### UNIVERSIDADE DE LISBOA

# FACULDADE DE MEDICINA VETERINÁRIA





# HABITAT SELECTION BY FREE-ROAMING DOMESTIC DOGS IN INDONESIA: RURAL VERSUS URBAN SETTING

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#### ABSTRACT

# Habitat Selection by Free-Roaming Domestic Dogs in Indonesia – Rural versus Urban setting

Free-roaming domestic dogs (FRDD) greatly impact human public health, known for playing key roles in the transmission of numerous zoonotic diseases. Dogs are responsible for 99% of human rabies cases worldwide and FRDD are particularly important as the main source for rabies transmission to humans. Dog-mediated rabies lays a heavy economic, environmental and social burden on human communities, especially on those most vulnerable. Sixty percent of dog-mediated rabies human fatalities worldwide occur in Asia with Indonesia registering, per year, the fourth highest human rabies cases number of the continent. Improved rabies control programs can be attained through the study of dogs' movements within their available habitat. Yet, little is known about FRDD habitat requirements, particularly in Indonesia.

By analysing data on 109 FRDD in two distinct habitats, this project aimed to investigate resources meaningful to FRDD habitat selection in relation to anthropogenic and geographical characteristics in a rural and urban landscape. In particular, we assess whether FRDD select habitat resources differently according to the setting. The chosen methodology employed was spatial mixed effects logistic regression models which, by having as outcome the presence or absence of FRDD in the available habitat resources, provides insight on which resources dogs are more likely to be found and are therefore preferred.

Habitat selection by FRDD disclosed slightly different preferences according to the setting. The most sought-after resources in both study sites were the buildings and roads. Vegetation covered areas were positively associated with FRDD presence in the semi-urban, but not in the rural study site. Nevertheless, in the semi-urban area, FRDD preferred the beach over vegetation covered areas. Slope, in the rural setting, and sea, in the semi-urban area, were identified as being negatively associated with the presence of FRDD.

Although these results should not be incautiously extrapolated to other regions and should be interpreted keeping in mind the Indonesian context, these results are still novel and relevant to future rabies control actions.

Keywords: Free-roaming domestic dogs; Dog-mediated rabies; Habitat selection; GPS telemetry.

#### RESUMO

# Seleção de Habitat por Cães Domésticos Errantes na Indonésia – Contexto rural versus contexto urbano

Cães domésticos errantes têm um impacto nefasto na Saúde Pública Humana, sendo cruciais na transmissão de inúmeras doenças zoonóticas. Os cães são responsáveis por 99% dos casos de raiva humana registados a nível mundial e, os cães domésticos errantes são a causa principal de transmissão de raiva para o Homem. A raiva humana transmitida por cães impõe um pesado fardo económico, social e ambiental sobre as comunidades humanas. Sessenta porcento das mortes humanas por raiva transmitida por cães ocorre na Ásia e a Indonésia regista, por ano, o quarto número mais elevado de casos de raiva humana no continente. Programas mais adequados de controlo da raiva podem ser conseguidos através do estudo sobre como os cães se movem dentro do seu habitat. No entanto, pouco ou nada se sabe sobre os requisitos de habitat dos cães domésticos errantes, em particular na Indonésia.

Através da análise de 109 cães domésticos errantes em dois habitats (ambiente rural e ambiente urbano), este projeto investigou quais os recursos significativos na seleção de habitat por estes cães. Especificamente, avaliou se a seleção de habitat por estes cães difere entre o ambiente rural e urbano. A metodologia empregue neste estudo foram modelos mistos espaciais de regressão logística que, ao utilizarem a presença/ausência do cão num determinado recurso do habitat, permitem inferir sobre quais os recursos onde os cães mais provavelmente se encontram, sendo por isso preferidos pelos mesmos.

A seleção de habitat por cães domésticos errantes revelou diferenças ligeiras de acordo com o espaço geográfico em análise. O recurso mais procurado em ambos os espaços geográficos foram os edifícios e as estradas. Áreas cobertas por vegetação estão positivamente associadas com a presença de cães no ambiente urbano, mas não em ambiente rural. No entanto, na área urbana, os cães preferiram a praia a zonas cobertas por vegetação. O declive, na área rural, e o mar, na área urbana, estão negativamente associados com a presença de cães.

Apesar destes resultados terem de ser interpretados tendo em conta o contexto indonésio e não poderem ser extrapolados incautamente para outras zonas do mundo, são ainda relevantes para ações de controlo da raiva transmitida por cães.

Palavras-chave: Cães domésticos errantes; Raiva humana transmitida por cães; Seleção de habitat; GPS.

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# ACRONYMS AND ABBREVIATIONS

DD	Decimal Degree
DMS	Degree, Minute and Second
ECVPH	European College of Veterinary Public Health
FAO	Food and Agriculture Organization of the United Nations
FRDD	Free-Roaming Domestic Dogs
FSR	Fix Success Rate
FVE	Federation of Veterinarians of Europe
GCS	Geolocated Contact Sensors
GIS	Geospatial Information System
GLMM	Generalized Linear Mixed Models
GPS	Global Positioning System
HDOP	Horizontal Dilution of Precision
iOS	iPhone Operation Systems
KAP	Kupang State Agricultural Polytechnic
LE	Location Error
MCP	Minimum Convex Polygon
NEOH	European Network for EcoHealth and One Health
OHLAIC	One Health Latin America, Ibero and The Caribbean Coalition
OIE	Office International des Èpizooties (World Organisation for Animal Health)
PET	Post-Exposure Treatment
QGIS	Open Source Geographic Information System
RABV	Rabies Virus
REML	Restricted Maximum Likelihood
RSF	Resource Selection Funtions
SATs	Spatiotemporal visualization and Analytical Tools
STRM	Shuttle Radar Topography Mission
UAM	Unmanned Aerial Vehicles
UHF	Ultra High Frequency
UTM	Universal Transverse Mercator
UN	United Nations
USGS	United States Geological Survey
VPHI	Veterinary Public Health Institute of the University of Bern
WGS84	World Geodectic System 1984
WHO	World Health Organization

#### 1. INTERNSHIP REPORT

In order to grasp the full responsibilities and gain further competences in the Veterinary field, from the 2<sup>nd</sup> of September 2019 until the 15<sup>th</sup> of January 2020, an extra-curricular internship at the Veterinary Hospital of the Faculty of Veterinary Medicine of the University of Lisbon was undertaken. It amounted to a total of 542 hours, approximately, and consisted of medical rotations in the specialities of general medicine, internal medicine, oncology, dermatology, imageology, surgery and at the infectious disease unit. Under attentive supervision, I executed detailed examinations and after proper anamnesis discussed following procedures, its results and adequate therapeutic intervention, observed and practised surgical skills and, most importantly, applied theory learned into practise.

Simultaneously, in order to develop the required competences for this project a training period was carried out. Under the supervision of Dr. Telmo Pina Nunes at the Faculty of Veterinary Medicine of the University of Lisbon, this training period was essential to the development of know-how regarding R programming, data handling and use of Geographic Information Systems, specifically QGIS.

As part of this project, the curricular internship amounting to 1296 hours, took place at the Veterinary Public Health Institute (VPHI) in Bern, Switzerland, from January 20th until June 20th 2020. Due to the SARS-CoV2 pandemic the world was facing at that time, the internship had to be continued remotely from the 17<sup>th</sup> of March (starting date of the lockdown in Switzerland) until the end of the internship period. The internship had financial support from the University of Bern through a grant fund and was supervised by Salome Dürr and Charlotte Warembourg.

Being part of such a highly dynamic team while working at the VPHI granted me the opportunity to participate in numerous activities promoting new learning opportunities on topics on Veterinary Public Health. The journal club where scientific papers of the presenter's choosing were discussed, the weakly VPHI seminars promoted to learn more on subjects being researched among veterinarians, the residency lunches where a different subject relevant to the veterinary public health residency exam was presented and the seminars on "Creative Problem Solving in Health Sciences" were all incredible educational moments that I had the chance to participate in. Thriving to fulfil the project's objectives while exploring functions and the R programming language, managing scripts and mastering statistical analysis discernment to ensure adequate model development prompted significant efficiency in manipulating R software. Likewise, the increased contact with the QGIS software, due to the spatial nature of the project's data, provided me an in depth understanding of vector and raster data, georeferenced data projection and manipulation employing raster and vector layers while creating new data layers and applying geoprocessing tools for data set edition and exploration.

Throughout my internship in Bern, as the dataset analysis progressed and the spatial modelling methodology became the main focus of the project, consulting meetings with colleagues from different backgrounds and areas of expertise (namely colleagues from the VPHI Institute as well a colleague currently working at the University of Minnesota) were held providing valuable advice and recommendations. Moreover, this international experience enabled me to explore outside my comfort zone, breaking linguistic barriers while building new friendships and growing immensely.

During the curricular internship period, besides the development of the project, other ventures and interest were explored. The Native Scientist, a non-profit award-winning organization, that aims to promote learning science in Portuguese held its first workshop in Switzerland on the 26<sup>th</sup> of February 2020 in collaboration with the Instituto Camões – Coordination for Portuguese Education in Switzerland. The participation in such an event, aiming to educate 11 to 16 years old children on science through interactive and creative explanations, was extremely enriching as it stimulated innovative thinking and resourceful problem-solving. The event was broadcasted by the Portuguese television network Rádio e Televisão Portuguesa (RTP) (Native Scientist 2020).

Even though the pandemic obliged all of us to adapt to a new reality it also made available new online learning opportunities as well as boosting the need for updated scientific knowledge on the ever-evolving circumstances. The passionate and highly stimulating discussions among the VPHI team on the COVID-19 situation worldwide led me to present, on the 24<sup>th</sup> of March, a scientific paper on the subject at the (online) journal club and sparked my interest on learning more on how the world was facing this crisis. To learn more on the subject I participated in the London School of Hygiene & Tropical Medicine three-week, four weekly study hours, course on the consequences worldwide of the surge of the novel coronavirus. The weakly themes focused on the recognition of the emergence of the COVID-19, the following public health efforts put in place and the future prospects and lessons we should retain (Future Learn 2020).

The urge for insight on the role of the veterinary sector on the COVID-19 pandemic responses worldwide prompted the creation of an online questionnaire that was spread globally. This project is an international collaboration including colleagues from the Veterinary Public Health Institute (VPHI) of the University of Bern (Switzerland), the European Network for EcoHealth and One Health (NEOH), the One Health Latin America, Ibero and The Caribbean Coalition (OHLAIC), the Federation of Veterinarians of Europe (FVE), the University of Zürich (Switzerland), SAFOSO AG (Switzerland), the City University of Hong Kong (Hong Kong SAR), the University of Ilorin (Nigeria), University of Damanhour (Egypt), the Applied Research Center of Chile (Chile) and the University of Sydney (Australia). Working alongside worldwide experts on a project based of a One Health approach, between the human and

animal health sectors, not only gave me exceptional exposure to valuable and diversified points of view and expertise, but also broaden my understanding on the importance and varied contributions and career options within the veterinary epidemiology field. The project's preliminary results were showcased at the annual European College of Veterinary Public Health (ECVPH) conference and in a webinar organized by the World Veterinary Association.

This project culminated in the co-authorship of a scientific article named "Comparative study of free-roaming domestic dog management and roaming behavior across four countries: Chad, Guatemala, Indonesia and Uganda", that is soon to be published, and the submission of a scientific article of my authorship named "Habitat Selection by free-roaming domestic dogs in Indonesia: rural versus urban setting" describing this project's findings.

#### 2. BIBLIOGRAPHIC REVISION

#### 2.1. Free-Roaming Domestic Dogs

Animal and human lives have been intertwined since ancient times. Food, safety and shelter prompted a reciprocal collaboration and consequent coevolution between animals and humans, as animals are sources of labour, companionship and food. *Canis familiaris*, domestic dogs, are one of the most universally distributed species and among the earliest domesticated animals (Vilà et al. 1997). Regarded as partners and guardians in hunting and fishing, ancient dogs were cherished for their reliability, wit and sharp intuition (Walsh 2009). The close bond between humans and dogs can be traced back to over 15000 years ago (Vilà et al. 1997; Driscoll and Macdonald 2010). In society, dogs take on multifarious roles as working animals, pets and family companions or venerated figures, with distinct ranges of assimilation amongst human communities (Serpell 2017). Disparities in dog management and purpose can also be found amid a single dog population, creating miscellaneous sub-populations with individual behaviour and movement patterns (Hughes and Macdonald 2013).

Of the estimated more than 700 million domestic dogs distributed across the globe (Hughes and Macdonald 2013), an important yet unspecified portion of the population roam freely or lack supervision (Arluke and Atema 2017). As rectified in 2019 by the World Organization for Animal Health (OIE), free-roaming domestic dogs (FRDD) are those allowed to roam freely or under no direct supervision but who have an owner, and those not owned and free-roaming. FRDD populations are prevalent in developing countries, due to traditional values, fast urban expansion and deficient prioritization of dog population control efforts (Arluke and Atema 2017).

Asia is one of the biggest and most populated continents in the world. Cultural and religious differences across regions impact dog ownership practises across Asia (Wandeler et al. 1988; Ceballos et al. 2014). Community dogs, i.e. dogs cared for by residents of a certain area, are a common existence in most Asian countries, especially in rural and suburban settings (Ceballos et al. 2014). The Indonesian archipelago is the world's largest island country and is located in Southeast Asia. Flores Island, part of the Lesser Sunda islands, with residents exceeding 1.8 million and a dog population of more than 0.2 million (Wera et al. 2015) is divided into eight regencies. In Indonesia, dogs are primarily kept for protection purposes, but dog meat consumption is also practised as their meat is an alternative protein source (Wera et al. 2013).

Across the world, FRDD movements have been the subject of many studies. Movement of dogs in Brazil (Baquero et al. 2020;Melo et al. 2020), Mexico (Ruiz-Izaguirre et al. 2015;López-Pérez et al. 2020), Chile (Sepúlveda et al. 2015; Garde et al. 2016; Pérez et al. 2018; Raynor et al. 2020), India (Tiwari et al. 2018), Tibet (Vaniscotte et al. 2011), Kygryztan (Van Kesteren et al. 2013) and Australia (Dürr and Ward 2014; Sparkes et al. 2014; Van Bommel and Johnson 2014; Bombara, Dürr, Gongora et al. 2017; Hudson et al. 2017; Molloy et al. 2017; Brookes et al. 2019; Hudson et al. 2019; Brookes et al. 2020) have been previously examined. Investigation on roaming predictors is of substantial importance as it can be of use for the design of adapted diseases control actions.

#### 2.2. FRDD as Public Health hazards

The public health implications of FRDD and feral dogs (those who were once domesticated but have since returned to a wild state and no longer rely on humans) (OIE 2019), have been thoroughly studied (Beck 1973; Rubin and Beck 1982; Daniels and Bekoff 1989; Boitani and Ciucci 1995; Slater 2001; Butcher and De Keuster 2012; Macdonald and Carr 2017). In many parts of the world, roaming dogs are a known and recognized presence by the human populations (Dalla Villa et al. 2010; Gompper 2014). These dogs are hazards to ecosystems and human communities (Vanak and Gompper 2010; Morters et al. 2014) as they, acting alone or in packs, bite, bark and attack livestock, wildlife and humans (Hagstad et al. 1987; Young et al. 2011; Ritchie et al. 2014). These dogs are also known to scavenge for food in dustbins scattering waste, they are a source of flea infestations, cause road accidents resulting in harm to themselves and humans, are a source of environmental pollution through their excrements (Rahaman 2017) and their sole presence is, for some, an identified source of nuisance and anxiety (Beck 1975).

Such freedom of movements associated with the close proximity to human communities greatly impacts human health, as it is crucial to zoonotic diseases transmission (Kachani and Health 2014; Devleesschauwer et al. 2016). Feral and FRDD can be equally responsible for the transmission of various zoonotic diseases (Butcher and De Keuster 2012). Dog-human contact, through indirect contact (i.e. dogs' secretions and excretions) or direct contact (i.e. dogs' bites), is known to be responsible for the transmission of at least 65 zoonotic diseases (Feldmann and Carding 1973). Dogs are responsible for 99% of human rabies cases worldwide (WHO 2018) and FRDD are particularly important as the main source for rabies transmission to humans (Hampson et al. 2015).

Caused by a lyssavirus infection, rabies is an acute progressive encephalitis (Fooks et al. 2014) with a most likely fatal outcome (WHO 2018). In over 100 countries and territories but, essentially in developing countries, dog-mediated rabies is to this day a widespread reality as rabies is still endemic in Asia, Africa, Central Asia, Middle East, Latin America and the

Caribbean (WHO 2018). An underestimated global death toll for rabies places deaths at 59000 fatalities per year (Hemachudha et al. 2013) with deaths overwhelmingly associated to rural, impoverished communities in Asia and Africa, where suitable access to post-exposure prophylaxis is difficult and a high incidence of dog-mediated human rabies exists (WHO 2018).

Rabies virus (RABV) cannot penetrate undamaged skin but gains access through direct contact with mucosa or wounds (WHO 2018). Depending on the proximity to the central nervous system from the virus entry point, viral load and the wound site motor endplates density, the incubation period for RABV varies. In humans it is usually 2-3 months, being able to fluctuate from 5 days up to several years, and rarely surpassing one year (Hemachudha et al. 2002; Hemachudha et al. 2013). Furious and paralytic are the two main manifestations of human rabies (Dumrongphol et al. 1996; Mitrabhakdi et al. 2005; Thanomsridetchai et al. 2011) with neuropathic pain at bite location being the first specific symptom (WHO 2018). Other possible signs of clinical rabies are paresthesia, aerophobia, dysphagia, hydrophobia, vomiting or nausea and localized weakness. Generally, if no intensive treatment is instated, 7-10 days after the onset of symptoms, furious or paralytic rabies will develop towards coma and death by respiratory failure or cardiac arrest (Petersen and Rupprecht 2011).

Besides rabies, other studies have investigated zoonotic diseases where the dog plays a crucial role such as Rocky Mountain spotted fever (López-Pérez et al. 2020), echinococcosis (Vaniscotte et al. 2011; Van Kesteren et al. 2013) and Leishmaniosis (Belo et al. 2013; Maia and Cardoso 2015).

#### 2.3. Rabies Burden

Dog-mediated rabies lays a heavy economic, environmental and social burden on human communities, especially on those most vulnerable and defenceless.

With a global economic loss estimated at 8.6 billion US dollars, dog-mediated rabies human fatalities are mostly recorded in Asia (59.6%) amounting to 35172 deaths (Hampson et al. 2015). Being a neglected disease, data is poor in regions with no control or surveillance systems put in place. Misdiagnosis, lacking surveillance and coordination efforts and underreporting are some of the causes leading to the miscalculation of dog-mediated rabies impact (Hampson et al. 2015). Impoverished rural areas in Asia are exemplary as regions where the burden is underestimated, with rabies impact being misconstrued due to underreporting (WHO 2018) as many patients choose not to seek medical treatment, instead opting for alternative treatments due to cultural beliefs (Ceballos et al. 2014). Difficulty

accessing post-exposure treatment (PET) may also hinder people from seeking medical care (Wera et al. 2013).

Forty-five percent of dog-mediated rabies cases worldwide occur in South East Asia (WHO 2012). After India, Bangladesh and Myanmar, Indonesia registers, per year, the fourth highest human rabies case number of the continent (WHO 2012). Flores Island, located in the eastern part of Indonesia, rabies introduction dates back to 1997 with the importation of dogs from Buton Island by a fisherman (Windiyaningshid et al. 2004). Afterwards, rabies spread throughout the island despite the implementation of control measures entailing massive killing of dogs from in and around affected villages (Windiyaningshid et al. 2004).

On Flores Island, for data on rabies patients to be registered and officially accounted for, patients must have visited hospitals or public health centres while manifesting clinical symptomatology. Consequently, data varies greatly depending on the reporting source. Officially, the Public Health Department registered 92 human rabies cases until 2012 whilst the Husbandry Department of East Nusa Tenggara Province registered 228 cases (Wera et al. 2015). Since 2000, the government of Flores Island has implemented annual dog vaccination campaigns with overall coverage of less than 50% and employing mostly short-lasting immunity vaccines, with immunity limits of one year (Wera et al 2013; Wera et al. 2015). The government also expends 0.39 million US dollars annually to ensure populations free access to PET (Wera et al. 2013). Nevertheless, rabies control efforts have not been successful (Wera et al. 2017). Wera et al. (2017) findings revealed that Flores Island campaigns would benefit from increasing the coverage to 70% and using long-lasting immunity vaccines (immunity of 156 weeks, almost 3 years) as it reduces number of cases and is more cost-efficient.

Even though Indonesia is determined to make the country canine rabies-free by 2020, through a national plan that dictates rabies control as a government priority (GARC 2013), the disease remains endemic in 26 provinces with only eight being rabies-free (Riau, Bangka Belitung, DKI Jakarta, Central Java, DI Yogyakarta, East Java, Papua and West Papua). Just in 2020, up until August, 24745 bites have already been communicated in Indonesia whilst in 2019, 100826 cases of people being bitten by rabid animals were reported (WHO 2020).

#### 2.4. Obstacles to rabies control and elimination

Eliminating dog-mediated rabies by 2030 is the challenging shared goal set by WHO, OIE and FAO (WHO 2015).

The Sustainable Development Goals have reaffirmed the ambition of ensuring access to affordable and adequate health care for all, propelling neglected tropical diseases, including

rabies, to global health and development programs (UN 2020). Although this fatal disease can be eliminated efficiently in a limited time span, and health leaders are more than ever aware of such fact, rabies efforts continue to be overlooked, slowing down progress (Shwiff et al. 2013; WHO 2018). Human health is the most impacted by dog-mediated rabies, however to achieve disease control, efforts must be placed on the reservoir species, which are the dogs.

Neglect is perpetuated in the absence of reliable data and estimates (Taylor and Nel 2015), boosting the demand for precise surveillance data to avoid underestimations on human rabies fatalities, which can amount to 100-fold (Cleaveland et al. 2002; Taylor et al. 2017). By educating communities on rabies it is possible to raise populations' consciousness and catalyze political action. Public awareness and proactivity are therefore determinant to impel nationwide action (Fahrion et al. 2017). The gap between organizational efforts at an international level and its practice at a national/local level has proven hard to overcome. Elimination program's planning require a One Health approach, which has been achieved at an international level. However, exercising such intersectoral collaboration at a national/local scale remains difficult (Fahrion et al. 2017). Therefore, lack of public engagement and political resolve, need to create intersectional transparent collaborative rabies elimination plans, and difficulties in accessing supplies have been named some of the obstacles to rabies elimination and control.

Another factor that makes dog-mediated rabies elimination challenging is contact between wildlife canid populations and domestic dogs (Bombara, Dürr, Gongora et al. 2017). Contact between these two populations heightens the possibility of rabies transmission and endemicity (Sparkes et al. 2015; Sparkes et al. 2016). Red foxes and wild dogs are recognized as relevant rabies reservoirs, and rabies elimination in these wild populations is taxing (Sparkes et al. 2015; Bedeković et al. 2019).

Regional and national disease programs in Asia aim to retain rabies-free areas whilst controlling and eliminating rabies from other regions through cooperative and strategic efforts (Miranda and Miranda 2020). Creation and safeguard of rabies-free zones as well as human rabies deterrence through mass dog vaccination, surveillance and epidemiology, enhancing diagnostic capacity, raising public awareness, risk communication, dog population management, enforcing governmental policies and pre and postexposure prophylaxis are efforts put in place by such programs (Miranda and Miranda 2020).

Mass culling of dogs and mass vaccination are two alternatives in rabies control strategies. However, mass culling is not a humane solution and is therefore considered as unacceptable. In addition, it does not bring benefits in the long run and may even be detrimental to vaccination campaigns, especially those aiming at free-roaming dogs (WHO 2018). Preventing human deaths through eradication or control of canine rabies remains the most adequate solution (Ceballos et al. 2014), and mass vaccination of dogs has been proven

as the crucial factor needed to eliminate rabies, as dogs are reservoirs and vectors of the disease (Gibson et al. 2020).

Mass vaccination is an economical, biological and technical viable solution for canine rabies control (Bogel and Meslin 1990; Lembo et al. 2010; Fitzpatrick et al. 2014; Wera et al. 2017; Gibson et al. 2020). Elimination is achievable when at least 70% of vaccination coverage in dogs is accomplished (Coleman and Dye 1996; Cleaveland et al. 2003). The campaigns success depends mainly on the achieved coverage, which in turn is dependent on dog populations turnover rate, and on the vaccines' induced immunity interval in connection with the campaign frequency (Wera et al. 2017). Difficulties regarding vaccination control programs fall under the category of technical obstacles. Other technical obstacles include the study and implementation of suitable dog vaccination campaigns, guarantee of adequate and timely vaccine supply and distribution, and addressing affordable diagnostic options (Fahrion et al. 2017).

Rabies is dependent on populations' lifestyle and behavior towards dogs. Understanding dog ecology and how dogs are kept in diverse sociocultural local backgrounds is necessary to achieve control. Expertise on region specific dog population turnover, dogwildlife contact rates and dog keeping practices enable more adapted and accurate vaccination coverage recommendations (Fahrion et al. 2017). This way, appropriate funding (Dürr et al. 2009), resource distribution (Dürr et al. 2008; Sparkes et al. 2014) and campaign frequency (Bilinski et al. 2016) are assured, and identification and targeting of relevant risk areas and sub-populations of dogs for the vaccination campaign can be carried out (Fahrion et al. 2017).

Intrinsic geographic, sociocultural and dog population dynamics as well as limited resources hinders attempts at achieving high vaccination coverage in Flores Island (Wera et al. 2017). The topography in the island means most villages are in remote areas with difficult access (Wera et al. 2015) and the dog population has high turnover rates (Wera et al. 2017). Together with the lack of veterinary infrastructures (Bingham 2001) and inadequate supply of resources, achieving 70% vaccination coverage in Flores Island is arduous (Wera et al. 2017).

Improved control programs can be attained through the study of how dogs move within their available habitat (Raynor et al. 2020). Studies on roaming predictors are distinctly consequential. In regions with limited resources, such studies are pivotal as they allow targeting of relevant sub-populations of dogs for vaccination. For example, dogs with larger home ranges or those who roam further away from their household as they might came into contact with more dogs or could spread the disease further (Hudson et al. 2019; Maher et al. 2019).

#### 2.5. Habitat Selection

Containing a combination of biotic (living components of ecological communities) and abiotic (non-living components of the ecosystem) features that impact the presence or not of an organism, habitat is a theoretical concept that refers to where an organism lives (Montgomery and Rollof 2013). The selection of biotic and abiotic available components for an organism's life purposes attainment, such as mating or raising offspring, is defined as habitat selection. Choice is the basic concept behind habitat selection, since it entails preference of a distinct location by an organism out of the available ones (Montgomery and Rollof 2013).

This concept first derived from animal observation by naturalists, being Aristotle one of the first recorded naturalist in history (Morrison et al. 2006). Naturalists in the 19<sup>th</sup> century found that important evolutionary outcomes could be attributed to the habitat (Darwin 1859). Methodologies for research conducted on habitat selection experienced a significant development in the 20<sup>th</sup> century, sharing the common goal of identifying chosen animal locations and study relevant features associated with such sites. Recording of habitat use and understanding why such habitat was elected by a species (using habitat used versus habitat available inferences) are generally the two steps undertaken for habitat selection examination (Montgomery and Rollof 2013).

Information on a habitat's relevant environmental features (resources), associated with information on a species of interest, and data on locations are needed to quantify a habitatspecies relationship (Brost et al. 2015). This has prompted Global Positioning System (GPS) telemetry usage in these studies, as it can collect information on an animal's location across time and space (Manly et al. 2002; Montgomery and Rollof 2013), with the aim of relating an animals spatial position to the habitat's environmental descriptive variables (Montgomery and Rollof 2013). It should be noted that GPS technology has been found to, in some cases, impact the behavior and survivorship of the organisms in which it has been deployed, given its weight and the resistance created by these units (Marcström et al. 1989; Swenson et al. 1999; Barron et al. 2010). Howbeit, in recent years, GPS technology has become increasingly lightweight and units can now be small enough to be carried by small mammals (McMahon et al. 2017) and birds (Bridge et al. 2011). Any GPS must obtain intelligence from a minimum of three satellites to identify a location. We can categorize two errors associated to GPS telemetry: location error (LE) and fix success rate (FSR) (Frair et al. 2004). Both error types are dependent on environmental (Moen et al. 1996; D'Eon et al. 2002; Recio et al. 2011), behavioural (Dussault et al. 2001; D'Eon and Delpart 2005) and technological elements (Gau et al. 2004). FSR represents the GPS inability to collect sufficient information leading to missing data, whereas the difference between the real and the estimated location of a targeted spot is defined by LE (Frair et al. 2004).

The addition of errors into data frequently occurs during data collection. With georeferenced data, the urge to prematurely evaluate the collected input can overshadow the need for basic data assessment and inspection (Cobos et al. 2018). A trustworthy database is fundamental for posterior accurate habitat selection inferences. Thus, knowledge of species GPS bias (according to the species carrying the GPS unit, different levels of interference with GPS caption should be expected) and choice of suitable methodology to tackle it is essential, to avoid habitat misclassification and erroneous trajectory interpretation (Cochrane et al.2019).

Unrelated to the kind of error that needs to be settled, data cleaning to produce appropriate data for subsequent analysis can be divided into two steps: error identification and error solving (Ilyas and Chu 2019). Since no technology is without its glitches, data cleaning is essential to data quality improvement. Failure to determine the exact position and some associated geographical error are examples of GPS shortcomings (Cochrane et al. 2019), which can lead to flawed deductions on species-habitat interrelation (Brost et.al 2015). It should nevertheless be noted that selection of unsuitable cleaning methodology will have a detrimental effect, implicating loss of precious material.

Apart from GPS telemetry other methodologies exist, such as close observation of animals. However, when compared to GPS telemetry which collects data remotely or through portable units, close observation of animals impacts animals' behavior through the presence of the scientist (Strum and Fedigan 2000). GPS telemetry enables the examination of an animal's movements human interference-free and non-intrusively (Montgomery and Rollof 2013; Cochrane et al. 2019), being an appropriate technique for habitat selection studies data collection.

Quantifying the utilization of a resource over its availability in the habitat is the aim of a habitat selection analysis (Manly et al. 2002; Brost et al. 2015). Mapping animal positions and the habitat's environmental resources is a mandatory step needed for posterior analysis. Several analytic techniques have been developed for the purpose to define habitat selection, with statistical models being its foundation for over 30 years (Montgomery and Rollof 2013). Statistical models based on animal presence and animal positions in relation to environmental covariates is a well-established technique (Montgomery and Rollof 2013). Resource Selection Functions (RSF) are a particular type of regression models often implemented for habitat selection studies. They model resource use in proportion to its availability (Boyce and McDonald 1999; Manly et al. 2002). Generalized linear models (GLMs) (McCullagh and Nelder 1989) or more contemporary, but also more complex, mixed effects models (GLMMs) (Pinheiro and Bates 2000; Wood 2006) are statistical models that can be used as RSF. Regressing predictor variables (generally relevant environmental habitat resources) against a continuous or binary (presence/absence of an organism) outcome is done employing linear and logistic regression models, respectively. Both are adequate approaches for habitat selection research.

Presence is the identification of an organism in a location, while absence can be determined through stratified or random sampling design (Keating and Cherry 2004). In random sampling design, absence is randomly designated to a set of locations whilst, in a stratified design, absence is conditional to certain pre-agreed conditions (Keating and Cherry 2004). The selection of the most appropriate sampling design is subordinate to the study-species, research question and the study site environmental variables (Montgomery and Rollof 2013).

Anthropogenic modifications to a natural environment constitute a serious challenge to wildlife conservation. Habitat fragmentation and its impacts on habitat selection by wildlife are a recurrent topic in scientific literature (Koprowski 2005; Cushman 2006; Arroyo-Rodriguez and Dias 2010; Fisher and Davis 2010; Gillies and Clair 2010; Spinozzi et al. 2012; Dias et al. 2019). However, habitat selection by FRDD remains a relatively unexplored field. Studies on habitat selection by free-roaming dogs have been undertaken in Bulgaria (Doykin et al. 2016), Australia (Meek 1999) and Chile (Sepúlveda et al. 2015). These studies highlighted a need for bigger and more accurate dog sample sizes. Besides free-roaming dogs, literature on habitat selection can also be found on African wild dogs in South Africa (Whittington-Jones et al. 2014), Australia (Robley et al. 2010) and Kenya (O'Neill et al. 2020). Nevertheless, to the best of my knowledge, studies on FRDD habitat selection are inexistent, moreover in contrasting settings (rural versus urban).

Disregarding data spatial dependency can inhibit accurate perception of disease dynamics (Albery et al. 2020), as inferences are weakened when space in unaccounted for in a study analysis (Tobler 1970; Pullan et al. 2012; Pawley and McArdle 2018). Understanding of FRDD ecology and how these dogs navigate their habitat is valuable for better and more adequate rabies control and elimination campaigns, as aforementioned. Through spatial data inclusion onto disease investigation, disease ecology analyses becomes more reliable and replicable (Albery et al. 2020). As Hahn et al. (2014) documented in flying foxes in relation with the Nipah virus, determining FRDD habitat preferences could help explain the spatial distribution of human rabies cases and overall aid in understanding the risk of zoonotic disease transmission. By fitting habitat selection models, we may be able to pinpoint previously unheard of relevant environmental resources and highlight regions, where a FRDD suitable habitat exists, but no reported human rabies cases. Additionally, identified preferred resources may be exceptional locations for disease transmission as the presence in such habitat can promote FRDD mingling and contacts, increasing the risk of intra- and inter-specific transmission of canine diseases, including rabies (Sorensen 2014).

#### 2.6. Project contextualization

Dog-mediated rabies mainly impacts the most vulnerable populations, emphasizing deep social gaps between developed and developing countries. To achieve control and elimination by 2030, a global effort is needed. Scientific work on further understanding FRDD is essential to the attainment of the 2030 rabies elimination goal. The main project, and consequently this thesis project, were developed with that purpose in mind.

This project developed under the guidance of Dr. Salome Dürr and Charlotte Warembourg, at the Veterinary Public Health Institute (VPHI) serves the purpose of feeding relevant information onto a larger project on domestic dog ecology in Chad, Uganda, Guatemala and Indonesia, Charlotte Warembourg's doctoral thesis. The main project's overall objectives were to provide new insights on FRDD ecology and its implications for population and disease control intervention and, in particular, improve FRDD research methods and comparative studies of its populations in four developing countries.

To overcome the issues involving FRDD and ensure favorable dog-human relationship, FRDD behavior and its implications on dog population and disease control interventions were studied and included in the main project: FRDD population size estimation methods, dog's roaming behavior, contact networks amongst dogs, demography and management and serological surveys. All these investigation topics bring valuable insights on FRDD ecology and how it impacts control measures. Besides estimating FRDD dog population size using Unmanned Aerial Vehicles (UAV) (Warembourg, Berger-González et al. 2020), comparing FRDD demography, management and roaming behavior across four developing countries (Warembourg, Wera et al. 2020) and examining how FRDD activity patterns can provide information about pet dogs animal welfare (Griss et al, in preparation), it also evaluated factors associated with immunity loss against rabies by dogs in Flores Island (Wera et al, in preparation).

The main project research span is consequent to the lack of knowledge on predictors for dogs roaming behavior, highly connected dogs, and likelihood of contact between two dogs in different settings which makes difficult the use of these predictors for targeted vaccination purposes. Population estimation models need to include data on dog ecology, such as habitat preferences data, to provide reliable population size estimates. Similarly, data on dog roaming patterns and its consistency are needed to inform studies based on the utilization of GPS technology. It highlights the need for knowledge on dog behavior to design appropriate methodological tools since vaccination campaigns need to consider region/country specific factors.

To contribute to the main project objective's, this project aimed to feed information for better disease control practices by studying FRDD population habitat selection in one of the

four countries in which the study was performed, Indonesia. By understanding the resources dogs spent time in the most we can inform on possible rabies spread locations. Additionally, it can allow the target of sought-after resources to ensure better rabies vaccination coverage. This study can also improve vaccination coverage in regard to oral vaccination by pinpointing resources where dogs are most probably in.

#### 3. OBJECTIVES

#### 3.1. Project Data

FRDD play a crucial part in rabies transmission, most significant in developing countries, thus, impacting human population's health and wellbeing.

By analysing data on 109 FRDD in two distinct habitats, this project aimed to investigate resources meaningful to FRDD habitat selection in relation to anthropogenic and geographical characteristics in a rural and urban landscape. In particular, the project assesses whether FRDD select habitats differently according to the setting.

The chosen methodology employed was spatial mixed effects logistic regression models, which, by having the outcome as the presence or absence of FRDD in the available habitat resources, provides insight on which resources dogs spent most of their time in (taking the number of GPS locations as a proxy of time spent) and are therefore preferred. This work will potentially demonstrate that habitat selection differs in urban and rural areas revealing which variables (resources) are significant to FRDD presence.

#### 3.2. GCS accuracy experiment

The GPS device used in this study has been developed recently. So far, little is known on the accuracy of the GPS fixes registered by those devices.

To investigate the GPS positioning accuracy and reliability of our project's deployed GCS devices, an experiment was conducted in settings with different vegetation complexity and density of buildings. The GPS experimental data was evaluated before and after applying the data cleaning process designed and applied to the project's dataset.

This experiment aimed to, not only objectively discern the real precision of the GPS data collected, and therefore the soundness of our project inferences, but also to validate the developed cleaning process.

#### 4. MATERIALS AND METHODS

#### 4.1. Data Collection

#### 4.1.1. Project Data

#### 4.1.1.1. Study Areas

Chosen study sites were located in Habi and Pogon, in the Sikka regency, at the eastern side of Flores Island, Indonesia (Figure 1). Sikka regency has a high incidence of human rabies (Wera et. al 2015) and dogs in this region are known to rarely be restricted and often roam freely (Wera et al. 2013). In this regency, human residents surpass 317,000 and there are over 37,000 dogs (Wera et. al 2015). Agriculture is the main financial activity in this regency (Wera et. al 2015).

The data field collection lasted from 13<sup>th</sup> of July until the 6<sup>th</sup> of September 2018 and was taken upon by collaborating teams from the Animal Husbandry and Health Department of Sikka Regency in Maumere, the Kupang State Agricultural Polytechnic (KAP) and the Veterinary Public Health Institute of the University of Bern (VPHI).

The study sites for data collection were meant to be chosen based on the expected local dog density. However, during field work it was noticed that the number, instead of the density of the dogs, was taken as criteria to choose the study sites. The distinction between regions for the analysis is therefore not based on density of dogs but rather semi-urban versus rural setting: Habi being the semi-urban area and Pogon the rural. In both study sites, a 1km<sup>2</sup> area was predefined within which the study took place. Within the predefined 1km<sup>2</sup> area, the teams visited all dog-owning households.



Figure 1 – Localization of the two study areas: Habi and Pogon.

#### 4.1.1.2. Data collection at households

In each household, the study was presented to an adult of the family, who was then asked if they owned a dog and if they were willing to participate in the study. After the dog owner's oral or written consent was granted, a questionnaire was answered, and the dogs collared. The handling of the dogs was performed by a trained veterinarian or a trained veterinary paramedic of the team.

Dogs were collared with Geolocated Contact Sensors (GCS). The GCS devices were developed by Bonsai System, a spin-off company of ETH Zurich (Bonsai Systems 2020) and comprise a Global Positioning System (GPS) module for tracking and registration of the dog's location and an Ultra-High-Frequency (UHF) sensor to record proximity events between dogs carrying GCS devices (Laager et al. 2018). The GPS module were set to record the dog position every minute. All participating owners were asked to report whenever they would transport their dogs while it was collared. Dogs had blood and hair samples taken for use in another study and were also vaccinated against rabies. All participating dogs were vaccinated except for two, who were too stressed.

The questionnaire data was collected through interviews with the dog owners. Multiple dogs per household could be included as multiple entries in the questionnaire. The detailed questionnaire contains information on the household location, the house's conditions of living (i.e. electricity, running water, construction materials), personal information on the dog owners (gender, ethnicity, religion, school level, job and monthly income), ownership of other domestic species, dog's origin (found, given, born in the household), and general information on the dogs (sex, age, breed, reproduction status, food source and how frequent), vaccination status, dog's purpose (pet, herding, hunting, meat source, for sell). It was also asked whether and when veterinary care was provided to the dogs and if and when they were transported. Finally, dog owners were interrogated whether and where dogs typically gather and if wildlife could be seen outside the house.

The ethical approval for the study was received from the Animal Ethics Commission of the Faculty of Veterinary Medicine, Nusa Cendana University (Protocol KEH/FKH/NPEH/2019/009).

#### **4.1.1.3.** Exclusion Criteria and refusal of participation

Dogs of less than four months of age, since they were not big enough to carry a collar, sick dogs and pregnant bitches, to avoid any risk of stress induced miscarriages, were excluded from the study. Other reasons listed as exclusion criteria were dog owner's absence, dog's absence, inability to catch the dog, and refusal of participation without explanation. Dogs up for slaughter within the following four days were excluded to ensure data collection for at least four to five days.

#### 4.1.1.4. Data Retrieval

One hundred dogs were equipped with a GCS in Habi and 52 in Pogon. In Habi, out of the 100 collars used, 99 devices were collected following the collared period and data from 92 devices was retrieved. In Pogon, all 52 devices used were collected afterwards but only data from 50 was downloaded. Out of all the data collected, only data from 73 GCS devices in Habi and 36 in Pogon were viable for the analysis (Table 1). Dogs remained collared from three to five days.

Country	Region	Regional classi- fication	Study teams involved	Ethical approval needed	Total nº. of collared dogs	Total nº. of GCS devices collected	Total nº. of data collected	Total nº. of usable data
	Habi	Urban	VPHI Animal Husbandry and Health Department of	Verbal or	100	99	92	73
Indonesia	Pogon	Rural	Sikka Regency in Maumere Kupang State Agricultural Polytechnic (KAP)	written consent	52	52	50	36



### 4.1.2. GCS experiment

In the interest of studying the performance of the GPS module within the GCS devices deployed in this project, twenty GCS devices were placed in a static experimental settings with growing vegetation complexity and density of buildings.

Data acquisition was conducted from the 7<sup>th</sup> until the 11<sup>th</sup> of April 2020 in the canton of Basel, Switzerland. For this experiment purpose, three environments were selected: a) an open field surrounded by small houses and single trees (Figure 2), b) a wooden area bordering a forest (Figure 3), and c) an urban setting encircled by houses (Figure 4). In all settings, the recording spanned over a two-hour period. After prolonged unuse (> 1 week) or location change of the GCS unit, a first GPS fix is required. The first GPS fix allows for the detection of the satellites by the device, and therefore for the device to be located. This process takes thirty minutes. The coordinates of the location of the GCS for each setting were independently documented in the World Geodetic System (WGS) 1984 projection (Table 2).



 Vermes
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 Figure 2 – Open Field captured GPS fixes. The black dots represent the GPS fixes captured in the Open field site.



Figure 3 – Wooden area captured GPS fixes. The red dots represent the GPS fixes captured in the Wooden area.



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 Figure 4 – Urban setting captured GPS fixes. The black dots represent the GPS fixes recorded in the urban setting.

Setting	Longitude	Latitude
Open field	7°30'52.87"E	47°27'6.58"N
Wooden	7°30'47.20"E	47°27'4.49"N
Urban	7°36'19.97"E	47°32'55.88"N

Table 2 - Coordinates in WGS84 Projection of the GCS location during the static experimental settings

Out of the twenty devices employed, data was retrieved from fourteen GPS modules in the open field, eight in the wooden area and six in the urban setting.

### 4.2. The Datasets

# 4.2.1. Project Data

### 4.2.1.1. GCS telemetry

The dataset collected in Habi compiled information on 73 FRDD, totalling 87900 GPS fixes whilst Pogon's dataset had information concerning 36 FRDD, adding up to 13259 GPS fixes. The study variables are listed in Table 3 and described thoroughly in the text.

	GCS identification data
•	Device name
•	Device ID
	GCS recorded parameters
٠	Timestamp of the GPS fix
•	Latitude of the GPS fix (unprojected)
•	Longitude of the GPS fix (unprojected)
•	HDOP <sup>1</sup> of the GPS fix
	Calculated parameters
٠	Time difference between consecutive GPS fixes
•	Distance between consecutive GPS fixes
•	Speed between consecutive fixes
•	Universal Transverse Mercator 51S projection

Table 3 – List of variables in the datasets. For more information on each variable, see main text

Within each database, all observations were identifiable by the device's name. The name variable encompasses the GCS unit number preceded by the capital letter D, standing for "dog". The device ID was unique to each GCS unit and was equally documented for each observation.

Throughout the time of recording, date, hour, GPS coordinates and signal quality (HDOP) raw data were collected by the GPS module and amassed into the workable databases. The timestamp given in the year-month-day hours-minutes-seconds format was fundamental to the posterior determination of the time difference between consecutive fixes. This was further used to calculate the time difference between two consecutive GPS fixes for all dogs.

The GPS fixes were originally recorded under the WGS 1984 projection in the Degree, Minute and Second (DMS) format. *Real* (unprojected) and *projected* are the two coordinate systems in existence. The first, determines spherical coordinates beginning at the centre of the Earth whereas with the second, the Earth's coordinates are determined through their own projection onto a 2-dimensional plan. The use of one or the other is conditional to its purpose (Kumar et al. 2019). In accordance with the *real* reference system, also known as the Universal

<sup>&</sup>lt;sup>1</sup> HDOP: Horizontal Dilution of Precision
Coordinate System, one's location latitude and longitude values are portrayed by DMS or Decimal Degree (DD). Given that such system presupposes a non-perfect sphere as the Earth's surface it is not viable to be used when evaluating distances and areas (Kumar et al. 2019). The *Projected* Coordinate System, also known as the Cartesian coordinate system, refers to map projections where the spherical Earth's surface must be reshaped into a flat plan, transforming the globe's three-dimensional shape into a two-dimensional form. This system estimates distances in horizontal and vertical directions which are represented through x and y dimensions, being the meter the linear unit of measurement. Various map projections exist, depending on the region on the globe, since this transforming process implicates distortion (Kumar et al. 2019). The WGS 1984 is a well-established *real* reference system in which coordinates are identified in relation to the World's centre of mass. Contrasting, the Universal Transverse Mercator (UTM) is an ellipsoidal *projected* coordinate system where the reference for each region of the Earth is distinctive and the *x* and *y* coordinates are in meters (Kumar et al. 2019).

In preparation for the posterior calculi required to obtain the distance variable, the coordinates were converted to the UTM 51S projection, the UTM projection exclusive to the study areas, creating the UTM projection variable. Following on this, the distance between each consecutive GPS fix in the UTM 51S projection was calculated in meters. The speed between each consecutive fixes, in meters per second, and estimated individually per dog, was calculated by dividing the previously determined distance variable by the time difference variable and later converted to kilometres per hour (km/h) through the process of multiplying the obtained values by 3.6.

The GPS module registers the HDOP values for each observation making up the HDOP variable.

#### 4.2.1.2. Questionnaire Data

Since the purpose of the questionnaire analysis was to obtain a deeper understanding of the dog population behaviour, only questions regarding this topic were examined. Dog owners were first asked to identify whether they had observed gathering behaviour by their dogs and whether this gathering behaviour took place in the owner's home, garage, party places, open-fields or restaurants (Gather Places). Afterwards, dog owners were asked if they could identify Specific Gather Places (those not listed in the questionnaire) where they had witnessed gathering behaviour, and these were noted down.

The number of households visited varied according to the location with 71 households located in Habi and 41 in Pogon (Figure 5).



Figure 5 – Number of answered questionnaires per study site in Indonesia.

#### 4.2.2. GCS accuracy experiment

The dataset consisted of 1645 GPS fixes recorded in the open field,1030 in the urban setting and 212 in the wooden area.

The date and time are portrayed by the timestamp variable in the year-month-day hours-minutes-seconds format and the quality of the signal is represented by the HDOP variable (see 4.2.1).

Similarly to the dog GPS database, the coordinates extracted from the GPS modules were registered according to the WGS 1984 projection in a degree, minute, second format. Subsequently, all coordinates were converted to the UTM 32N projection, exclusive to the experimental settings.

# 4.3. Data Cleaning

# 4.3.1. Project Data

## 4.3.1.1. GCS telemetry

GPS data was stored in two apps developed by Bonsai Systems, which work using a mobile application and operating system compatible with Apple (iOS iPhone Operation Systems). The data was later downloaded, each GPS unit information being transferred as an individual CSV file, uploaded and analysed in R (<u>http://cran.r-project.org</u>, version 3.6.1).

Thanks to the spatial nature of the data, projection and visualization of the data enabled the clear identification of error locations. Habi being a sea-side city(Figure 6), the presence of error GPS fixes was especially noticeable through GPS positions in the sea distant from the shore, when compared to Pogon (Figure 7).



Figure 6 – Habi GPS fixes before cleaning, represented in black.



Figure 7 – Pogon GPS fixes before cleaning.

A three-step data cleaning process was undertaken with the purpose of error repairing through the elimination of the discernible and inconspicuous GPS fixes present in the study databases. The chosen criteria include a species-specific (speed), a technology-specific (HDOP) and an individual-specific (trajectory angles) parameter. Safekeeping data representability, for reliable future study outcomes, 5% of the data was defined as the maximum threshold for data loss throughout the entire cleaning process.

As a first step, the databases had been previously subjected to a pre-cleaning process where all observations with unreasonable speed values were eliminated. Just as done by Dürr and Ward (2014), the speed limit was defined at 20km/h given the unlikelihood of a dog running at such speed over a one-minute timespan. These computed high-speed values were attributed to GPS error and therefore were eliminated. It is noteworthy that car travel cause speeds between two consecutive GPS fixes of over 20km/h and should therefore not be classified as errors. However, as we were interested in analysing the dog's behaviour outside of car transports, we did not distinguish between car travel and high-speed values due to error fixes.

Even if environmental and behavioural factors are uncontrollable, technologically dependent elements are susceptible to enhancement. Horizontal dilution of precision is the GPS accuracy measurement recorded by the GPS units and fluctuates between 1 and 99.9.

Higher values are associated with precision errors. High HDOP values elimination is a frequently chosen criteria applied by researchers (Dore et al. 2020). Second, GPS fixes with high HDOP values were excluded. As demonstrated by Lewis et al. (2007), eliminating GPS fixes with HDOP values above 5 deepens precision by eliminating the majority of gross errors. After examination of the datasets HDOP values distribution (Figure 8), the same approach was enforced. A posterior data loss check, upon the elimination of all observations with HDOP values above five, revealed a data loss in the Habi dataset totalling 1.33% while in Pogon it added up to 2.2%.



Figure 8 – HDOP values distribution per study area.

As a third point, movement patterns of the dogs were examined in terms of their biological and behavioural understanding. As attested by Shimada et. al (2012), additional recognition of non-realistic animal movement patterns is a reliable solution. Using the R software *atan2* function, all angles between three consecutive positions of each dog were calculated in radians and later converted to degrees. When considering animal movement and studying dog's individual trajectories, acute inner angles are often connected to error GPS fixes (Shimada et al. 2012). After a trial-and-error process, aiming to insure minimum data loss, the exclusion of the acute inner angles within a 0.025 quantile was enforced, meaning the elimination of the 2.5% acutest angles.

2.62 % of data was excluded in the Habi dataset and 2,95% in Pogon after the application of the angle rule.



Figure 9 – Three-step process used to clean the raw data collected through free-roaming domestic dogs who were collared for this study purposes.

After the cleaning was concluded, some obvious error GPS fixes were still prevailed in the Habi dataset. Obvious error fixes were defined as those in unrealistic placements, unachievable and inexplicable by a dog's behaviour. These points were fixes in locations over 200 meters from the shoreline and those clearly resulting from motorized dislocations (Figure 10). Using QGIS (<u>http://www.qgis.org</u>, version 3.4 Madeira), a free Geospatial Information System (GIS) software, the elimination of such points was carried out. Fixes from motorized dislocations were manually removed. The buffering spatial analysis tool enabled the creation of a buffer vector that demarked the 200-meter distance from Habi's shoreline (Figure 11). Afterwards, all fixes located outside the delimited buffer marking were manually removed. Collectively, fourteen fixes were eliminated amounting to a 0.016 % data loss.

No GPS fixes were manually removed in the Pogon dataset.



Figure 10 – Habi data plotted after cleaning. Obvious error GPS fixes examples are marked and explained.



Figure 11 – Polygon vector buffer delimitating the 200-meter distance from Habi's shoreline created using the QGIS software.

### 4.3.1.2. Questionnaire data

The questionnaire data underwent a simple cleaning procedure.

Although ineligible for the project's purpose over being too little to carry the GCS collars, dogs under the age of four months can still be included in the questionnaire collected

information. However, the complementary nature of this dataset to the project's objectives makes observations from unqualified dogs unnecessary. Data concerning these dogs was excluded.

Due to the qualitative nature of the data, all missing data on the dog's gathering places was also not considered for further analysis.

#### 4.3.2. GCS accuracy experiment

To select the data concerning the GCS experiment, timestamp was filtered to include only data from the days the experiments were carried out.

Technology specific factors had to be considered and incorporated into the cleaning. During the first thirty minutes of the experiment, devices were acquiring the first GPS fix. Data collected during this step consists of fixes mirroring locating efforts by the GPS telemetry and was therefore not used for analysis purposes since they are unreliable. These fixes were eliminated.

The same three-step cleaning process (speed, HDOP and 0.025 acute angles quantile) was also applied to this dataset (Figure 9).

## 4.4. Data Analysis

# 4.4.1. Project Data

## 4.4.1.1. Definition of habitats and other covariates

To analyse the type of habitat used by the collared FRDD, habitat types were identified within the area the dogs accessed. This area was defined by the Minimum Convex Polygon (MCP) of all GPS fixes per study site. MCP is a commonly used method that determines the area encompassing all GPS fixes of the dataset and was defined using QGIS (Figure 12).



Figure 12 – Habi (left) and Pogon (right) GPS fixes plotted over a Google satellite imagery layer with its respective outlined computed Minimum Convex Polygon (MCP) delimitating the available study population habitat.

Habitat is made up of resources, which animals use to survive and to proliferate (Hall et al. 1997). Habitat resources were chosen within the MCP area, taking into consideration habitat features likely to impact movement patterns of dogs, landscape satellite topography and information on relevant gathering places for FRDD collected through the questionnaire. When overlaying the collared dogs GPS fixes onto a satellite imagery layer in QGIS, it became evident that fixes seemed to cluster in households and around roads, information corroborated by the questionnaire data. Roads and buildings were, thus, identified as relevant habitat resources. While analysing both study areas topography, distinguishing features were identified. Pogon is heavily forested, most of its available area is covered by dense forest, which makes it a paramount resource. On the other hand, in Habi, beach, sea and vast open fields disrupted by small tree covered areas are inherent pertinent resources.

All habitat relevant resources were first manually identified within the available area (MCP) in QGIS using satellite imagery. All building-like structures were categorized, using vector polygons, under the layer Buildings. The same principle was applied to pinpoint tree coverage areas in Habi. Roads were manually traced, using vector lines. A buffer vector polygon was generated with a five-meter width in Habi and a two-meter width in Pogon, to encompass the full potential length of the roads. The difference in the buffer width can be attributed to how developed each site infrastructures were. In Habi, the same methodology

was applied when generating the *Beach* vector layer. Following the line tracing of Habi's shoreline, using vector lines, the beach was defined by generating a five-meter buffer, which demarked the beach's limits. The *Sea* vector polygon is the result of the difference between the MCP sea outer limit and the beach buffer polygon. The *Open Field* and *Forest* resources, in Habi and Pogon respectively, were the last vector layers to be established since they are the result of the difference between the MCP total area and all other polygon vector resource areas combined. After all habitat resource vector polygons had been created, an encompassing vector layer was generated by merging all resource polygon vectors. This newly created vector layer was named *Habitat classification* (Figure 13).

After the construction of the habitat resources, all GPS dataset fixes were classified according to which habitat resource they were present in, using the QGIS *join attributes by location* tool. The MCP vertices were individually and manually classified since they were located at the extreme borders of the *Habitat classification* vector layer. It should be noted that, due to the close proximity between habitat resource polygons, some fixes were located in between two different resources and QGIS automatically assigned two different classifications to these observations. To avoid such double classification, data was imported into R where a one observation-one classification principle was assured through the creation of habitat resources lists with preferential choosing order, applying the *ifelse* function. The order was decided based on the habitat resources most likely to be adjacent to one another and have fixes located in between them: for Habi the order decided upon was Buildings, Roads, Tree coverage, Open field, Beach and Sea while for Pogon it was Buildings, Roads and Forest.

As such, the categorical explanatory variable named *Habitat* was created, corresponding to the labelling of each observed GPS fix according to its habitat resource presence.

As part of the Habi's *Habitat classification*, the airport terminal and runaway as well as waterways enclosed in the MCP area were identified. However, since these resources had no GPS fixes presence, they were excluded from the analysis.



Coordinate 13607053,-966352 😵 Scale 1:17252 💌

Figure 13 – Habi's *Habitat classification* vector layer. The different habitat resources, identifiable by colour, were merged to create the comprehensive *Habitat classification* vector. *Buildings* are coloured red, *Tree coverage* green, *Roads* black, *Beach* yellow, *Sea* dark blue, *Airport* grey, *waterways* light blue and *Open field* light orange. The airport area (gray) was not classified as separate habitat layer and excluded from further analysis.



Figure 14 – Pogon's *Habitat classification* vector layer. Habitat resource vector *Forest*, coloured dark green, *Buildings*, coloured red, and *Roads*, coloured black, were merged to create this comprehensive vector layer.

The mountainous topography in Pogon raised suspicions on whether the steepness would influence the dog's movement patterns. The degrees of slope were calculated by applying the *terrain analysis* raster function for slope calculation to an Indonesia altitude raster with a 30-meter raster-cell resolution (STRM 1-Arc Second Global, downloaded from the United States Geological Survey (USGS) Earth Explorer, <u>https://earthexplorer.usgs.gov/)</u>. This raster had been cut to enclose Pogon's MCP area and projected to the UTM 51S projection before the slope raster was generated and, subsequently, converted into a vector layer (Figure 15). Conversion into a vector layer was necessary to ensure posterior classification of each GPS fix according to their degree of slope, and thus, constituting the *slope* explanatory variable. GPS fixes slope values ranged from 1.69 to 50.9 degrees, with mean slope at 14.68 degrees.



Figure 15 – Pogon slope raster with its respective caption, indicating for each degree of slope the corresponding colour shade. Higher degrees of slope are identifiable by the red shading and the smaller degrees are showcased in green.

Accounting for human influence on dog movements was compulsory due to the close contact between the dogs and human communities. The *Buildings* resource vector encompassed all building-like structures identifiable from the satellite imagery, but, since there is an observable connection between dogs and households, further investigation was needed. Therefore, the *minimum distance* from each GPS fix to the closest dog-owning household in our dataset was calculated and used as a covariable in the analysis to correct for the bond between FRDD and humans. This variable was calculated utilising the functions available in R packages *rgdal* and *FNN*, and the coordinate household data collected in the questionnaires.

#### 4.4.1.2. Statistic model building

In order to quantify habitat selection, RSF compare resource features in sites used by animals with the resource features of sites considered available (unused by animals) (Freitas et al. 2008). To determine the resource characteristics of the habitat available area random points had to be generated. Adapting the methodology applied by O'Neill et al. (2020), as many random points as observed GPS fixes were generated within the MCP area, using the *Random points in layer bound* vector tool from QGIS. The same number of random points generated as their recorded GPS fixes were randomly allocated to each dog and suitably, these random

observations were named according to the device number. For example, if dog "D300" had 100 recorded fixes its 100 random points were named "D300". Random points were then allocated to the *Habitat classifications* as previously done with the observed GPS fixes, regarding their presence in the habitat resources. In Pogon, the random points were also allocated to the slope of the terrain, as done for the observed GPS fixes. Random points slope degrees ranged from 2 to 51, with a mean of 21.29 degrees of slope.

Here, the observed GPS fixes are the fixes collected by the dogs' GCS devices, and those accessible by the dogs are the randomly generated points within the MCP. Based on a previous study on African wild dogs (O'Neill et al. 2020), a mixed effects logistic regression model was created to study the differences between accessible (i.e. randomly generated points) and used habitat (i.e. observed GPS fix), using the *glmer* function in the *lme4* package from R. The model's binary outcome variable was defined as either observed (1) or random (0) GPS fix with the random effect variable being designated as the dog's device name. The explanatory variables for the model were the *Habitat (buildings, roads, tree-covered areas, forest, beach, sea, open fields), Minimum distance to the closest household* and the *slope* (in Pogon only) (Table 4). The independent variables, habitat resources (buildings, roads, tree-covered areas, forest, beach, sea, open fields), were coded according to the presence in the resource of a GPS fix (1) or a random point (0). The independent variable slope was coded according to the degrees of slope each observation was recorded in.

Logistic regression models are sensible to variable's scaling. Scaling warnings compromise the models fit and were therefore scrutinized. As per indicated in the *Ime4* R package, the continuous explanatory variable *Minimum distance to the closest household* was rescaled to the distance to closest household per 100 meters to settle such issue. For Pogon, the *Minimum distance per 100 meters* was calculated at 0.001, the maximum at 13.04 and the mean at 2.65. In Habi, the mean distance *per 100 meters* was calculated at 2.86, with a minimum distance of 0.0004 and a maximum of 15.15.

Study Area	Habitat Variable				Other relevant variables		
Habi			Tree coverage	Beach	Sea	Minimum distance to	
Pogon	Buildings	ings Roads	Forest			Household per 100 meters	Slope

Table 4 summarizes this project explanatory variables.

Table 4 – Summary table of each study site selected variables.

Observations independence is a fundamental presupposition of any regression model. However, the spatial nature of the project's point-referenced data permits perception of spatial dependence. When in QGIS, GPS fixes were overlaid onto a satellite imagery layer and the data's spatial independency was questioned. This premise was therefore tested. Spatial dependency was inferred by applying the Moran's I test (Moran 1950) to the residuals from our mixed effect logistic regression models, using the *moran.test* function from the *spdep* R package. Spatial autocorrelation was proven for both study sites.

Confirmation of the data's spatial dependency made the creation of a spatial regression model imperative, which takes into consideration spatial autocorrelation while exploring the effects of the study variables. Also known as "geostatistical data", point-referenced observations originated from the dogs who had been collared after the household visits. All households had to be located within the pre-determined 1km<sup>2</sup> area of the study site, meaning, the households represent pre-set locations. It can be arduous to designate spatial dependency and neighbours in point-referenced data, since each location has various variables that describe it and dependence in-between and over observations is expected (Kanankege et al. 2020). Generalized linear mixed models (GLMM) which consider random effects measurements of spatial correlation were created using the R spaMM package (Rousset and Ferdy 2014; Shutt et al. 2018). The random effect was defined as each dog's household locations. Household information was obtained from the questionnaire data. For three dogs in Pogon and four dogs in Habi information on the GPS coordinates of their homes were missing, either due to the household location not being recorded or due to an obvious error of the household location (i.e. dog's GPS fixes are far from the recorded household location or household located outside of the 1km<sup>2</sup> predefined area). For those missing household locations, one was defined according to their GPS fixes distribution. The dog's fixes were overlaid onto a satellite imagery layer, the mean of coordinates calculated, using QGIS vector analysis tool mean coordinate, and the closest household within the dataset determined and established as their own (Figure 16).

The restricted maximum likelihood (REML) through Laplace approximations, which can be applied to models with *non-Gaussian* random effects (Noh and Lee 2007), and the Matérn correlation function were used to fit the spatial models. The parameter nu denotes the Matérn family dispersion parameter indicator of strength of decay in the spatial effect was set at 0.5 (Shutt et al. 2018).



Coordinate 13609367,-964564 👏 Scale 1:10087 🔻 🧁 Magnifier 100% 🗢 Rotation 0,0 G

Figure 16 – Defining the household for dog "D249" for which the household location was missing. The distances between the mean coordinates (green) of the observed GPS fixes (dark yellow) and the surrounding household locations (red) were measured, and the closest household defined as the suitable one.

The same explanatory variables were used for the mixed effect logistic regression models considering spatial autocorrelation as for the model without considering spatial autocorrelation (table 4), with the exception of the *Minimum distance to the closest household*. This variable was excluded from the list of explanatory variables because the spatial component has already been captured by the spatial autocorrelation object.

### 4.4.2. GCS accuracy experiment

For all study sites the data was analysed pre and post-cleaning. The analysis was conducted in R using the *geosphere* package.

Data analysis entailed the calculation of the shortest distance in meters between the recorded GPS fixes and the real location of the GCS unit (*distReal*), represented by the study sites coordinates indicated in Table 2. The *distReal* was calculated using *distHaversine* function. In each site, the centroid of all the GPS fixes was determined, using the *colMeans* function. Subsequently, the shortest distance from the centroid to the observed GPS fixes (*distCentr*) was calculated. Lastly the minimum distance between consecutive GPS fixes (*distConsec*) of each unit was determined and used as a third measurement for accuracy.

Wilcoxon test was used to compare the pre and post-cleaning dataset, for each study site, to study the impact of the cleaning process on the improvement of the calculated distances (*distReal, distCentr, distConsec*) and, thus, data reliability.

## 5. RESULTS

## 5.1. Project Data

## 5.1.1. GCS telemetry

Results from the mixed effects logistic regression models disclosed confirmation of selection of habitat by FRDD, as habitat resources chosen by FRDD were significantly different from those of the random points generated.

Open field, in Habi, and Forest, in Pogon, were used as the reference resources for the non-spatial models. If no spatial autocorrelation had been determined, these models' results would showcase that all habitat resources and complementary variables (slope and minimum distance to closest household per 100 meters) had a strong association to FRDD's presence. They could also infer that only the slope in Pogon, the sea in Habi and the minimum distance to the closest household are negatively associated with the presence of FRDD since all other variables reported positive associations to FRDD's presence.

Table 5 and Table 6 depict in more detail the results obtained in each study site.

Study site	Fixed effects	Coefficient	Standard error	z-value	p-value
	Intercept	2.64965	0.13065	23.28	< 0.001
	Buildings	1.79928	0.08536	21.08	< 0.001
	Road	2.12232	0.14140	15.01	< 0.001
Pogon	Slope	-0.08399	0.00276	-30.43	< 0.001
	Minimum distance to closest HH per 100 meters	-0.66281	0.01049	-63.20	< 0.001

Table 5 – Mixed effects logistic regression model results for Pogon using open field as the reference resource.

Study site	Fixed effects	Coefficient	Standard error	z-value	p-value
	Intercept	2.65591	0.11359	23.38	< 0.001
	Beach	1.21224	0.15723	7.71	< 0.001
	Buildings	2.05190	0.02843	72.17	< 0.001
	Sea	-1.12754	0.08284	-13.61	< 0.001
Habi	Road	0.73433	0.05514	13.32	< 0.001
	Tree	0.47720	0.04195	11.38	< 0.001
	Minimum distance to closest HH per 100 meters	-3.15054	0.02454	-128.40	< 0.001

Table 6 – Mixed effects logistic regression model results for Habi using forest as the reference resource.

As previously stated, non-spatial models do not consider spatial dependency and are therefore biased, making their results unreliable.

For the regression models considering the spatial autocorrelation, the different habitat resources were used as reference interchangeably. In Pogon, FRDD roads was the resource dogs were recorded in the most. Asides from the dog's predilection for roads, buildings were positively associated with FRDD presence whilst the forest resource showed a negative association with FRDD presence. Concerning the slope variable, model results indicated FRDD preference for flat slopes.

In Habi, results attested that the dogs preferred resource was buildings (Table 8). Besides buildings, dogs preferred, in succeeding order, roads, beach, tree covered areas and open fields. Dogs are unlikely to be located in the sea.

	Fixed effects	Coefficient	Standard Error	t-value
	Intercept (Roads)	4.65	0.21	21.97
	Buildings	-0.24	0.14	-1.72
	Forest	-2.55	0.12	-21.30
	Fixed effects	Coefficient	Standard Error	t-value
	Intercept (Buildings)	4.42	0.19	23.31
Pogon	Forest	-2.31	0.07	-31.29
	Roads	0.24	0.14	1.72
	<b>Fixed effects</b>	Coefficient	Standard Error	t-value
	Intercept (Forest)	2.11	0.18	11.85
	Buildings	2.31	0.07	31.29
	Roads	2.55	0.12	21.10
	Slope	-0.13	0.002	-53.02
able 7 – P	ogon's spatial model detailed r	oculte		

Table 7 and Table 8 report each study site results in more detail.

Table 7 – Pogon's spatial model detailed results.

	Fixed Effects	Coefficient	Standard Error	t-value
	Intercept (Sea)	-2.52	2.82	-0.89
	Beach	2.44	0.11	21.82
	Tree coverage areas	2.43	0.07	35.84
	Roads	2.54	0.07	36.02
	Buildings	4.51	0.07	68.20
	Open field	1.78	0.07	27.19
	Fixed effects	Coefficient	Standard Error	t-value
	Intercept (Open field)	-0.74	2.82	-0.26
	Beach	0.66	0.09	7.24
	Buildings	2.73	0.01	194.98
	Sea	-1.78	0.07	-27.19
	Road	0.76	0.03	26.93
	Tree	0.66	0.02	30.89
	Fixed effects	Coefficient	Standard Error	t-value
	Intercept (Beach)	-0.08	2.82	-0.03
	Tree coverage areas	-0.004	0.09	-0.04
	Roads	0.1	0.1	1.09
	Buildings	2.07	0.09	22.53
	Open field	-0.66	0.09	-7.24
	Sea	-2.44	0.11	-21.82
Habi				
Habi				
Παυι	Fixed effects	Coefficient	Standard Error	t-value
Παυι	<b>Fixed effects</b> Intercept (Tree coverage areas)	Coefficient -0.08	Standard Error 2.82	<b>t-value</b> -0.03
Παρι	Fixed effects Intercept (Tree coverage areas) Roads	Coefficient -0.08 0.11	Standard Error 2.82 0.03	<b>t-value</b> -0.03 3.14
Παρι	Fixed effects Intercept (Tree coverage areas) Roads Buildings	Coefficient -0.08 0.11 2.07	<b>Standard Error</b> 2.82 0.03 0.02	<b>t-value</b> -0.03 3.14 88.01
парі	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field	Coefficient -0.08 0.11 2.07 -0.66	<b>Standard Error</b> 2.82 0.03 0.02 0.02	t-value -0.03 3.14 88.01 -30.89
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach	Coefficient -0.08 0.11 2.07 -0.66 0.004	Standard Error           2.82           0.03           0.02           0.02           0.09	t-value -0.03 3.14 88.01 -30.89 0.04
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43	Standard Error 2.82 0.03 0.02 0.02 0.09 0.07	t-value -0.03 3.14 88.01 -30.89 0.04 -35.84
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43	Standard Error           2.82           0.03           0.02           0.02           0.09           0.07	t-value -0.03 3.14 88.01 -30.89 0.04 -35.84
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient	Standard Error           2.82           0.03           0.02           0.02           0.09           0.07           Standard Error	t-value -0.03 3.14 88.01 -30.89 0.04 -35.84 t-value
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads)	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07	t-value -0.03 3.14 88.01 -30.89 0.04 -35.84 t-value 0.01
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03	t-value -0.03 3.14 88.01 -30.89 0.04 -35.84 t-value 0.01 65.54
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.03	t-value -0.03 3.14 88.01 -30.89 0.04 -35.84 <b>t-value</b> 0.01 65.54 -26.93
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Buildings Open field Beach	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.1	t-value         -0.03         3.14         88.01         -30.89         0.04         -35.84         t-value         0.01         65.54         -26.93         -1.09
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.1         0.07	t-value -0.03 3.14 88.01 -30.89 0.04 -35.84 <b>t-value</b> 0.01 65.54 -26.93 -1.09 -36.02
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea Sea Tree	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54 -0.11	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.03         0.01         0.07         0.03         0.03         0.03         0.03         0.03	t-value -0.03 3.14 88.01 -30.89 0.04 -35.84 <b>t-value</b> 0.01 65.54 -26.93 -1.09 -36.02 -3.14
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea Tree Intereet	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54 -0.11	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.1         0.07         0.03         0.03         0.03         0.03         0.03         0.1         0.07         0.03	t-value         -0.03         3.14         88.01         -30.89         0.04         -35.84         t-value         0.01         65.54         -26.93         -1.09         -36.02         -3.14
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea Tree Fixed effects Fixed effects	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54 -0.11 Coefficient Coefficient	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.01         0.03         0.03         0.03         0.03         0.03         0.03         0.1         0.07         0.03         0.1         0.07         0.03	t-value         -0.03         3.14         88.01         -30.89         0.04         -35.84         t-value         0.01         65.54         -26.93         -1.09         -36.02         -3.14
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea Tree Fixed effects Intercept (Buildings)	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54 -0.11 Coefficient 1.99	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.03         0.03         0.03         0.03         0.03         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.282	t-value         -0.03         3.14         88.01         -30.89         0.04         -35.84         0.01         65.54         -26.93         -1.09         -36.02         -3.14         t-value         0.07
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea Tree Fixed effects Intercept (Buildings) Open field	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54 -0.11 Coefficient 1.99 -2.73	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03	t-value         -0.03         3.14         88.01         -30.89         0.04         -35.84         t-value         0.01         65.54         -26.93         -1.09         -36.02         -3.14         t-value         0.07         -194.98
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea Tree Fixed effects Intercept (Buildings) Open field Beach	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54 -0.11 Coefficient 1.99 -2.73 -2.07	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.03         0.03         0.03         0.03         0.03         0.03         0.03         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.01         0.09	t-value         -0.03         3.14         88.01         -30.89         0.04         -35.84         t-value         0.01         65.54         -26.93         -1.09         -36.02         -3.14         t-value         0.07         -194.98         -22.53
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea Tree Fixed effects Intercept (Buildings) Open field Sea Tree	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54 -0.11 Coefficient 1.99 -2.73 -2.07 -4.51	Standard Error         2.82         0.03         0.02         0.02         0.09         0.07         Standard Error         2.82         0.03         0.03         0.03         0.03         0.03         0.03         0.03         0.03         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.01         0.02         0.01         0.09         0.07	t-value         -0.03         3.14         88.01         -30.89         0.04         -35.84         0.01         65.54         -26.93         -1.09         -36.02         -3.14         0.07         -194.98         -22.53         -68.2
Παυι	Fixed effects Intercept (Tree coverage areas) Roads Buildings Open field Beach Sea Fixed effects Intercept (Roads) Buildings Open field Beach Sea Tree Fixed effects Intercept (Buildings) Open field Beach Sea Tree Fixed effects Intercept (Buildings) Open field Beach Sea Road	Coefficient -0.08 0.11 2.07 -0.66 0.004 -2.43 Coefficient 0.02 1.97 -0.76 -0.1 -2.54 -0.11 Coefficient 1.99 -2.73 -2.73 -2.07 -4.51 -1.97	Standard Error         2.82         0.03         0.02         0.09         0.07         Standard Error         2.82         0.03         0.03         0.07         Standard Error         2.82         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.1         0.07         0.03         0.01         0.03         0.01         0.09         0.01         0.09         0.01         0.09         0.07         0.03	t-value         -0.03         3.14         88.01         -30.89         0.04         -35.84         0.01         65.54         -26.93         -1.09         -36.02         -3.14         0.07         -194.98         -22.53         -68.2         -65.54

Table 8 – Habi's spatial model detailed results.

#### 5.1.2. Questionnaire data

A total of 100 and 51 dogs in Habi and Pogon, respectively, had their information collected via questionnaires answered by their owners. Majority of dogs were females (Habi:67%; Pogon:69%) and young dogs (Dogs below 12 months of age in Habi:68%; Pogon:63%). Gathering behaviour was confirmed when owners reported seeing their dogs meeting other dogs in particular locations. Most owners observed gathering behaviour (71.8%) of their dogs, i.e. their dogs meet other dogs on a regular basis. Whilst, 3.5% of owners were not aware if gathering behaviour ever occurred, 17.6% negatively answered and 7.0% did not respond (Figure 17).



Figure 17 – Visual representation of the answers concerning gathering behaviour being observed by the dog's owners.

Characterization of gathering behaviour, as observed by the owner, was analysed and the information revealed that most dogs preferred gathering in specific places (65.38%) instead of in any of the questionnaire listed gathering places (see Appendix 4). In Habi, open fields were the second most reported answer (37.1%) and next were places where parties were being held (party places: 6.45%). In Pogon, the order was inverted with party places being favoured (11.9%) over open fields (9.52%).

Specific gathering places were inquired, and in both study sites, most dogs were found to gather in the neighbourhood with diverging preferences in the subsequent gathering places disclosed. In Habi, the subsequent preferred locations were the garden (14.29%), the beach (5.71%) and around the household and in the terrace, an extended area of the house in which a family member can relax and drink coffee or tea in the afternoon (2.86%) (

Figure 18). In Pogon, alternative gather locations were the street (18.18%) and around the household (3.03%) (Figure 19).



Figure 18 – Habi's dogs specific gathering places, apart from those listed in the questionnaire as possible choices, reported by the owners. Most of the dogs were reported to gather in the neighbourhood.



Figure 19 – Pogon's dogs specific gathering places, apart from those listed in the questionnaire as possible choices, reported the owners. Most of the dogs were reported to gather in the neighbourhood.

# 5.2. GCS accuracy experiment

In all experimental settings, data was analysed prior to and after the implementation of the cleaning process. All calculated distances displayed improvements post-cleaning, with smaller mean and median distances being recorded for every study variable except for the post-cleaning consecutive distances medians (Figure 20). Figure 20, Figure 21 and Figure 22 detail the pre and post-cleaning distances boxplots for each site. All post-cleaning *distConsec* medians were higher than its pre-cleaning precedents and in the urban setting the mean also increased (Figure 23, Figure 24 and Figure 25).

For more information on the calculated distances, their maximum, minimum, mean and median are displayed in Appendix 1, Appendix 2 and Appendix 3.



Figure 20 – Pre and post-cleaning measurements of *distReal* across all settings with its respective Wilcoxon test results.



Figure 21 – Pre and post-cleaning measurements of *distCentr* across all settings with its respective Wilcoxon test results.



Figure 22 – Pre and post-cleaning measurements of *distConsec* across all settings with its respective Wilcoxon test results.



Figure 23 – Open field pre and post-cleaning calculated consecutive distances (distConsec).



Wooden Area

Figure 24 – Wooden area pre and post-cleaning calculated consecutive distances (distConsec).

# **Urban Setting**





Wilcoxon testing was undertaken to evaluate if cleaning methodology significantly impacted calculated distances. Cleaning was confirmed to have a statistically significant effect on the open field and urban setting (all *p*-values < 0.05), with distances post cleaning significantly smaller. In the wooden setting however, apart from the consecutive distance between GPS fixes, distances were not significantly affected by the data cleaning process (*p*-values: estimated to real location distance = 0.15; estimated to centroid location distance = 0.09), although still improved in accuracy (smaller distances for the post-cleaning dataset, except *distConsec* that showcased an increase in its post-cleaning distances mean) (Table 9).

Study site	Distances	p-value
Open field	distReal	< 0.001
	distCentr	< 0.001
	distConsec	< 0.001
Wooden area	distReal	0.15
	distCentr	0.09127
	distConsec	0.0011
Urban area	distReal	0.02807
	distCentr	0.003052
	distConsec	< 0.001



#### 6. DISCUSSION

#### 6.1. Project Data

#### 6.1.1. GCS telemetry

FRDD are dogs are owned but often roam freely, and they pose a serious threat to human and animal health. Nevertheless, studies focusing on FRDD ecology remain rare (Slater 2001; Dürr et al. 2017) and studies focusing on how the urban landscape impacts the movement of FRDD are especially lacking.

The project data allowed for a detailed habitat selection study by FRDD in Indonesia. In total, 109 FRDD's habitat resource preferences were explored in two different settings, with slightly contrasting surroundings.

Non-spatial models were ran solely as an intermediary analysis for the construction of spatial models. In there, we detected spatially clustered model residuals, which provided evidence to models considering spatial autocorrelation. Therefore, results of the non-spatial models will not be discussed.

Published studies on FRDD mostly focused on rural areas with little literature available from urban settings (Meek 1999; Dürr and Ward 2014; Van Bommel and Johnson 2014; Sepúlveda et al. 2015; Hudson et al. 2017; Raynor et al. 2020). Studies published in rural settings demonstrated an impactful human influence in dog's movement patterns (Meek 1999; Dürr and Ward 2014; Van Bommel and Johnson 2014; Sepúlveda et al. 2015; Doykin et al. 2016; Hudson et al. 2017; Laager et al. 2018; Raynor et al. 2020). In agreement with previously published studies, in both the urban and rural site, buildings were significantly influential to FRDD presence. In Habi, this preference prevailed over any other resource whereas, in Pogon it was the second most sought resource (Table 7 and Table 8). Human interaction is known to influence roaming behavior (Newsome et al. 2014; Ruiz-Izaguirre et al. 2015) and preference of building resources was expected as in human premises dogs are provided with food, water and shelter.

Roads have been shown to influence dogs' movements and contacts, specifically in rural areas (Sepúlveda et al. 2015; Bombara, Dürr, Machovsky-Capuska et al. 2017). Road's influence has also been found in feral dogs and dingos (Robley et al. 2010), African wild dogs (O'Neill et al. 2020) and pumas (Zeller et al. 2017). Roads are the most used habitat in the densely forested region Pogon. In such settings, they can be used as pathways for uninterrupted movement, as direct access to buildings is tortuous and traffic is sporadic. As demonstrated by Sepúlveda et al. (2015) roads also ease movement into areas to foray. The same logic is applicable to urban areas, such as Habi, where important food sources (i.e. garbage collection sites) are generally near roads. Here, roads equally facilitate access to all other available resources. Dissimilar building density and the sites topography may explain the

encountered difference of the dominant resource. Pogon has few buildings and those existing are sparse apart, separated by dense forest, making the roads, as movement facilitators, the more prominent resource. On the other hand, Habi being an urban region, has a high building density with buildings close together and without dense forest or vegetation.

Contradicting results are described regarding FRDD preference for vegetation-covered locations (Sepúlveda et al. 2015; Bombara, Dürr, Machovsky-Capuska et al. 2017). A study in Bulgaria found that feral dogs tend to prefer dense vegetation covered areas (Doykin et al. 2016) whilst wild dogs in Kenya preferred less tree coverage (O'Neill et al. 2020). FRDD in rural and urban settings spent time distinctly in vegetation covered areas. In Habi tree covered areas demonstrated a positive association to FRDD presence. This could be due to the fact that in the hot climate these areas offer dogs shade, protecting them from the sun. As Bombara, Dürr, Machovsky-Capuska et al. (2017) preconized, beaches and vegetation covered areas are prime resources for contact between dogs so, a positive association to FRDD presence was anticipated. Habi, being a region of extensive coastal line and scarce tree coverage, the beach was preferred over tree covered areas. In Pogon, despite the abundance of its forest resource, models revealed a negative association between the resource and the presence of FRDD. Foraging activities may be superfluous since dogs have an easier access to food in areas closest to human presence, and so the forest, less rich in food resources, becomes unattractive from the dog's perspective. Another relevant explanation is that forest may act as a barrier to movement (Sepúlveda et al. 2015).

In Habi, the sea was understandably connected with absence of dogs. Dogs may be capable of swimming, but such activity is impractical were water is not shallow, such as in Habi. GPS fixes are subjected to interferences and it is possible that dogs present at the beach had their fixes erroneously detected as being in the sea. Misclassification bias cannot be excluded since satellite imagery, a snapshot of the landscape at a given time, is conditional to the time the image was captured and influenced by sea tides and terrain conditions. Therefore, the border between shore and sea may not have been accurately determined, affecting the classification of GPS fixes. Open fields were the least preferred resource by FRDD in Habi. Although extensive in area, this resource is overshadowed by the opportunities that the other available resources offer to dogs. It can be concluded that both, open fields and sea, are resources that are visited by dogs occasionally, but are not paramount for dogs.

Flat slopes were favored by FRDD in Pogon. In the steep landscape around Pogon, this finding may be due to the ease of movement and foraging behavior in flat areas. This may infer to the conclusion that topographic feature building steep slopes, such as hills, mountains and volcanos, can serve as hurdles for dog movement. It is noteworthy to mention that the steep slopes in Pogon go up to 50.9 degrees (Figure 15). To the best of my knowledge, this is the first-time slope has been investigated regarding its impact on FRDD presence. Comparing

with wildlife species, slope has been investigated with concern to prairie dogs (Avila-Flores et al. 2010) and pumas (Zeller et al. 2017) and evidence of flat slope predilection was reported. Slope influence in FRDD presence was only investigated in Pogon since Habi is a flat area.

There are potentially additional predictors to FRDD habitat selection that were not investigated. Notably, the time period over a day may influence the presence of the dogs. Such an investigation was explored but, due to time constraints, not implemented. Incorporating these variables would have let us know whether dogs are near buildings at times when humans are expected to be there as well or if they prefer to go near buildings when humans are most likely out, and whether dogs' preferences change according to seasonality. This would need further data collection during different seasons for investigation. It should be equally noted that short duration of the collaring period and the implemented cleaning process are possible limitations of this study design. Long-term collaring would have provided a more detailed and reliable insight on dogs' movements while the cleaning process did not eliminate all the outliers, begging the question whether further criteria should be implemented or whether the criteria chosen should be changed.

The lacking available literature on habitat selection by FRDD makes external validity of presented results challenging. Investigation in other communities, regions and environments of FRDD habitat selection is needed for results to be extrapolated.

In Flores Island, Indonesia, where our two study sites are located, rabies has a considerable economic impact on the government and owners (Wera et al. 2013). This is the case even though it was reported that most dog owners are well informed on the disease and its control measures, with owners from Sikka regency displaying higher participation rates in vaccination campaigns (Wera et al. 2015). One factor still blocking rabies control is the lack of necessary knowledge on dog ecology, which was reported as one of the research gaps in regard to rabies control (Fahrion et al. 2017). More adapted and pragmatic dog vaccination coverage requirements are determined through improved knowledge on keeping practices, dog population turnover, and contact rates between dogs and wildlife at the regional/country level (Fahrion et al. 2017). Some studies have focused their attention on bettering vaccination campaigns , aiming for better vaccination strategies and supplies distribution, by investigating novel approaches for rabies control based on dog ecology and study of dogs' movement (Hudson et al. 2017; Laager et al. 2018; Hudson et al. 2019; Raynor et al. 2020).

Nevertheless, documentation on FRDD behavior and insight on how movement occurs in urban and rural settings is deficient. By understanding the resources dogs spent time in the most we can inform on possible rabies spread locations and target these habitat resources to ensure better rabies parental vaccination coverage. This study is also relevant in regard to oral vaccination of dogs (OVD). OVD is a promising approach for bettering vaccination coverage, in combination or not with parental vaccination. This approach is particularly important to

achieve better vaccination coverage in free roaming dogs (WHO 2007). One of the possible methods that can be employed to ensure adequate oral vaccine distribution is to set the baits in locations known to be visited by free-roaming dogs (WHO 2007). By pinpointing resources where dogs are most probably in, studies on habitat selection by FRDD, can enable efficient allocation of baits permitting accurate distribution of the baits to the target population, and purposeful use of funds.

#### 6.1.2. Questionnaire data

FRDD roaming behavior regarding dog population characteristics (Sparkes et al. 2014; Molloy et al. 2017; Dürr et al. 2017; Pérez et al. 2018; Melo et al. 2020), reproductive status (Garde et al. 2016; Melo et al. 2020), their habitat (Sepúlveda et al. 2015; Raynor et al. 2020) and interactions with wildlife (Ruiz-Izaguirre et al. 2015; Bombara, Dürr, Machovsky-Capuska et al. 2017), has been described in scientific literature. These studies have contributed to deepen existing knowledge on FRDD ecology and inform infectious diseases control strategies (Warembourg, Wera et al. 2020).

A portion of the data collected by the questionnaire in Indonesia was analyzed aiming for a better understanding of the perceived dog behavior and identification of important resources to be considered as predictors of FRDD habitat selection in Indonesia. The presented analysis is therefore in no way detailed and served as a complementary analysis to the project's data.

Specific gathering places were described by dog owners as the preferred dog gathering spots. Amongst specific places for gathering, owners reported seeing their dogs assembling with others in the neighborhood the most. Such result was to be expected since neighborhoods are prime locations for dogs, as they have facilitated access to food, water and shelter (Figure 18 and Figure 19). In hindsight, the description of specific gather place as "around the household", "garden" and "street" could have been included in the "Neighborhood" category and it would have probably made interpretation easier. Even so, results showed clearly that dogs are partial to human proximity. This closeness to the buildings, including garden and yard, was also found by the analysis of our GPS data.

Listed gather places were seldom identified by owners as places of dog's gathering. Although questionnaires were designed by teams on the field, it is often difficult to get so well acquainted with the study communities that one can grasp the general mindset of the population. It is therefore not surprising that the listed questions were seldom selected but the named specific gather places identified by distinct owners were more concordant.

It would have been interesting to further investigate the data provided by the questionnaire, as it was very detailed and pertinent. Relate the owner's described gathering places to site features that may attract dogs (i.e. garbage collection sites, restaurants, markets)

would have been important to better understand dog's movement patterns. This option was explored but was not feasible within the time frame available for my internship as it implicated considerable field data collection. Another intriguing future study perspective would be to investigate the human population movements and gathering behavior, and examine whether a connection can be made between both species behavior.

#### 6.2. GCS accuracy experiment

Data loss, data precision and malfunctioning are frequent liabilities when opting for GPS technology (Johnson et al. 2002; Molloy et al. 2017).

Although 20 GCS devices were employed in this experiment, the number of GCS's that recorded GPS data was not consistent throughout the experimental settings. In the wooden and urban areas, less GCS devices recorded than in the open field (see 4.1.2). One possible explanation for such observation could be that in areas with more interference (i.e. with large trees or buildings) satellite signal caption is more challenging (Glasby and Yarnell 2013). However, during the onset of the experiment it became apparent that some devices were not recognized by the Bonsai Systems apps or, after successfully concluding their GPS fix, did not record further. After contacting the manufacturer for an explanation no reason for such phenomenon was found. Henceforth, one can assume that this result is evidence of malfunction.

Assessment of GPS unit's efficiency and accuracy in a specific study site should be conducted prior to choosing GPS telemetry as a data collection source (Johnson et al. 2002; Cochrane et al. 2019). GPS accuracy and investigation on possible bias, characteristic to the environmental settings of the study site and the study species, can be evaluated using stationary tests (Cochrane et al. 2019). Denser vegetation coverage and buildings in urban settings impact GPS precision (Glasby and Yarnell 2013). Surprisingly, contrary to what was to be expected, all pre-cleaning calculated mean distances (distReal, distCentr, and distConsec) presented larger values in the open field setting that in the urban or wooden setting (Figure 20-22). The open field setting selected was located amongst small houses and single trees which may have impacted signal caption. Other possible explanation is that the greater observed dispersion of GPS fixes in the open field setting influenced the mean distance, sensitive to extremes values (Figure 2). A study on FRDD behaviour in Australia employed stationary tests to estimate accuracy of deployed GPS units and determined mean distance between recorded locations to the centroid to vary between 14.6-22.8 meters (Dürr and Ward 2014). Intrinsic performance differences between the GCS device developed by Bonsai System for this project and the ones used by Dürr and Ward (2014) can explain why all calculated pre-cleaning mean distances were slightly more elevated that those previously

reported. These values can still be considered as acceptable for the purpose of the study for which the units were used.

Cleaning was expected to diminish all calculated distances. Howbeit, all post-cleaning *distConsec* medians were higher than its pre-cleaning precedents and in the urban setting the mean post- cleaning also increased (Figure 23,Figure 24 and Figure 25). Mean urban *distConsec* increase could be due to the elimination of GPS fixes, which reduced the overall number of observations, associated to the keeping of only distances below 80 meters after cleaning, meaning all the outlier distances were eliminated (Figure 25). One can easily demonstrate this phenomenon through a practical example. Imagine there were 10 observations pre-cleaning with *distConsec* values of 10,5,20,30,10,20,5,10,30 and 200 meters, which totals a mean distance of 31 meters. After cleaning, 8 observations remained with values of 10,20,10,10,20,30,80,80 meters which gives a calculated mean distance of 32.5 meters. Most *distConsec* values are small, meaning most GPS fixes are quite close to one another (Figure 23,Figure 24 and Figure 25). With cleaning, the outlier distances were eliminated which, again, associated with the smaller number of observations in the post-cleaning data, lead to increases in the median. Using the previous example, the median pre-cleaning was of 15 meters while the median post-cleaning was calculated at 20 meters.

Data cleaning was expected to significantly impact the accuracy of estimated GPS fixes, validated through the Wilcoxon tests. Cleaning significantly impacted all calculated distances, except for the *distReal* and *distCentr* in the wooden setting (Table 9). The wooden setting recorded the least amount of GPS fixes (see 4.2.2). Small sample size impacts test's power, which might justify why cleaning was not statistically significant in the wooden *distReal* and *distCentr*.

This experiment did not investigate species-specific or other possible causes that may impact GPS accuracy (i.e. region satellite cover) which may have had an influence when testing the GPS unit in a different region than the one of the fieldwork.

#### 7. CONCLUSION

By using spatial mixed effects logistic regression models, this project explored the habitat resources associated with FRDD presence in a rural and an urban setting in Indonesia. Additionally, two complementary analysis were conducted: an experiment to test the projects' GPS unit's accuracy and a brief exploration of the collected questionnaire data for a better understanding of the project sites habitat.

Questionnaire data analysis unveiled that most dog owners in Indonesia had perceived gathering behavior by their dogs. Gathering behavior took place mostly in the neighborhood. Other chosen gathering places identified by owners were the garden, beach and terrace in Habi and the street in Pogon. In both sites, around the street was also an identifiable gathering spot. Open fields and party places were reported as the gathering point least used by dogs.

Habitat selection by FRDD disclosed slightly different preeminent preferences according to the setting. The most sought-after resources in both study sites were the buildings and roads. In the urban area, buildings were favored over roads whilst in the rural setting the roads were preferred over buildings. It can by hypothesized that the two crucial predictors of FRDD presence, independent of peculiar habitat resources, are buildings and roads, globally proximity to human dwellings.

Vegetation covered areas were associated with the presence of FRDD in Habi but not in Pogon. Each study site has their distinct resources, characteristic of the habitat, but some common resources can be found. In Habi, apart from the mentioned common resources described also in Pogon (buildings, roads and tree covered areas), dogs' presence was associated with open fields but not with the sea. In this study site the beach was also found to be favoured over tree covered areas. In Pogon it was determined that dogs avoid steep slopes. While buildings and roads may be two invariably sought after resources in Indonesia, the choosing of other resources by FRDD is a consequence of the topographic features available in the habitat (i.e.beach and sea exist in Habi but not in Pogon; Vegetation covered areas in Pogon are represented by its dense forest while in Habi by tree-covered areas).

The GPS unit's accuracy experiment revealed that the devices deployed in Indonesia had moderate accuracy with mean distance from centroid to estimated fixes considered as acceptable across all settings. Investigation on the validity and benefit of the cleaning process applied to the Indonesian dataset was investigated during a static test of the employed units. The cleaning process was overall beneficial to the improvement of GPS precision, providing strength to the habitat selection results.

While these results are novel and relevant, they should not be incautiously extrapolated to other regions. Habitat resources are particular to each world region and GPS collars performance is affected by study species and site-specific characteristics. Due to time

constraints and unpredictable events, the project development was hindered with the analysis focused only on Indonesian datasets. For a broader understanding of habitat selection by FRDD it would be important to repeat this analysis in different settings to assess relevant discrepancies and significant habitat selection predictors in different countries and communities.

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## 9. APPENDIXS

Setting	Minimum	Median	Mean	Maximum	
Open field	PRE-CLEANING				
	Distance from the real to estimated locations				
	0.034	5.232	29.271	15673.612	
	Distance from centroid to estimated locations				
	0.742	9.999	32.936	15669.287	
	Distance between consecutive GPS fixes				
	0	2.621	41.477	15695.046	
	POST-CLEANING				
	Distance from the real to estimated locations				
	0.034	4.493	10.58	667.774	
	Distance from centroid to estimated locations				
	0.325	4.306	10.49	664.706	
	Distance between consecutive GPS fixes				
	0.045	5.636	14.889	699.592	

Appendix 1 - Pre and post-cleaning calculated distances from the open field experimental setting.

Setting	Minimum	Median	Mean	Maximum	
Wooden area	PRE-CLEANING				
	Distance from the real to estimated locations				
	0.71	12.241	24.19	739.652	
	Distance from centroid to estimated locations				
	0.951	12.379	24.225	738.818	
	Distance between consecutive GPS fixes				
	0.137	8.318	32.329	706.959	
	POST-CLEANING				
	Distance from the real to estimated locations				
	0.71	11.014	14.109	61.314	
	Distance from centroid to estimated locations				
	0.886	11.023	14.007	61.971	
	Distance between consecutive GPS fixes				
	0.824	13.211	17.133	74.687	

Appendix 2 - Pre and post-cleaning calculated distances from the wooden area experimental setting.

Setting	Minimum	Median	Mean	Maximum	
	PRE-CLEANING				
Urban	Distance from the real to estimated locations				
	0.544	14.991	22.569	242.953	
	Distance from centroid to estimated locations				
	0.347	12.354	20.72	246.72	
	Distance between consecutive GPS fixes				
	0.025	1.264	3.832	219.797	
	POST CLEANING				
	Distance from the real to estimated locations				
	0.544	14.59	19.334	242.953	
	Distance from centroid to estimated locations				
	0.22	11.602	17.201	246.684	
	Distance between consecutive GPS fixes				
	0.075	12.734	15.69	79.105	

Appendix 3 - Pre and post-cleaning calculated distances from the urban experimental setting.



Appendix 4 – Indonesia's questionnaire structure.