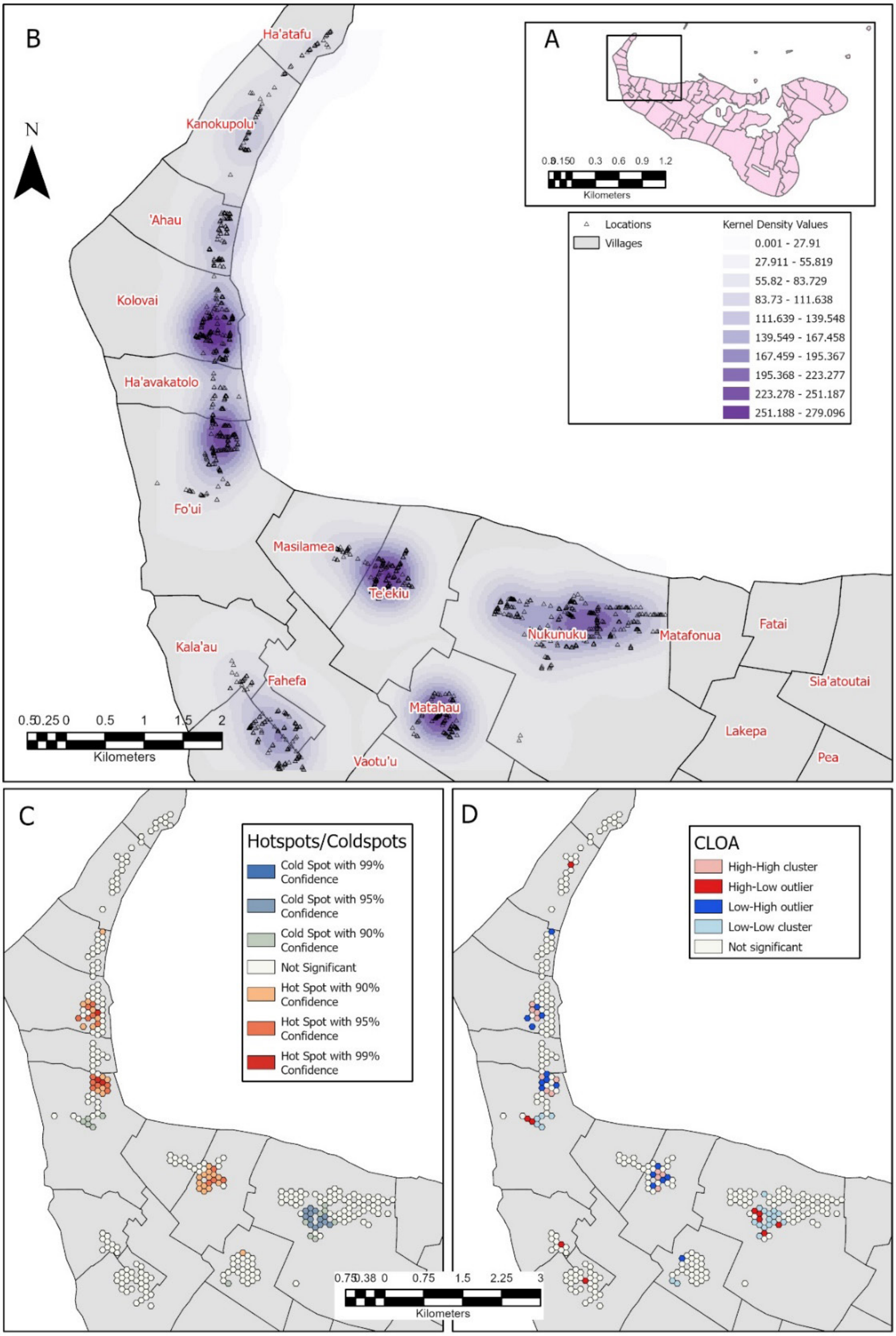

Figure 4. A. Data collected with the area inset showing its location in the island. B. Dog locations with kernel density raster. C. Hotspots and coldspots determined by the Getis Ord Gi* statistic. D. Cluster and outlier analysis map.

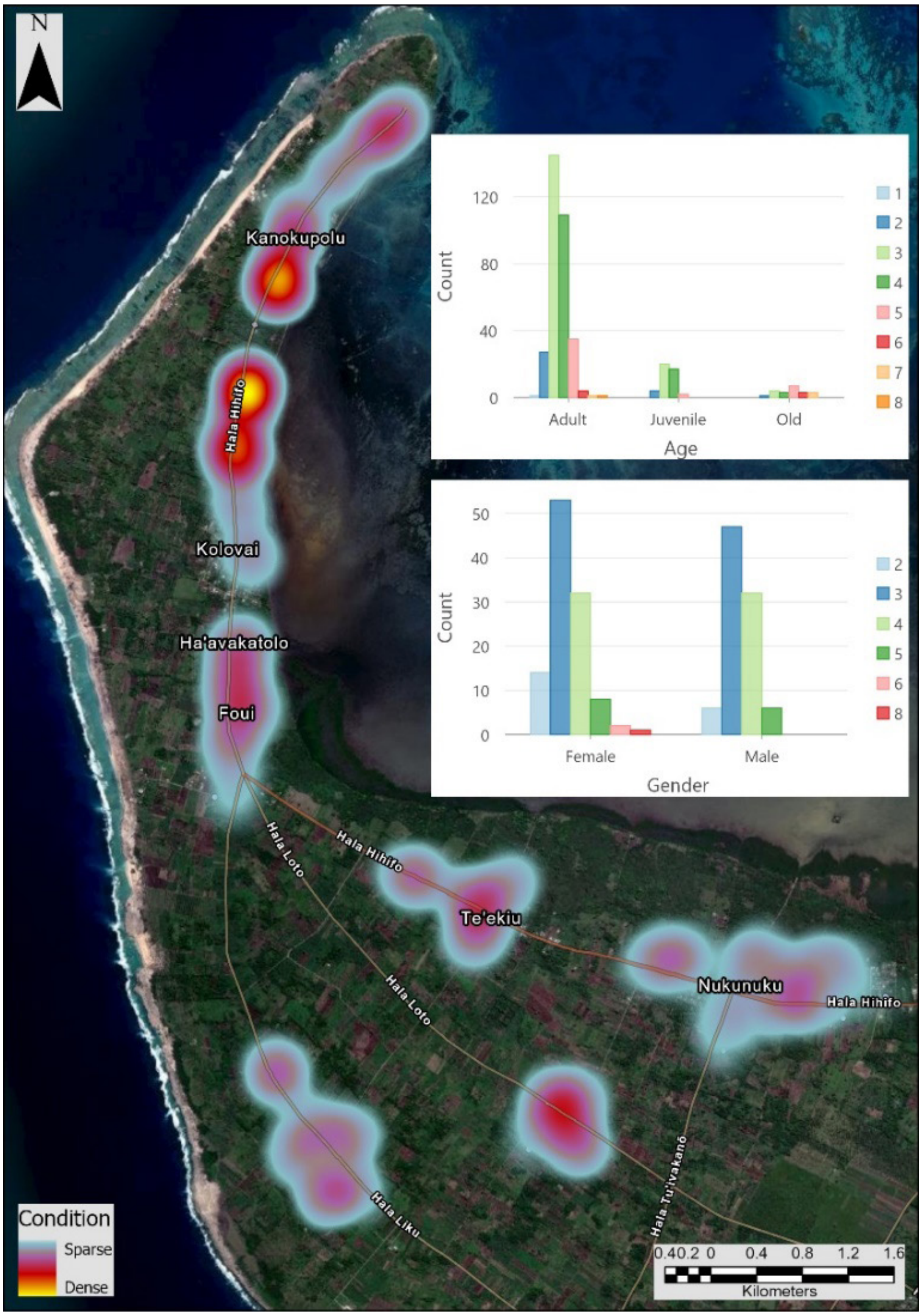

Figure 5. Hotspots of condition score values with charts of dog counts of scores (1–9) according to age and sex.

the mean body score was moderately low, at 3.58 (SE=0.049). A hotspot map of body condition, depicting areas where higher score values are concentrated (or more dense), shows that Ahau and Kanokopolu had higher body scores than the other sites (Figure 5). Female body scores (mean = 3.409; SE=-.092) and male body scores (mean = 3.422; SE = 0.075) both showed non-normal distribution with significant Shapiro-Wilk Test (P = 0.00000) for both categories. When compared using chi-squared values, there was no association of the body scores between sex types ($\chi^2 = 5.976$, df = 5, P = 0.30856). Looking at the different age groups, adults comprised 83.6% of the total, with a mean score of 3.53 (SE = 0.05), while juveniles had a mean score of 3.95 (SE=0.111), and old dogs had a mean score of 4.76 (SE = 0.3155). Both adults and juveniles showed non-normal distribution with Shapiro Wilks Test p-values of 0.00000, while the old dog category had a normal distribution with a p-value of 0.16377. When the categories were compared pairwise, there was no association of body scores between adults and juveniles ($\chi^2 = 16.094$, df = 20, P = 0.710752), between adults and old dogs ($\chi^2 = 11.090$, df = 15, p-value = 0.74616335), and between juveniles and old dogs ($\chi^2 = 6.591$, df = 6, P = 0.360263).

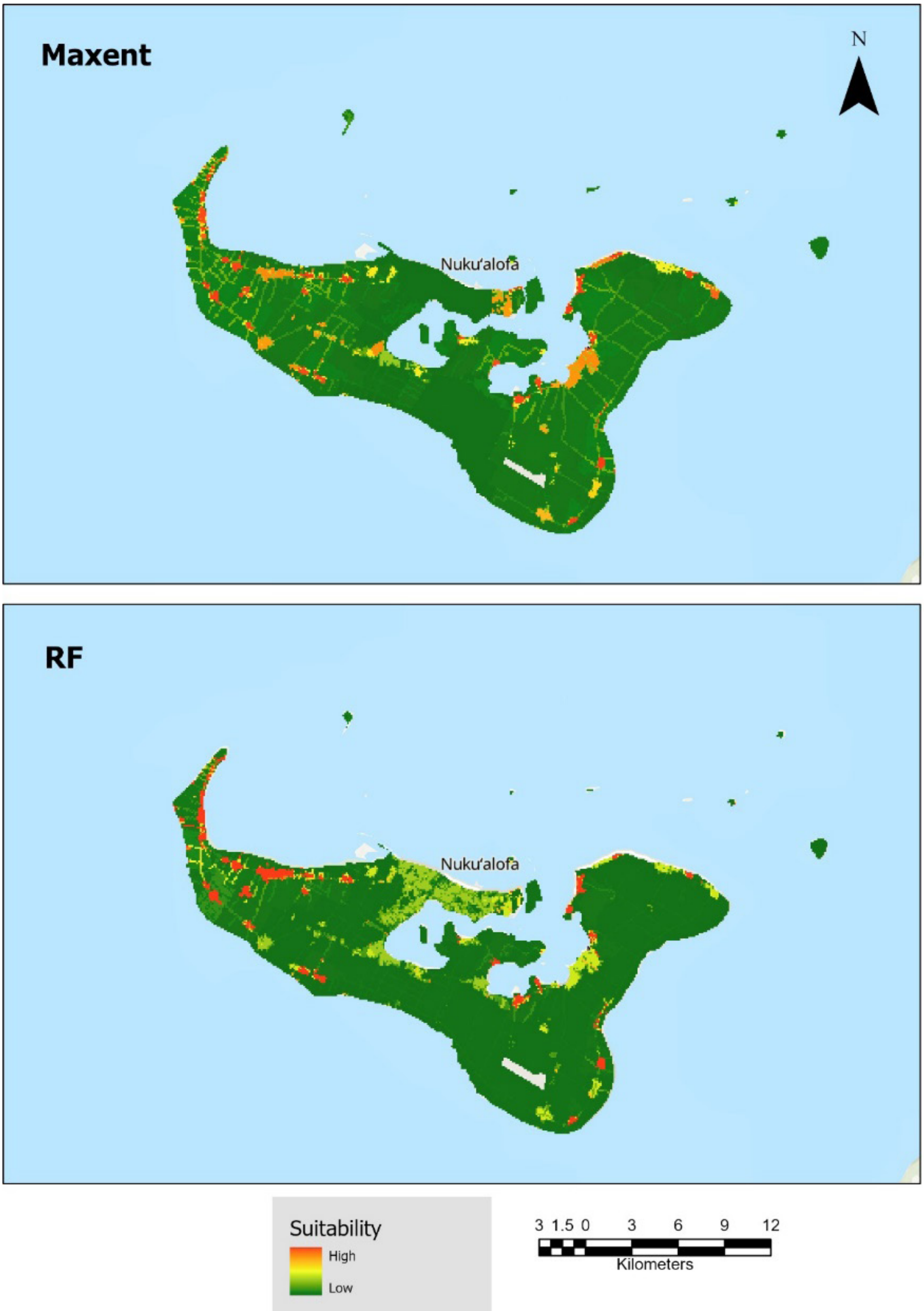

Figure 6. Results of Maxent and RF species distribution modelling.

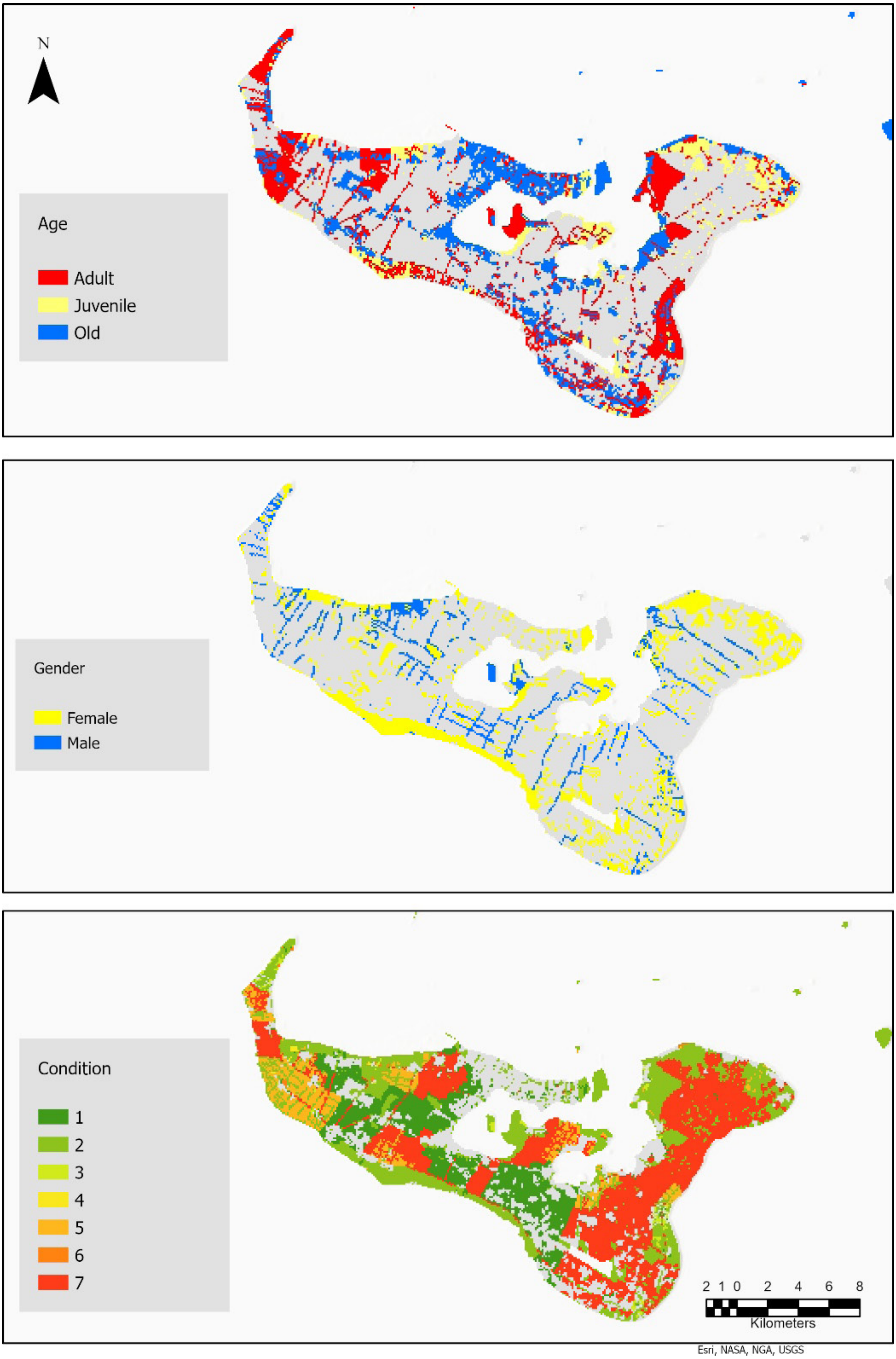

Figure 7. Maps of the variable prediction models using the RF algorithm showing age (top), sex (middle) and body condition (bottom) predicted raster values for Tongatapu island.

Species distribution modelling projection for the whole island

Cross-correlation checking of the variables showed acceptable results below the cut-off value of 0.7, with Pearson correlation coefficient values of 0.55, 0.59, and 0.45 for the pairing of roads vs population, land use vs population, and roads vs land use, respectively. VIF scores of the variable pairs were all less than 7.5 (2.22, 2.38 and 4.42 for similar pairings), meeting the criteria for assessing multi-collinearity.

Results of both Maxent and RF modelling show that, consistent with population density, the residential areas and roads have the highest suitability for the free-roaming dogs (Figure 6). Some slight differences between models in terms of the degree of suitability are evident, particularly in the urban areas of Nuku‘alofa, where the RF results show greater suitability than Maxent. The Maxent model reported a test AUC of 0.9584, an indication of model robustness. In terms of the first Maxent calculation of variable contribution, the estimated variable contribution for land use was 65.9%, population 21.6% and road type 12.5%. When the second estimate of variable contribution in terms of permutation importance was calculated, land use contributed 40.4%, population 48.4% and road type 11.2%. The included Maxent test of variable importance showed that land use had the most important information when evaluated by itself, while the population was shown to have the most information that was not present in the other variables. The RF model showed that population had a contribution of 49.4%, road type 29.5%, and land use 21.1%.

RF maps predicting values of age groups, sex and body condition over the entire island are shown in Figure 7, with prediction sensitivity and accuracy shown in Table 2.

Table 2. Assessment of RF models for predicting the values of variable categories.

Category	F1-Score	MCC	Sensitivity	Accuracy
Sex				
Female	0.40	0.33	0.45	0.87
Male	0.19	0.10	0.33	0.78
Body Score				
1	0.75	0.36	0.70	0.69
2	0.00	-0.02	0.00	0.94
3	0.19	0.23	0.67	0.86
4	0.31	0.25	0.24	0.85
5	0.00	-0.03	0.00	0.88
6	0.40	0.39	0.60	0.93
7	0.00	-0.01	0.00	0.97
8	0.00	-0.02	0.00	0.95
Age Group				
Adult	0.25	-0.02	0.21	0.59
Juvenile	0.14	0.09	0.17	0.90
Old	0.05	0.01	0.67	0.38

Discussion

The survey resulted in four different measures of dog density that can be compared with related work. In terms of humans per dog, the closest value is reported in Shimotsu, Japan, at 5.2 (Kato et al. 2003), quite close to these study results at 5.78. For dogs per area, the nearest is from the Philippines (Childs et al. 1998) at 4.68, slightly more than this study outcome of 4.24 (Table 3). There is a range of values from the different towns surveyed in terms of dogs/km, from 17.20 at Nukunuku to 40.87 at Kanoupolu. This is significantly higher than those found in other areas of the world (0.78–27.14), with only one zone in Kathmandu (Kato et al. 2003) reporting a comparable dogs/km value. When three parameters (humans/dogs, dogs/km, and dogs/ha) were tested with Kruskal-Wallis they were found to be independent ($P = 0.000002$). Factors that need to be considered further in the preceding comparison include temporal relevance, updated or accurate census data, modes of survey and differences in conditions between the study areas. Overall, the results of the dog measurement parameters that came from this study do not differ drastically from values of cited studies, and provide some measure of confidence in their future usage.

The actual total dog population in the area is probably greater than the results of the survey. This is presumed based on the observation of several female dogs at different lactating stages, indicating the presence of unsighted puppies. The count covered roads accessible by car; however, inaccessible tracks or trails between towns that lead to houses or structures in farms or remote areas indicate human habitation and the potential presence of dogs. Hence the total number of 1152 dogs counted during the survey is qualified as dogs sighted,

Table 3. A comparison of dog density values in several measures from different sources.

Location	Household / dogs	Humans / dogs	Dogs / hectare (area)	Dogs / km (road length)	Reference
Kolovai, Tonga (and surrounding towns)	1.03	5.78	4.24	24.05	This study
West Bengal, India			1.56–2.14		(Pal 2001)
Dhaka, Bangladesh		828	0.52		(Tenzin et al. 2015)
Kathmandu, Nepal		4.7	29.30		(Kato et al. 2003)
Shimotsui, Japan		5.2	2.25		
Bhutan (urban)		16.30			(Rinzin et al. 2016)
Bhutan (rural)		8.43			
Goa, India			2.77	8	(Meunier et al. 2019)
Valencia, Spain			1.27–13.04		(Font 1987)
Sorsogon, Philippines			4.68		(Childs et al. 1998)
Bosnia				0.78–9.07	(Hiby & Hiby 2017)
Panama City				1.07–5.62	
Puerto Rico				1.13–1.73	
San Jose, Costa Rica				1.50–4.09	
Kathmandu, Nepal				8.40–27.14	
Machakos, Kenya (Urban)			1.1		(Kitala et al. 2001)
(Rural)			0.06–0.21		

and more accurately represents the *minimum* number of dogs in the 12 towns surveyed. Since the roads covered and areas for each survey trip were different between towns, there was minimal probability that dogs were counted more than once. The results of the different parameters can be used to estimate the total number of the free-roaming dogs for the entire island in consideration of the requirements of similar future surveys. A more accurate estimate of the total number would greatly benefit from covering the entire island and regular monitoring after project implementation.

In conducting the survey, we found roads that did not exist on the map, with residential areas having been newly developed. These include houses recently built as part of the reconstruction effort following of the very destructive Cyclone Gita in 2018. The available downloaded road layers were modified for accuracy. In terms of using the humans/dogs measure, some changes in population data from the available 2016 census are expected, and the estimate may change when the next census is finalised.

The identification of hotspots, or areas where free-roaming dogs are numerous, provide information on where to focus measures and projects to assess biosecurity risks and plan projects that contribute to appropriate mitigation measures. This would cover high-population areas, where most dogs are found, and the vicinity of streets or roads where they roam regularly. Concentrating efforts on those locations would allow scarce resources to be employed effectively, and would also allow for community engagement in any project to be implemented.

The score on the leaner side of the ideal body scores (middle of the range at 4–5) indicates general conditions of undernourishment in the free-roaming dog population. This can be compared with other countries with contrasting conditions, such as those in Japan (Usui et al. 2016), and serves to indicate a need for projects or interventions in future. Statistical results of the relationships between body-condition score and the different categories of sex and age, which showed no significant differences, also indicate an inherent and widespread distribution of undernourished circumstances within the dog population.

Results of SDM in projecting the model to the entire island show that residential areas and roads are the most suitable places for these free-roaming dogs. When predictions of the variables are mapped in RF, old dogs are found in the urban Nukunuku area, while adults dominate in the other town centres and juveniles are concentrated on the eastern side of the island. A comparison of the model results shows a greater area suitability resulting from the RF model compared to Maxent, but with both algorithms showing consistent results on greater suitability in residential areas and presence in residential, tertiary, secondary and primary roads. In terms of sex, most males are predicted to be found on the roads, with females in the towns. For all variables, the wide range of accuracy values limits confidence in the prediction maps for the variable categories. The values for MCC are also quite low, with the highest score at +0.39, and, although accuracy values are high, MCC is shown to provide a better evaluation of model robustness (Chicco et al. 2021). Consideration for improvement may include the use of other modelling algorithms and increased survey coverage.

In terms of dog ownership, it was observed that some of the dogs belonged to several households or to none, with many being fed regularly by caretakers. This may have implications in planning projects that require dog capture and release, such as desexing or vaccination campaigns.

Conclusion

This work is the first of its kind to assess the nature of the dog population in the Kingdom of Tonga, and provide spatial information for improvement of the country's biosecurity system and animal welfare conditions. It provides information required to underpin the management of a ubiquitous and living feature of Tongan life involving a companion animal. The resulting measures of dogs counted versus households, human population and road length provide a means to estimate the dog population of the entire country, as well as a means of comparison with other areas of the world. The maps showing spatial patterns of distribution, including kernel density, hotspots and cluster and outlier maps, depict the concentration of dogs in relation to residential areas and roads. Maps of suitability resulting from SDM algorithms provide a measure of understanding on what areas have conditions that are most suitable for the dogs, therefore providing some guidance or focus of efforts on needed interventions and further investigations.

Author Contributions

Glenn Aguilar: Conceptualisation; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing – original draft, review and editing

Vanya de Felice: Software; data curation; formal analysis

Declaration of Competing Interest

The authors declare that they have no known competing interests or personal relationships that could have appeared to influence the work reported in this paper.

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