# SPATIAL ECOLOGY AND HABITAT USE OF THE

# ENDANGERED ELONGATED TORTOISE

# (*INDOTESTUDO ELONGATA*) IN THE SAKAERAT

# BIOSPHERE RESERVE

**Matthew David Stanley Ward**
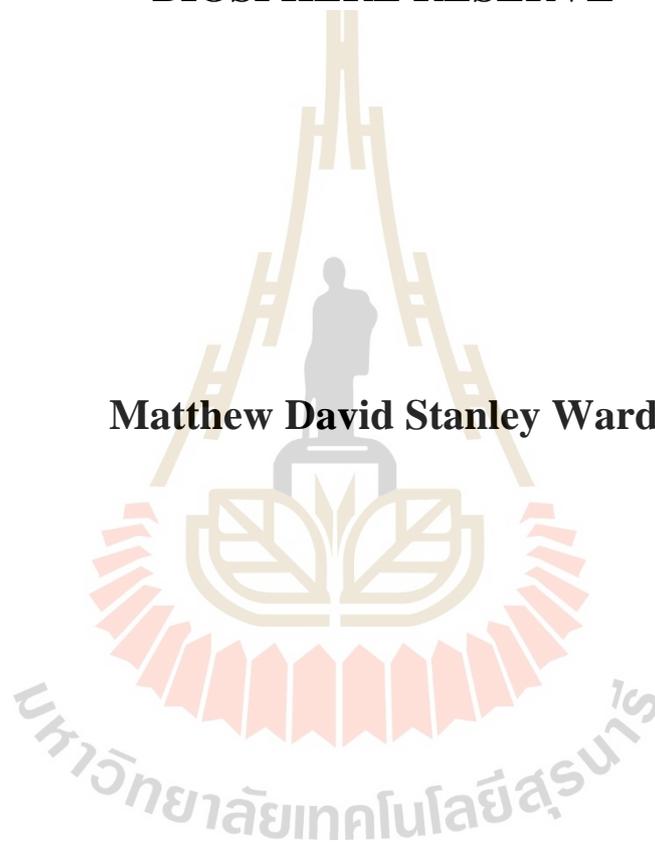
**A Thesis Submitted in Partial Fulfillment of the Requirements for**

**the Degree of Master of Science in Environmental Biology**

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นิเวศวิทยาการเคลื่อนไหวและการใช้ที่อยู่อาศัยของเต่าสีเหลือง

(*INDOTESTUDO ELONGATA*) ในเขตสงวนชีวมณฑลสะแกราช

นายแมธธิว เดวิด สแตนลีย์ วาร์ด

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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# ENDANGERED ELONGATED TORTOISE (*INDOTESTUDO*

# *ELONGATA*) IN THE SAKAERAT BIOSPHERE RESERVE

Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for a Master's Degree.

Thesis Examining Committee

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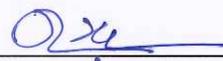
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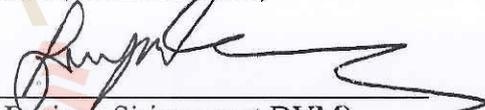
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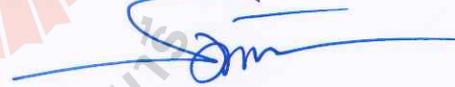
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แมธธิว เดวิด สแตนลีย์ วาร์ด : นิเวศวิทยาการเคลื่อนไหวและการใช้ที่อยู่อาศัยของเต่าสี
เหลือง (*INDOTESTUDO ELONGATA*) ในเขตสงวนชีวมณฑลสะแกราช (SPATIAL
ECOLOGY AND HABITAT USE OF THE ENDANGERED ELONGATED
TORTOISE (*INDOTESTUDO ELONGATA*) IN THE SAKAERAT BIOSPHERE
RESERVE). อาจารย์ที่ปรึกษา : อาจารย์ ดร.คลอลิน โทมัส สไตร์น. 78 หน้า

เต่าเหลือง (*Indotestudo elongata*) เป็นเต่าขนาดกลางที่พบได้ในแถบเอเชียตะวันออกเฉียง
ใต้และแม้ว่าเต่าเหลืองมีขอบเขตการแพร่กระจายทางภูมิศาสตร์ที่กว้างขวาง (จากภาค
ตะวันออกเฉียงเหนือของอินเดียไปจนถึงภาคใต้ของจีน) แต่กลับพบว่าปริมาณประชากรของเต่า
เหลืองมีขนาดลดลงในช่วงหลายทศวรรษที่ผ่านมา ส่งผลให้เต่าเหลืองกลายเป็นสายพันธุ์ที่ใกล้สูญ
พันธุ์จากการจัดลำดับของ IUCN Red List วิทยานิพนธ์ฉบับนี้จะให้ข้อมูลพื้นฐานที่นำไปสู่การ
พัฒนาการศึกษาในอนาคต และเปรียบเทียบกับการศึกษาที่มีมาก่อนหน้านี้ข้าพเจ้าติดตามศึกษาการ
ใช้ชีวิตของเต่าเหลืองทั้งหมดจำนวน 17 ตัว (เพศชาย 5 ตัว และเพศหญิง 12 ตัว) ระหว่างเดือน
มีนาคม ปีพ.ศ. 2559 – กันยายน ปีพ.ศ. 2561 โดยใช้เครื่องวิทยุติดตาม อาทิตย์ละ 3 ครั้งข้าพเจ้า
ประเมินขนาดพื้นที่อาศัยของเต่าเหลืองด้วยวิธี Minimum Convex Polygons (MCP) และวิธี Kernel
Density Estimators (KDE) และศึกษาการรูปแบบการเคลื่อนที่ด้วยการคำนวณความน่าจะเป็นของ
การเคลื่อนที่ในทุกโอกาส รวมกับค่า Mean Daily Displacement (MDD) ในหน่วยเมตร นอกจากนี้
ข้าพเจ้ายังได้ทำการนับบริเวณที่เต่าเหลืองใช้อยู่อาศัย และสัดส่วนเวลาที่เต่าเหลืองใช้ในบริเวณ
ดังกล่าวตลอดฤดูกาลเพื่อระบุการใช้พื้นที่อาศัยของเต่าเหลือง จากการศึกษาพบว่าขนาดพื้นที่อยู่
อาศัยของเต่าเหลืองมีค่าเฉลี่ยอยู่ที่ 26.34 เฮกตาร์ สำหรับการศึกษาด้วยวิธี MCPs และ 23.76
เฮกตาร์ สำหรับการศึกษาด้วยวิธี KDEs โดยไม่มีข้อแตกต่างอย่างมีนัยสำคัญระหว่างเพศของเต่า
เหลืองและวิธีการศึกษา โดยเต่าเหลืองเคลื่อนที่มากที่สุดในช่วงฤดูฝนด้วยค่าความน่าจะเป็นเท่ากับ
0.98 มากกว่าฤดูแล้งอย่างมีนัยสำคัญด้วยค่าความน่าจะเป็นเท่ากับ 0.73 และ 0.72 ในฤดูหนาว
การศึกษาด้วยโมเดล GLM พบว่าความน่าจะเป็นในการเคลื่อนที่ของเต่าเหลืองในช่วงที่มีฝน (0.91)
มีความแตกต่างอย่างกันอย่างมีนัยสำคัญกับช่วงที่ไม่มีฝน (0.79) เต่าเหลืองที่อาศัยอยู่ในป่าเต็งรัง
และบริเวณชายขอบของพื้นที่อาศัยสองประเภท (EDGE) มีค่า MDD มากกว่าเต่าเหลืองที่อาศัยอยู่
ในป่าดิบแล้ง อย่างมีนัยสำคัญ โดยเต่าเหลืองจะใช้พื้นที่อาศัยในป่าดิบแล้งมากกว่าในฤดูแล้ง และ

ใช้พื้นที่อาศัยในพื้นที่ป่าเต็งรังมากกว่าในฤดูฝน งานเขียนที่มีอยู่ในปัจจุบันมีความสอดคล้องกับผล
การศึกษาของข้าพเจ้า โดยพบว่าความน่าจะเป็นในการเคลื่อนที่ของเต่าเหลืองเพิ่มขึ้นตามปริมาณ
น้ำฝน อย่างไรก็ตาม ผลการศึกษาแสดงให้เห็นว่า ค่า MDD ลดลงอย่างมีนัยสำคัญในป่าดิบแล้ง แต่
ความน่าจะเป็นในการเคลื่อนที่กลับเพิ่มขึ้น ซึ่งเป็นไปได้ว่าความแปรปรวนของทรัพยากรที่มีอยู่
และสิ่งแวดล้อมที่ไม่มีชีวิต น่าจะส่งผลต่อความน่าจะเป็นในการเคลื่อนที่ด้วยเช่นกัน นอกจากความ
ผันแปรตามฤดูกาลที่จำกัดแล้ว ป่าดิบแล้งยังเป็นป่าทึบที่มีความชื้นเฉลี่ยต่อปีสูง และมีอุณหภูมิพื้น
ล่างต่ำ เต่าเหลืองเป็นเต่าสายพันธุ์ที่มีความยืดหยุ่นในการกินอาหารและที่อยู่อาศัย ทำให้การศึกษา
รูปแบบที่ชัดเจนในกลุ่มตัวอย่างขนาดเล็กเป็นไปได้ยาก โดยเต่าเหลืองบางตัวมีระยะทางเฉลี่ยใน
การเคลื่อนที่มากกว่าเต่าเหลืองตัวอื่น ๆ ทั้งที่อยู่อาศัยในพื้นที่เดียวกันและต่างกันงานวิจัยของ
ข้าพเจ้าช่วยยืนยันข้อมูลที่มีอยู่ของงานวิจัยในอดีต และยังเป็นข้อมูลพื้นฐานสำหรับการเปรียบเทียบ
การศึกษาการย้ายถิ่นฐานของเต่าเหลืองอีกด้วย

สาขาวิชาชีววิทยา       ลายมือชื่อนักศึกษา_____

ปีการศึกษา 2561       ลายมือชื่ออาจารย์ที่ปรึกษา_____

MATTHEW DAVID STANLEY WARD : SPATIAL ECOLOGY AND
HABITAT USE OF THE ELONGATED TORTOISE (*INDOTESTUDO
ELONGATA*) IN THE SAKAERAT BIOSPHERE RESERVE. THESIS
ADVISOR : COLIN THOMAS STRINE, Ph.D. 78 PP.

ELONGATED TORTOISE / HOME RANGE / MOVEMENT / HABITAT USE /
GLM

The elongated tortoise (*Indotestudo elongata*) is a mid-sized tortoise species
found across Southeast Asia. Despite a broad geographic range (from Northeast India
through to Southern China) *Indotestudo elongata* has declined in population in recent
decades leading to an endangered species status from IUCN Red List. This thesis will
provide a wild baseline for the previous studies and future studies to build off and
compare. Two sample groups of 17 individuals (5 males and 12 females) were tracked
using radio-telemetry between March 2016 - September 2018. Home range size was
estimated with both minimum convex polygons (MCP) and kernel density estimators
(KDE) and movement patterns were determined by calculating the probability of
movement on any occasion combined with mean daily displacement (MDD) in
meters. Sites that tortoises used were counted and the proportion of time spent were
considered in the site over the season to identify habitat use. The mean home range
size was 26.34ha for MCPs and 23.76ha for 95% KDEs, with no significant difference
between the sex. The wet season had the highest movement probability (0.98),

significantly greater than the dry (0.73) and cold (0.72) seasons. A generalised linear model (GLM) suggested there was a significant difference in the movement probabilities in the presence of rain (0.91) than without rain (0.79). Tortoises in Dry dipterocarp forest (DDF) and edge habitat (EDGE) had significantly higher MDD than in dry evergreen forest. I observed seasonal differences in habitat use; The tortoises used DEF habitat most during the dry season but mainly used DDF during wet seasons. Existing literature concurs with my findings that movement probabilities increase with rainfall. As MDD is significantly lower in DEF habitat, but movement probability significantly higher; it is possible that variation in available resources and abiotic environment affects movement probability as well. The DEF is a dense forest with higher annual average humidity and lower ground temperatures in addition to limited seasonal variability. This species is a generalist with its diet and habitat and has observable personality differences which make it hard to find significant variations with small sample sizes. Some individuals appear to move greater average distances than others with differences in the shelter usage also common among individuals of the same area. This study confirms natural history information from previous work and acts as a baseline for comparison with translocation based studies of *Indotestudo elongata*.

School of Biology          Student's Signature_____

Academic Year 2018          Advisor's Signature_____

# ACKNOWLEDGEMENTS

I finally want to show my appreciation to my family, my Sakaerat family and my amazing wife Ysabella. It is not easy conducting research, it is not easy managing a team and it is not easy balancing personal life with busy research life, school work and field work. My wife has supported and inspired me to continue this path each day and I am incredibly thankful. I also need to acknowledge Indy the canine assistant. He has motivated me throughout by always finding a way to lift mine and my wife's spirits, along with others at Sakaerat when things seem bleak.

Matthew Ward
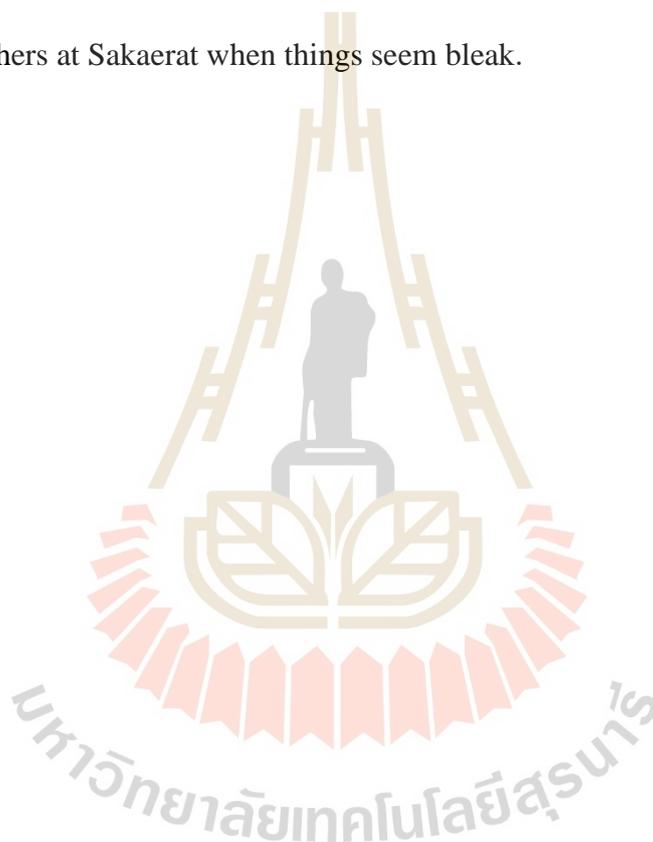
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# LIST OF ABBREVIATIONS

AIC     =     Akaike's Information Criterion

DDF     =     Dry evergreen forest

DEF     =     Dry dipterocarp forest

EDGE    =     Ecotone/edge habitat between dry evergreen forest and

              dry dipterocarp forest

GLM     =     Generalized linear model

GLMM    =     Generalized linear mixed models

KDE     =     Kernel density estimator

MCP     =     Minimum convex polygon

MDD     =     Mean daily displacement

SERS    =     Sakaerat Environmental Research Station

TISTR   =     Thailand Institute of Science and Technological

              Research

# CHAPTER I

# INTRODUCTION

## 1.1 Introduction

Effective conservation strategies require a broad ecological understanding (Groves *et al*., 2002). Understanding movement patterns of priority species are particularly important for species and landscape level (Groves *et al*., 2002, Pressey *et al*., 2007). Conservation planning involves many steps, stakeholders and resources but requires rigorous science (Groves *et al*., 2002, Pressey *et al.*, 2007).

The elongated tortoise (*Indotestudo elongata*) is a mid-sized tortoise species found across Southeast Asia (Ihlow *et al.*, 2016). It has been documented in multiple habitat types across the region including bamboo forest, dry dipterocarp forest, wet and dry evergreen forest, savannah grassland and agricultural areas yet no habitat type is considered to be its primary preference (van Dijk, 1998, Ihlow *et al.*, 2016). The species is a generalist, feeding on numerous leafy vegetation, root tubers, fungi, dead vegetation, flowers, fruits and seeds, dead and live invertebrates, carrion and faeces (McCormick, 1992, Ihlow *et al*., 2012, Sriprateep *et al*., 2013). Despite a wide geographic range (Northeast India, Southeast Asia & Southern China) *I. elongata* populations have declined in recent decades. Listed as endangered by the IUCN Red List in 2000 the population figures have not been updated since (IUCN 2016). Trade affects many chelonia in the region however *I. elongata* is threatened by local and

international trade from the food, exotic pet and Asian medicine markets (Holloway, 2003; Asian Turtle Conservation Network, 2006; Cheung and Dudgeon, 2006).

There are conservation projects and researchers actively involved in *I. elongata* currently but they are very low in number, with less than 5 articles relating to *I. elongata* published in the last two decades. The literature and current work on *I. elongata* suggests that the current information is either contradictory or extremely vague, with current studies largely focused on ecology of translocated individuals or within non-natural environments not identifying a wild baseline (Ihlow *et al*., 2016).

My study aims to identify a baseline of movement patterns and seasonal variation in habitat use and activity. I use generalised and/or mixed-effects models, to identify variables affecting probabilities of movement and mean distances moved as variation parameters. Predicitive models included seasonal, sex, weather, and habitat types to identify which factors affects movement patterns. Better understanding of home ranges and movement patterns will inform population based study designs thus allowing more accurate estimates and more appropriate conservation measures.

The data from my study are comparable to other study areas throughout Southeast Asia, although my study is limited to a single Thai population. Making the implications broadly applicable for conservation planning and protected area managers. In addition, the natural history observations will be useful for ex-situ conservation institutions like Zoos and reptile farms.

## 1.2 Research Objectives

1.2.1 Identify the home-range size of adult *I. elongata* and compare males and females using Minimum Convex Polygons and Kernel Density Estimators.

1.2.2 Use generalised linear models to identify the most influential recorded environmental factors in predicting movement probability, movement distance and habitat use.

1.2.3 Identify the habitat used most frequently by adult *I. elongata* in each season.

1.2.4 Record biometric measurements of *I. elongata* caught in the Sakaerat Biosphere Reserve to assess dimorphic characteristics, and identify any influence of body size on home range size.

## 1.3 Hypotheses

1.3.1 The home-range of an adult *I. elongata* will be between 20ha and 40ha based on estimates by Ihlow *et al*. (2016).

1.3.2 Male home ranges will be significantly larger than female home ranges (Ihlow *et al.,* 2016).

1.3.3 There will be a significant difference in proportional *Dry Evergreen* forest use and *Dry Dipterocarp* forest use in the dry season (March-August).

1.3.4 Dry dipterocarp forests will be used more frequently during rain.

1.3.5 Rainfall (in mm) will be positively correlated with mean daily displacement (in m).

1.3.6 Home range size (ha) will have no association with morphometric characteristics when correlated with body size in cm (width:length).

## 1.4 Scope and Limitations

I collected field data from March 2016 to April 2017 using radio-telemetry for the first sample of 10 individual (5 male and 5 female) tortoises. The second sample

of 10 females were tracked from September 2017- October 2018. My team collected GPS fixes with telemetry locations, observed behaviours, and visual data from habitat and microhabitat elements. We also collected photographic evidence at fix locations for post-hoc review. I collected data in the dry evergreen forests, bamboo forests and dry dipterocarp forests of the core area within 5km of the Sakaerat Environmental Research Station (SERS).

The study makes use of VHF radio-telemetry which is negatively impacted by high humidity or rainfall. Radio telemetry also requires human observers to manually locate and potentially disturb the subject each time it is tracked. Alternatively, GPS telemetry uses devices linked to satellites to record the same movement and location data without any human disturbance. GPS telemetry costs approx. $1000 per transmitter over the equivalent $180 VHF telemetry transmitter. In addition, the accuracy of GPS devices is questionable in heterogeneous landscapes like the dry evergreen forest which has high canopy cover. Accuracy estimates are also often impossible because researchers collect data remotely. Due to the price range and variable accuracy ranges of GPS telemetry, I elected to used VHF telemetry in spite of the known limitations.

# CHAPTER II

# LITERATURE REVIEW

## 2.1 Tortoise Conservation and Research

### 2.1.1 Asian Tortoise Conservation

There are between 80-90 chelonia (turtle and tortoise) species in Asia, with at least 60% of these present in the Indo-Burma and Sundaland biodiversity hotspots of southeast Asia (Buhlmann *et al*., 2009). Approximately 30% of the worlds chelonia species and 75% of those threatened with extinction (Turtle Conservation Fund, 2002).

In Asia, habitat destruction for agricultural use, including rice or cassava, plantations, traditional medicine, exploitation for human consumption and illegal trade represent the most important factors for chelonians 'population decline (Asian Turtle Conservation Network, 2006). The illegal trade in Southeast Asia is mainly driven by an increasing demand in China where chelonians are traded as pets, delicacies or for several purposes correlated with traditional medicine (Bradley and Phipps, 1996). According to Touch *et al.* (2000), Cambodia is heavily involved in the trade of chelonians, domestically as well as to China via Vietnam. The Asian Turtle Conservation Network (2006) projected ten million chelonians are traded annually (Asian Turtle Conservation Network, 2006). Further, Holloway (2003) found *I. elongata* to be the most commonly traded species in Cambodia; With most traded *I.*

*elongata* bound for Chinese markets through Vietnam. Population declines resulting from illegal international trade may result in *I. elongata* extinction (Holloway, 2003).

The Tortoise and Freshwater Turtle Specialist Group determine threatened status for all Asian chelonians by cooperating with both IUCN and CITES. Policy then regulates trade based on population trends (Turtle Conservation Fund, 2002). Focused conservation based research of Chelonian species has thus become a priority throughout the region; So novel investigations into the natural history of vulnerable species are necessary. The Chelonia Research Foundation and Turtle Survival Alliance are both active in conservation research for a plethora of threatened Asian chelonia species by collaborating with zoological partners and passionate individuals world-wide. As a result, theChelonia Research Foundation recently updated the global distributions for turtles and tortoises and revised conservation status according to regional conservation areas  (Buhlmann *et al*., 2009).

**2.1.2 Tortoise Research**

Currently most tortoise research comes from North American or European tortoise species with projects on the Desert Tortoise (*Gopherus agassizi*) and Gopher Tortoise (*Gopherus polyphemus*) ongoing for the last 40 years in the United States of America. Investigators use radio telemetry to identify movement behaviour and habitat use worldwide on endangered tortoise species (table 2.1). Radio telemetry spatial ecology and movement studies measure home-range sizes, movement patterns, behavioural ecology and habitat use (Freidenfelds *et al*., 2011). Subjects have a small device (usually less than 5% of their total body mass) attached to them which emits a radio-signal, which is received by the researcher. Because tortoises are elusive and

easy to disturb, radio telemetry is often the most cost effect method for investigating home range, habitat use, and movement patterns (Ihlow *et al*., 2014, Berardo *et al*., 2015, Greenspan *et al*., 2015). Behavioural observations and population study through mark-recapture and location marking can broaden inferences from home range assessments by combining the data (Sriprateep *et al*., 2013, Wanchai *et al*., 2013).

## 2.2 The Elongated Tortoise

The elongated tortoise (also known as yellow tortoise or yellow headed tortoise) *Indotestduo elongata* is a medium sized tropical tortoise species, measuring between 20-36cm in length and 1.4-4kg in mass for adults. The species is disjunct throughout Southeast Asia, Northern India, Nepal and Southern China however its current global population and population ranges within sites are not well known (McCormick, 1992, IUCN 2016). It was listed as endangered in 2000 due to declines from trade and habitat loss within its known range (IUCN, 2016). The elongated tortoise has limited published natural history information; in fact all but two studies used translocated animals or animals in an altered environment (Sriprateep, 2013, Ihlow *et al*., 2016). Thus the information pertaining to *I. elongata* ecology is sparse with the little information we have on *I. elongata* comes primarily from natural history observations. Elongated tortoises likely have no territorial behaviour or intraspecific competition according to the literature, with the exception of one publication showing male to male combat over access to a female (Ward *et al*., 2018).

**Table 2.1** Tortoises studied through radio-telemetry with the study focus and species body mass.

| Tortoise Species | Average Male Body Mass | Study Focus | Researchers |
|---|---|---|---|
| Speckled Padlopper (*Chersobius signatus*) | 140g (World Association Zoos and Aquaria) | Home range and habitat use. | Loeher, 2015 |
| Mediterranean Tortoise (*Testudo graeca*) | | Thermal ecology and implications for conservation of habitat. | Moulherat *et al.,* 2014 |
| Elongated Tortoise (*Indotestudo elongata*) | 1.8-2.5 kg (Ihlow *et al.,* 2016) | Home range and habitat use. | Ihlow *et al.,* 2014 |
| Gopher Tortoise (*Gopherus polyphemus*) | 5.5 kg (Animal Diversity Web) | Survival of translocated individuals. | Tuberville *et al.,* 2008. |
| Ploughshare Tortoise (*Astrochelys yniphora*) | 10.3 kg (IUCN) 5.5-18.9 kg (Animal Diversity Web) | Movement patterns of translocated/released captive individuals. | Pedrono and Sarovy, 2000. |
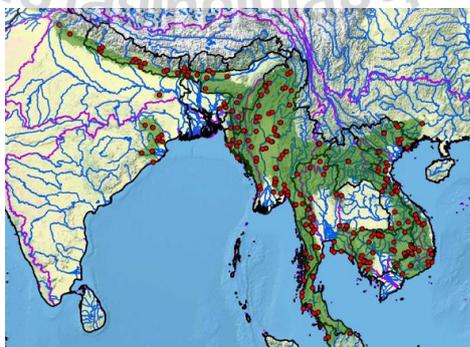


**Figure 2.1** Distribution map of *I. elongata* range across south and southeast Asia (Ihlow *et al.,* 2016).

## 2.3 Analysis with Models

Mathematical models are simple representations of nature. Ecological models help identify influential factors determining species movements, habitat selection, and behaviour (Powell and Gale, 2015). Difficulties in using standard statistics for ecological or behavioural studies include the use of non-normal data, categorical or discrete data and the investigation of random effects (Bolker *et al*., 2008). When studies assess selection, preference or individuals choices they are investigating individual variation which involves random variable relationships (Melbourne and Hastings, 2008). Estimating variability allows extrapolation of statistical results beyond the individual or population being studied. In this situation, investigators can use generalized linear mixed models, to avoid transforming data or corrupting assumptions of classical frequentist statistics, generalised linear mixed models (Bolker *et al*., 2008). The generalised linear models (GLMs) can measure the distribution of a stochastic response variable against the mathematical functions of stimulus variables (Venables and Dichmont, 2004). Mixed models are an ideal tool for analysing non-normal data that involve random effects (Bolker *et al*., 2008). The mixed models identify a distribution, link function and structure of the random effects. Investigators use mixed models widely in the ecological sciences, not always correctly, nevertheless they are increasingly useful tools in ecological and evolutionary biology studies (Bolker *et al*., 2008).

## 2.4 Modelling in Ecology

In ecology, one of the fundamental question researchers aim to answer is: Where is my study species distributed and why is it in that particular location? An

experimental approach is often ineffective or inappropriate for answering this question so instead we can model associations with habitat types and environmental covariates. The use of models allows us to see changes in predictor covariates or combinations of covariates and how our response variable (Habitat selected or distance moved) reacts to these changes. In this instance the analysis of the habitat use and any indication of association with temporal and abiotic conditions will be conducted through the use of generalised linear modelling and generalised linear mixed-modelling. This will accompany the construction of similar generalised linear models and mixed models in attempting to identify associations in movement distances and probabilities with the accompanying abiotic factors and seasonal classifications.

## 2.5 Study Site

The Sakaerat Biosphere Reserve (SBR) is a UNESCO Man and Biosphere Reserve established in 1967 (United Nations Educational, Scientific, and Cultural Organization; Tongyai, 1983). The establishment of SBR and the Sakaerat Environmental Research Station (SERS) within aimed to encourage the "conservation of nature and scientific research in the service of man". Additionally the reserve aimed to "provide a standard against which can be measured the effects of man's impact on his environment" (M'Bow, 1977). The SBR has 3 zones, the Transition Zone, Buffer Zone and Core. The Transition Zone is where anthropogenic activity is allowed, including economic and human development which is socio-culturally and ecologically sustainable and appropriate. The Buffer Zone surrounds the Core area and allows some anthropogenic activity including education, training or scientific

research of the ecology and environment. The Core has restricted access and researchers may undertake non-invasive and non-destructive scientific research, to allow the conservation of landscapes, ecosystems, genetic flow and species richness (UNESCO, 2017). The SBR Core area consists of predominantly dry evergreen forest (60%) and dry dipterocarp forest (18%) with patches of bamboo forest, grassland and plantation regrowth forest sparsely distributed. Within these forests there is a diverse number of species including >79 mammal species, >290 bird species, >82 reptile species (including only one tortoise species, *I. elongata*).



**Figure 2.2** Map of Sakaerat Biosphere Reserve with Transitional, Buffer and Core zones illustrated.

# CHAPTER III

# METHODS

## 3.1 Study Area

My team investigated tortoise home range size with Radio-telemetry in the dry evergreen, dry dipterocarp and bamboo forests of the Sakaerat Biosphere Reserve. The study focuses on a section of the core area of the reserve near the central Sakaerat Environmental Research Station (SERS). The core area of the reserve is 7800 ha however the specific study area encompasses only 446 ha bordered by the highway 304.I selected the study area based on ease of access as many trails lead to the surrounding forest area and stream beds. My study area boundaries consisted of the maximum outer home range points for all my radio-tracked animals.

I used weather data (rainfall and temperatures) from a static weather station at the research station collected daily by SERS staff. Over the previous decade this data has recorded the temperatures, humidity and rainfall of each day consecutively enabling researchers to look at trends and correlations with subject movements and habitat use (table 3.1).

**Figure 3.1** Study area containing the home ranges of the 10 study subjects. Combination of dry dipterocarp forest, dry evergreen forest and bamboo forest bordered by the highway 304.

**Table 3.1** Abiotic data from 2006-2016 taken from SERS weather station.

| Year | Mean Max Temp (°C) | Mean Min Temp (°C) | Mean Humidity rH(%) | Total Annual Rainfall (mm) |
|------|------|------|------|------|
| 2006 | 31.3 | 21.1 | 88 | 854.9 |
| 2007 | 31.1 | 22.0 | 91 | 1079.6 |
| 2008 | 30.1 | 21.3 | 90 | 1131.9 |
| 2009 | 34.6 | 19.5 | 86 | 811.5 |
| 2010 | 33.9 | 20.2 | 82 | 1219 |
| 2011 | 32.3 | 19.5 | 82 | 1155.2 |
| 2012 | 33.8 | 20.2 | 81 | 1132.4 |
| 2013 | 33.9 | 20.6 | 79 | 1419 |

**Table 3.1** Abiotic data from 2006-2016 taken from SERS weather station (Continued).

| Year | Mean Max Temp (ºC) | Mean Min Temp (ºC) | Mean Humidity rH(%) | Total Annual Rainfall (mm) |
|------|--------------------|--------------------|---------------------|----------------------------|
| 2014 | 33.2 | 20.5 | 78 | 969.4 |
| 2015 | 35.0 | 20.6 | 78 | 1015.5 |
| 2016 | 34.8 | 19.6 | 72 | 1072.5 |
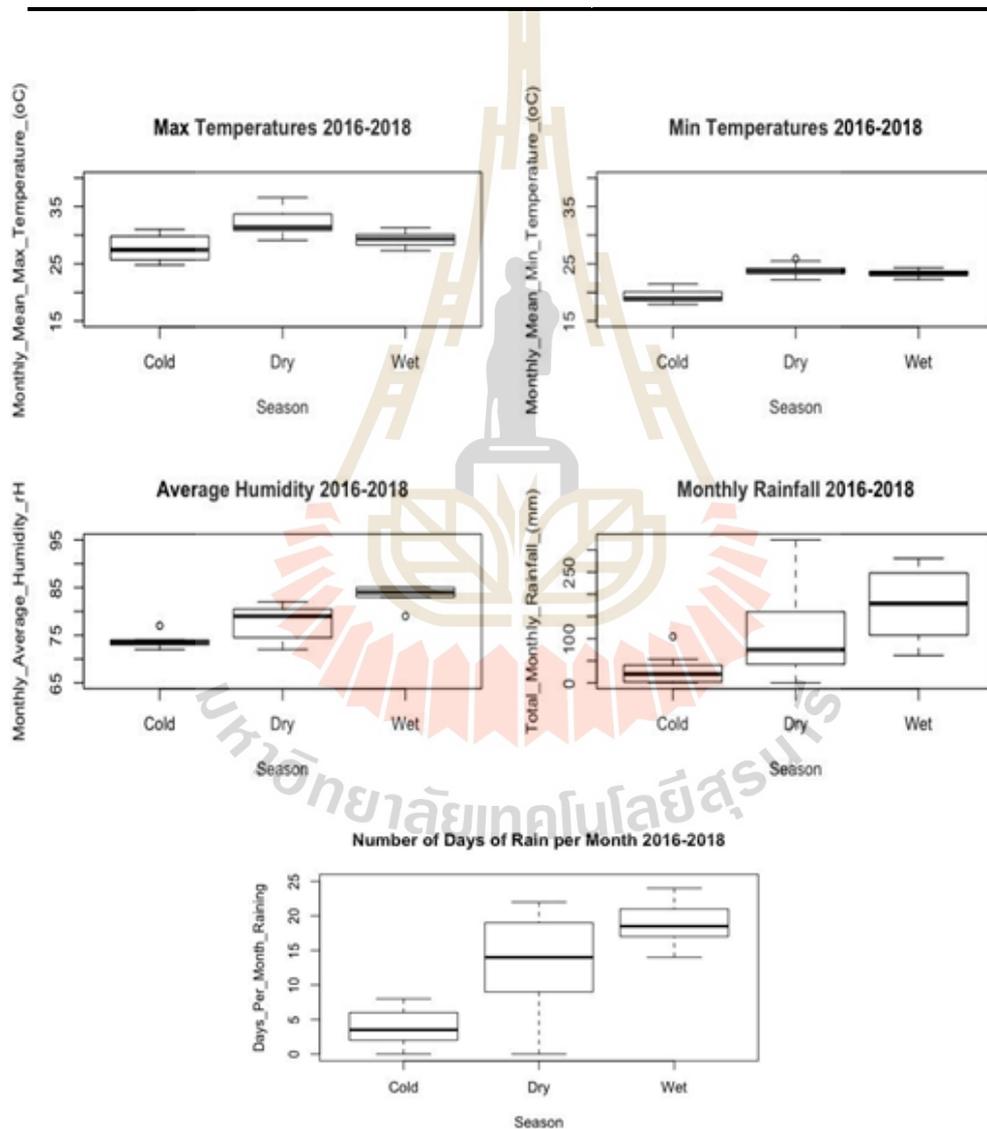


**Figure 3.2** Abiotic changes across the Cold, Dry, and Wet seasons in Sakaerat Environemtnal Research Station according to Sakaerat weather station.

## 3.2 Spatial Ecology and Movement.

### 3.2.1 Radio Transmitter Attachment

I captured 10 adult tortoises (5 male and 5 female) in March 2016 for the initial sample with the second sample of 9 adult females caught between September and October 2017. I processed the tortoises recording their length and width in cm and mass in kg. I attached a 9g Holohil Ri-2B transmitter to their carapace with epoxy resin, in guidance with the method used by Ihlow *et al.* (2016) and other tortoise telemetry studies (Nafus *et al.*, 2015; Deepak *et al.*, 2016).

I placed the transmitter on the anterior of the carapace and ran the antenna along the lower section of the anterior costal scutes (anterior to posterior). In order to reduce chance of the antenna becoming loose or inhibiting natural behaviour the antenna had to be placed away from the rear carapace of females. The antenna and transmitter were held in place with electrical tape whilst I placed epoxy resin (50/50 combination resin and hardener) to the base of the transmitter and the across the top of the antenna in horizontal strips. I put the tortoise into a sealed box until the next day when the tape was removed (as long as the epoxy is hardened) and I released the subject where it was found.

**Figure 3.3** Ri-2B Holohil transmitter attachment and release of telemetered *Indotestudo elongata*. (Starting Left-Right: Epoxy attachment to transmitter, Transmitter attachment to anterior carapace of subject, Fixing of transmitter and antenna to carapace using tape to seal bond with epoxy, Release of subject with hardened epoxy).

I tracked the subject 48hrs after release in order to allow time to de-stress and reacquire a shelter. This was an arbitrary figure however given the species observed reactions to handling and disturbance I deemed it long enough to allow for continued natural behaviours and movement to a chosen location.

### 3.2.2 Radio Tracking

I tracked each subject once every two days using radio-telemetry. Each subjects' individual frequency was tuned into the radio receiver and the I followed the signal directly to the subject. When I located a subject their exact location was recorded via handheld *eTrex*-10 or 64SMap Garmin GPS devices with an average of 4m error. This was succeeded by the collection of habitat, behaviour and movement data before the I moved on to the next subject. I never directly touched the subjects and replaced any debris, leaflitter or vegetation that was moved in the process of observing the subjects live location. I would usually spend less than 10min within 10m proximity of the subject before moving on.

### 3.2.3 Data Collection

I collected data on a custom made data-sheet from the app epi-collect on an iPad mini. I recorded individual identification, date of data collection, time of data collection, whether the subject had moved and if so its new GPS coordinates (in UTM WGS84), distance from its last location and direction of movement. The individual behaviour at first contact (from an ethogram of pre-classified behaviours), the habitat it was currently in (from a list of categories) and finally a description of the subjects micro-habitat and shelter (if it was in one) were also recorded. Finally, I took a

photograph for documentation purposes of the subject in its micro-habitat and/or shelter before the moving on. Data concerning weather measurements (rainfall, temperature etc.) were input later from the daily collected data at the static weather stations.

## 3.3 Habitat use

Each time I tracked the subject the habitat type was recorded. I selected a habitat types from a categorical list of dry dipterocarp forest (DDF), dry evergreen forest (DEF) and ecotone or edge habitat (EDGE). Some habitat types previously listed within the data-sheet were congregated into the above 3 primary habitats. I also congregated some habitats into other dominant habitat types, for example combing the variants of edge habitats into one label EDGE and incorporating the rarely used bamboo forest into DEF as the dominant containing the small patches of bamboo. Burnt dipterocarp forest was also included within the DDF group as this was a temporary habitat type lasting less than 2 months. If there was to be any variation because of this habitat it should be picked up with the monthly and seasonal covariates within the models.

## 3.4 Morphological Measurements

I recorded the straight line length and width in cm (with a 30cm ruler), carapacial dome length and width in cm (using a flexible tape measure) and mass in kg (using digital hanging scales) of each animal within the study. These measurements were taken at the time of first capture, during 6 month health checks and at the time of transmitter removal. The average weight across these periods along

with the final length/width measurements were then used for the analysis. Along with the measurements I recorded note-worthy marks or damage to the individual and parasites before photographing the animal for ID purposes.

## 3.5 Data analysis

### 3.5.1 Spatial Ecology and Movement

Significance testing for the home range sizes and other analyses within this document largely consists of non-parametric frequentist methods such as Wilcox or Kruskal-Wallis tests for more flexibility within underlying assumptions. Parametric frequentist test assumptions expect normality of data distribution, homogeneity of variance and large representative samples of unbiased, random individuals (Vargha and Delaney, 1998). Within most ecological studies these assumptions, particularly unbiased sampling and normal data distributions can rarely be met and so the non-parametric alternatives are opted (Povtin and Roff, 1993). Sacrificing some of the statistical power for the flexibility of manoeuvring around the assumptions.

#### 3.5.1.1 Home Ranges

I estimated the home range sizes using 95% and 50% kernel density estimators (KDE) in hectares and minimum convex polygons (MCP). I used program R with background maps from ArcGIS to create the MCPs and KDEs for visualisation. I wanted to use autocorrelated kernel density estimators (AKDE) as standard kernel density estimators and minimum convex polygons assume independence between each datapoint. Regular KDEs work on the assumption that each datapoint is independent of one another. Using 95% locations of telemetry data

with intervals of 1-3 days this independence assumption is violated and so AKDEs were intended to work around this spatial and temporal autocorrelation. However the infrequent tracking regime and inconsistent movement patterns prevented AKDEs from working. I also include the home range estimates and imagery of 100% MCPs as these are regularly used in the literature to illustrate home ranges and although do not account for movement patterns can often encompass larger areas for conservation.

### 3.5.1.2 Movement Data

The movement patterns were analysed using the probability of movement and the distances moved between datapoints calculated as a mean daily displacement (MDD). Before creating any models I tested the covariates for collinearity using the "pairs" function in program R. Any highly correlated variables were identified and only one of either variable used in each model. Using program R and package *lme4* I created Generalised Linear Models (GLMs) to identify which individual or combination of covariates; temperature (maximum and minimum), humidity, rain (presence/absence) and rainfall (in mm), habitat type, month and season, sex, sample period and tortoise ID, would identify the highest probability of movement (table 3.2). The GLM was required because of the need to use a Binomial distribution, in the prediction of probabilities. I used the "dredge" function from package *MuMIn* to compare the entire set of covariates for their impact on the probability of movement, aiding the selection of key covariates and which dependent or collinear covariates to remove. The dredge output shows the covariates used, coefficient estimates (for continuous covariates), log likelihood (model fit), number of parameters, model weight and AIC and delta AIC score, with the models listed in

order of lowest AIC score (delta AIC = 0) with the best predictors of movement probability at the top of the table (table 3.2). These probabilities could then be identified through the "plogis" function in the *wiqid* package in R, which translates log-odd coefficients into binomial probabilities. I used further GLMs to investigate which of the covariates above best predict the observed MDD in each individual. The use of a GLM was necessary as the model used a non-normal distribution or a natural log link to fit the model to the MDD data. I further investigated the effect of habitat type on MDD with the use of Kruskal-Wallis non-parametric significance test and pairwise Wilcox tests.

**Table 3.2** List of top 10 models to predict movement probability created by "dredge" function, ranked according to AICc score. + indicates categorical covariate is used, slope coefficients represented for numerical covariates. (*Int* = Intercept, *Hbt* = Habitat type, *Hum* = Humidity, *Mx. Tmp* = Max temperature, *Mth* = Month, *R. 24* = Rain since previous datapoint, *R. mm* = Rainfall amount in mm, *Smp* = Sample group, *Sex* = Sex, *Trt. ID* = Tortoise ID, *df* = Degrees of freedom, *lg LIK* = Log Likelihood, *AICc* = Corrected AIC, *delta* = delta AIC, *Wt* = Model weight).

| Int | Hbt | Hum | Mx.Tmp | Mth | R.24 | R. mm | Smp | Sex | Trt. ID | df | lg LIK | AICc | delta | Wt |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -5.180 | + | 0.114 | -0.081 | + | | | | | + | 32 | -631.7 | 1328.5 | 0.0 | 0.13 |
| -5.180 | + | 0.114 | -0.0814 | + | | | | + | + | 32 | -631.7 | 1328.5 | 0.0 | 0.13 |
| -5.231 | + | 0.111 | -0.075 | + | 0.183 | | | | + | 33 | -631.2 | 1329.6 | 1.08 | 0.07 |
| -5.231 | + | 0.111 | -0.075 | + | 0.183 | | | + | + | 33 | -631.2 | 1329.6 | 1.08 | 0.07 |
| -5.505 | + | 0.115 | -0.076 | + | | | + | | + | 33 | -631.2 | 1329.6 | 1.09 | 0.07 |
| -5.505 | + | 0.115 | -0.076 | + | | | + | + | + | 33 | -631.2 | 1329.6 | 1.09 | 0.07 |
| -5.105 | + | 0.112 | -0.080 | + | | 0.003 | | | + | 33 | -631.6 | 1330.4 | 1.91 | 0.05 |

**Table 3.2** List of top 10 models to predict movement probability created by "dredge" function, ranked according to AICc score. + indicates categorical covariate is used, slope coefficients represented for numerical covariates. (*Int* = Intercept, *Hbt* = Habitat type*, Hum* = Humidity, *Mx. Tmp* = Max temperature, *Mth* = Month, *R. 24* = Rain since previous datapoint, *R. mm* = Rainfall amount in mm, *Smp* = Sample group, *Sex* = Sex, *Trt. ID* = Tortoise ID, *df* = Degrees of freedom, *lg LIK* = Log Likelihood, *AICc* = Corrected AIC, *delta* = delta AIC, *Wt* = Model weight) (Continued).

| Int | Hbt | Hum | Mx.Tmp | Mth | R.24 | R. mm | Smp | Sex | Trt. ID | df | lg LIK | AICc | delta | Wt |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -5.105 | + | 0.112 | -0.080 | + | | 0.003 | | + | + | 33 | -631.6 | 1330.4 | 1.91 | 0.05 |
| -5.552 | + | 0.113 | -0.070 | + | 0.180 | | + | | + | 34 | -630.7 | 1330.7 | 2.20 | 0.04 |
| -5.552 | + | 0.113 | -0.070 | + | 0.180 | | + | + | + | 34 | -730.7 | 1330.7 | 2.20 | 0.04 |

### 3.5.2 Habitat Use

For all tortoises I ran Pearson's chi-squared tests and Kruskal-Wallis significance tests against the use of each of the habitats to see which habitats were used more frequently than others. These tests identified whether there was any difference in habitat use between seasons, sexes and sample years.

### 3.5.3 Morphological Variation

I compared the average weights, body and carapace dimensions and length/width ratio using Wilcox non-parametric significance tests, Kruskal-Wallis non-parametric significance tests and Pearson's chi-square. These tests were used to

compare males against females with models made to look at the affect of these variations in sizes against habitat use, movement probability and MDD.

### 3.5.4 Model Selection

Model selection is the decision making process for the most suitable models out of a model set and whether the models are viable or meet the required assumptions (Powell and Gale, 2015). I am using Akaikes Information Criterion (2k-2ln($L$)) (AIC) and the sample corrected AICc as the selector of the best model within a set. AIC weighs the fit of the model (ln($L$): model likelihood estimates) and the complexity (k: number of parameters). The aim is to have the fewest possible parameters to explain the most variance within the changes in response variable (Bolker, 2008, Powell and Gale, 2015). I decided whether the covariates and models were appropriate and fit the necessary assumptions to be used through the use of visual and test diagnostics. I tested covariates for distribution using histograms, density plots and Shapiro-Wilks tests of normality, with model linearity and QQ normality tests to identify if the model predictions fit assumptions of a GLM.

# CHAPTER IV

# RESULTS AND DISCUSSION

## 4.1 Results

### 4.1.1 Home Range Estimates

Animal F5 was tracked in both sample years, as such I created home range estimates for each year. The two years had similar home range estimates and a combined home range estimate non-significantly (p=0.5) larger (95% KDE and MCP) than the two previous years (table 4.1). For all home range comparisons I used only F5 first sample home range estimates. I found non-significant variation in the MCP and 95% KDEs *within* the females in each sample (S1- MCP: 36.35-14.71ha, KDE: 33.14-13.53ha) (S2- MCP: 70.97-3.55ha, KDE: 25.58-3.38ha) and no significant difference (W = 24, p-value = 0.3434) *between* the samples of females. There was a significant difference between the samples in 95% KDEs (W = 37, p-value = 0.02214) including males of sample 1. I tested for differences between the sexes in sample 1 but found no significant difference between male and female MCPs or 95% KDEs ( MCP- W = 18, p-value = 0.3095, KDE- W = 21, p-value = 0.09524).

I modelled the home range estimates of the individuals with their body mass and body lengths. The model output suggests that there is no correlation between body size and home range size.

**Table 4.1** Home range estimates of all study individuals using 50% and 95% KDEs and 100% MCPs (F5 is combined points from sample year 1 and sample year 2).

| Tortoise ID | MCP area (ha) | 95% KDE area (ha) | 50% KDE area (ha) |
|---|---|---|---|
| M1 | 12.41 | 14.59 | 3.52 |
| M3 | 44.94 | 33.24 | 3.76 |
| M4 | 29.74 | 33.64 | 8.87 |
| M5 | 35.47 | 50.43 | 14.49 |
| M6 | 48.73 | 54.30 | 9.80 |
| F1 | 36.35 | 33.14 | 5.12 |
| F2 | 14.71 | 13.53 | 2.14 |
| F3 | 25.86 | 29.96 | 7.25 |
| F4 | 17.08 | 23.17 | 5.77 |
| F5a | 21.77 | 24.09 | 4.65 |
| F5b | 26.28 | 26.32 | 4.80 |
| F5 (combined) | 38.61 | 28.33 | 4.78 |
| F6 | 41.69 | 22.69 | 4.10 |
| F8 | 70.97 | 25.58 | 5.21 |
| F9 | 12.05 | 12.41 | 3.13 |
| F10 | 15.83 | 16.61 | 3.24 |
| F12 | 11.39 | 5.71 | 1.01 |
| F14 | 5.41 | 4.91 | 1.02 |
| F15 | 3.55 | 3.38 | 0.72 |
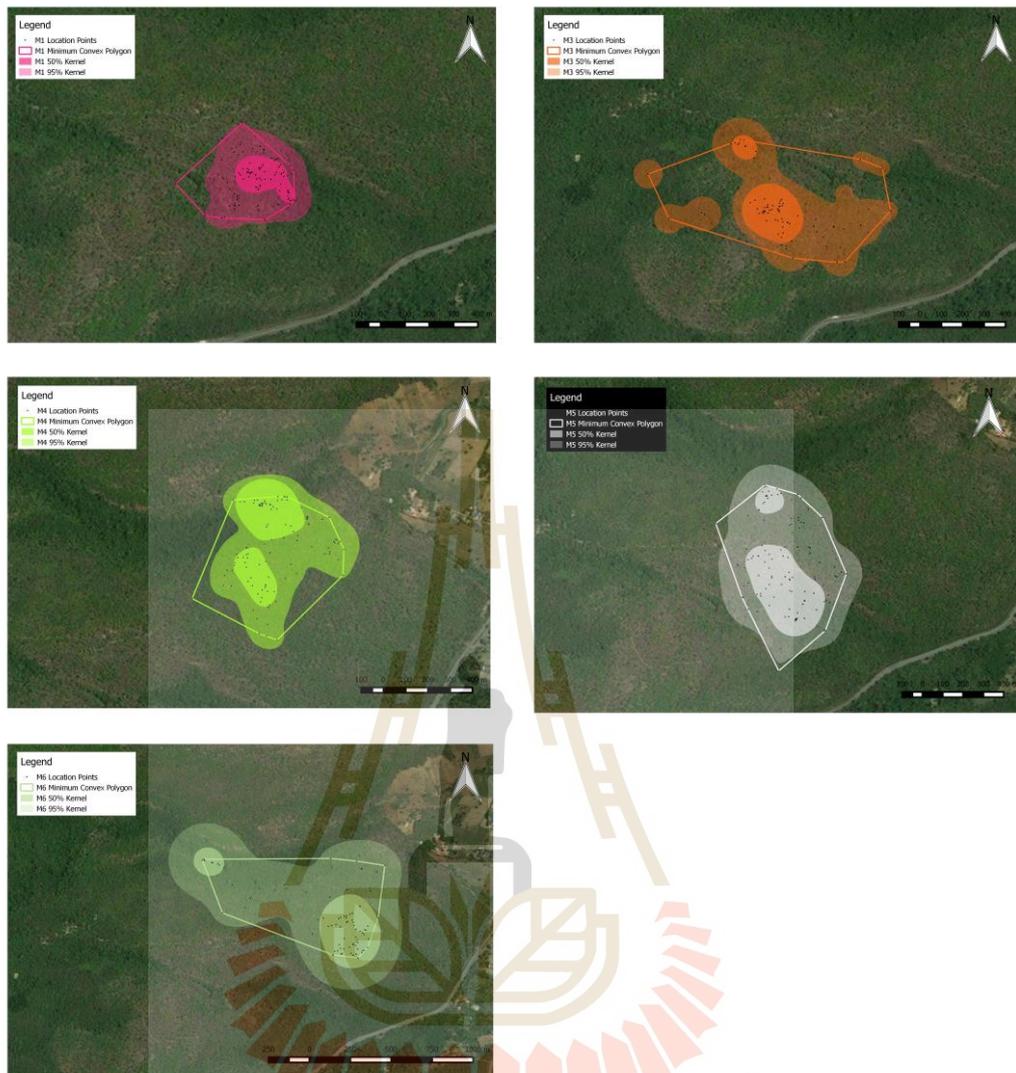
**Figure 4.1** Home ranges maps of male individual study animals with 100% relocation points, MCPs, 95%KDEs and 50%KDEs (reading left-right in rows; M1, M3, M4, M5, M6.
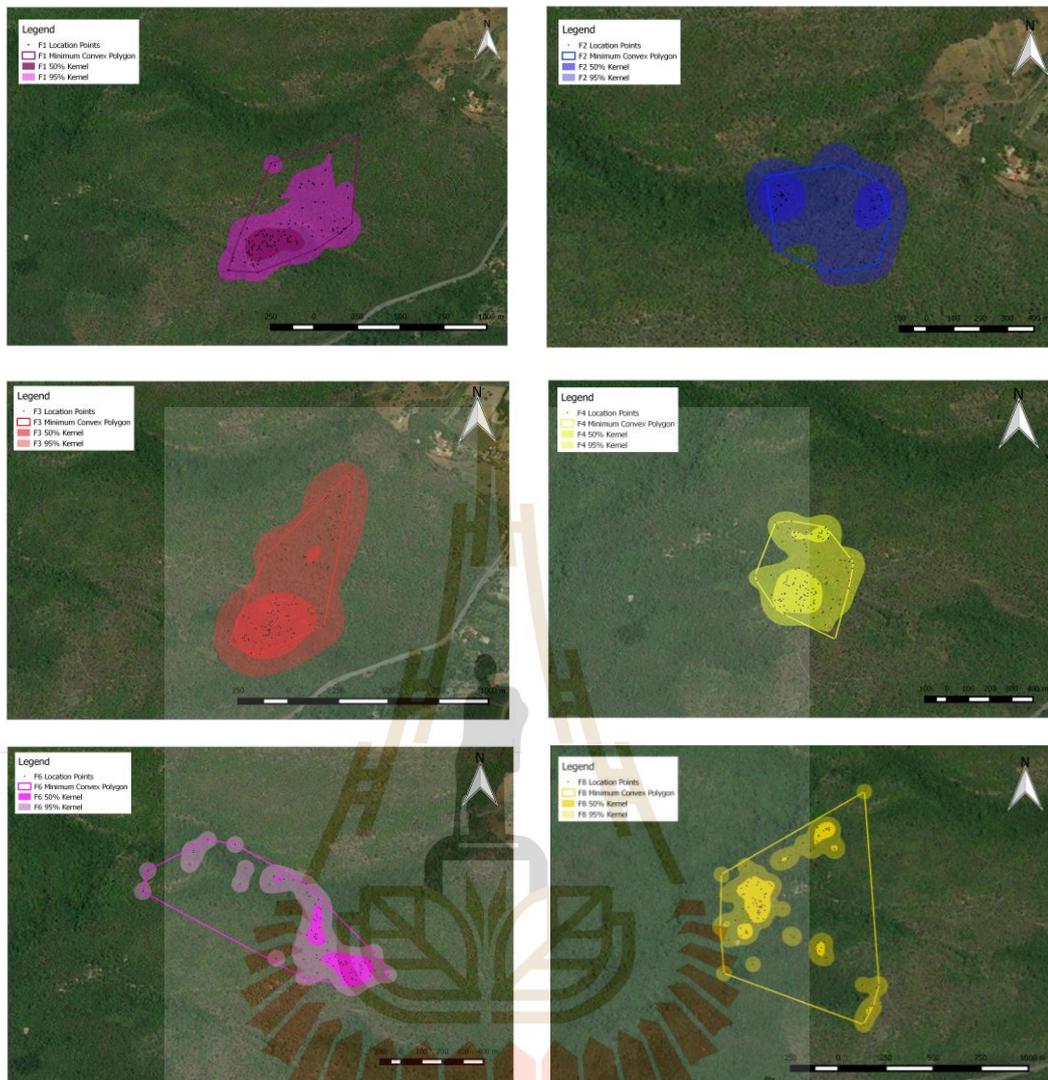
**Figure 4.2** Home ranges maps of female individual study animals with 100% relocation points, MCPs, 95%KDEs and 50%KDEs (reading left-right in rows; F1, F2, F3, F4, F6 and F8).
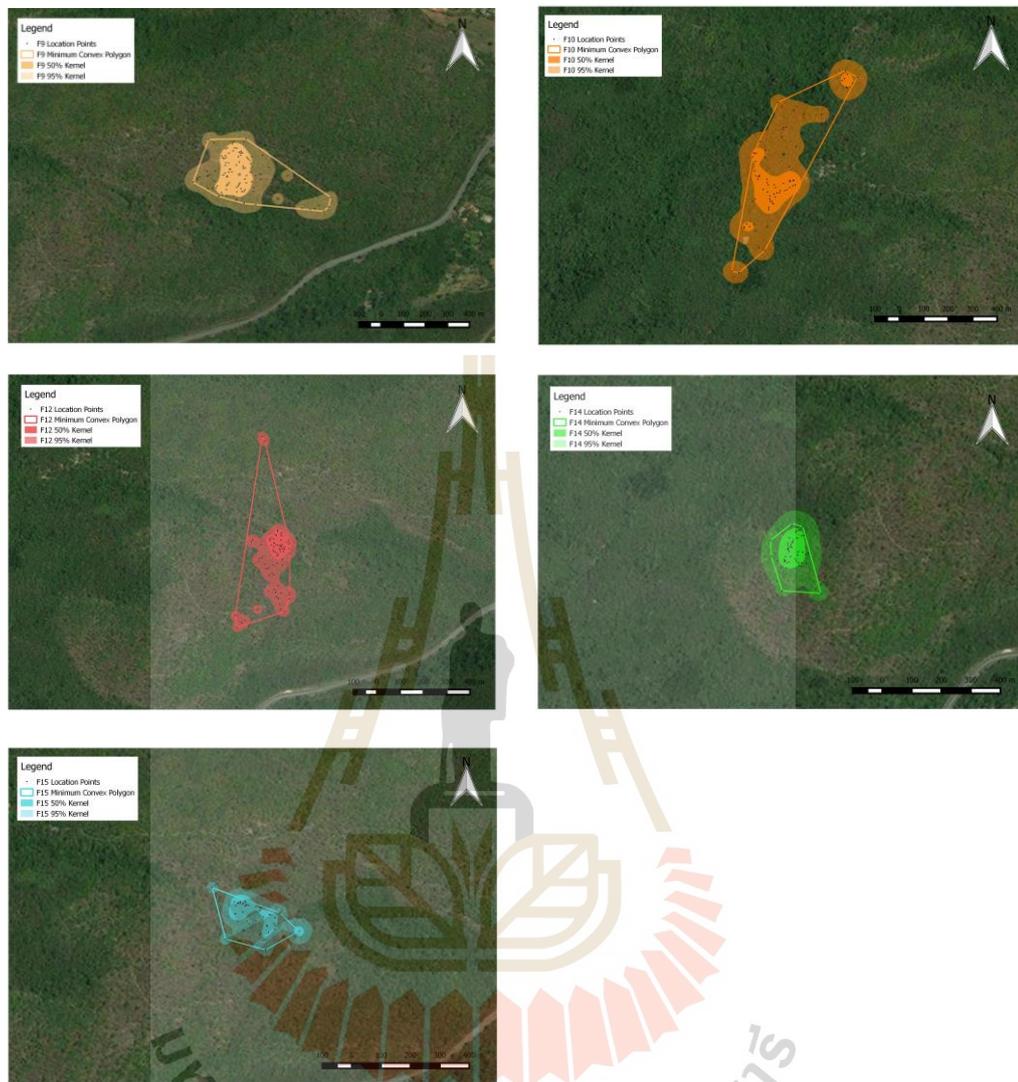
**Figure 4.3** Home ranges maps of female individual study animals with 100% relocation points, MCPs, 95%KDEs and 50%KDEs (reading left-right in rows; F9, F10, F12, F14 and F15).
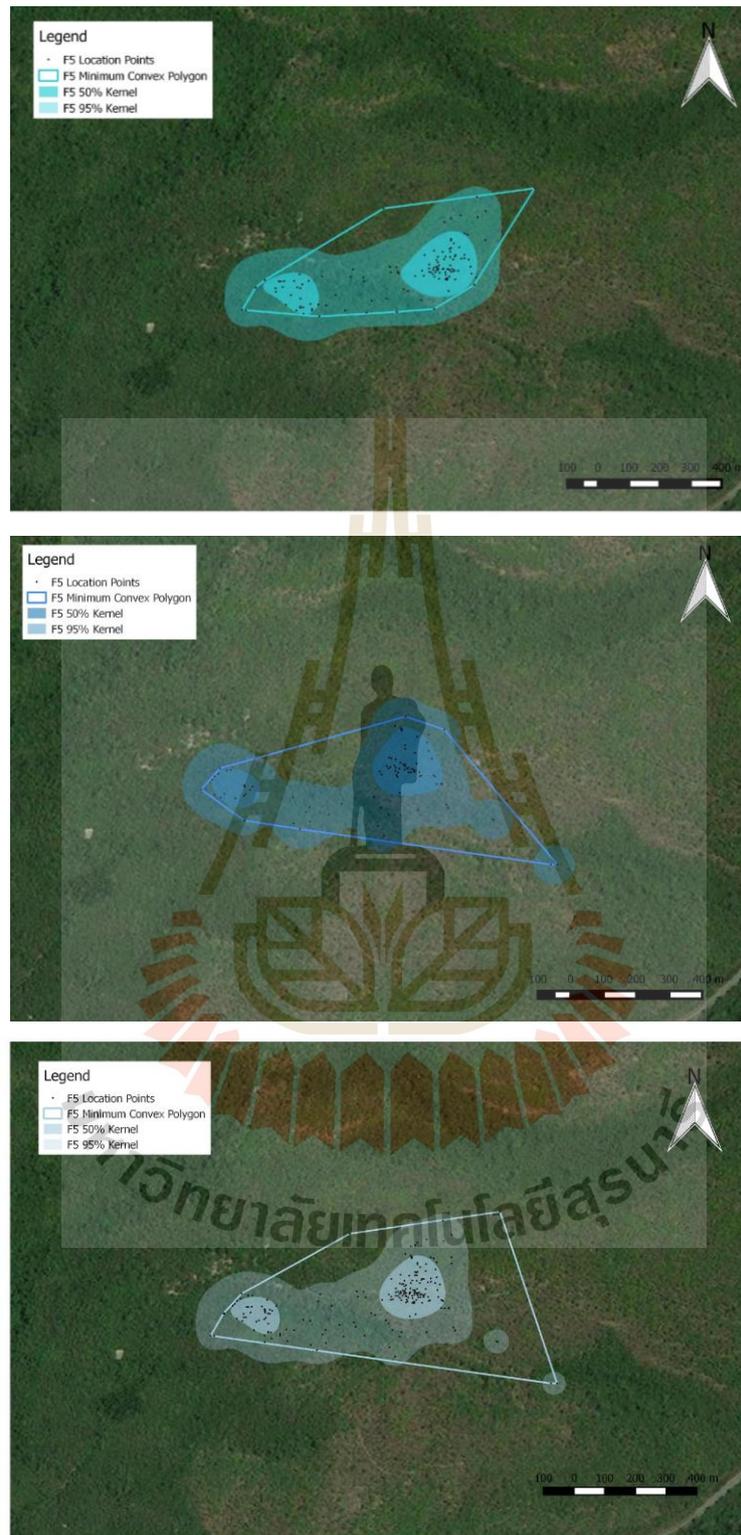
**Figure 4.4** Home range map of individual F5 during Sample year 1 (top), Sample year 2 (middle) and combined both years (bottom).

### 4.1.2 Movement Probabilities

#### 4.1.2.1 Base Movement Probabilities

Using program R I created a null model to identify the probability of movement of all individuals. I created a generalised linear model (GLM) using the response variable of Moved (Yes= 1, No= 0) and and null denominator 1, with a binomial distribution. I used the plogis function to transform the log-odd intercept into a binomial probability (Table 4.3). I created further GLMs to investigate the effect of sex and sample year on probability (Table 4.2).

**Table 4.2** Model outputs for movement probability.

| Model | Response | Covariates | Output | *P* value |
|-------|----------|------------|--------|-----------|
| Null | Moved (Y/N) | *null* | 0.84 | n/a |
| Sex | Moved (Y/N) | Sex | 0.80 m, 0.86 f | $p < 0.05$ |
| Sample | Moved (Y/N) | Sample Year | 0.82 (1), 0.86 (2) | $p < 0.05$ |

The model output claimed differences between the sexes and samples to be significant (table 4.2) however using Wilcox tests against the individual movement probabilities (table 4.3) for sexes or sample proved non-significant. For males vs females a one-way wilcox test with alternative= "less" provided statistics of W = 20.5, p-value = 0.1712. For sample 1 vs sample 2 a one-way wilcox test with alternative= "less" provided statistics of W = 28.5, p-value = 0.1641. There is also no significant variation in probabilities amongst all individuals (V = 99.5, p-value = 0.5559).

**Table 4.3** Base movement probabilities of each individual.

| Tortoise ID | Sample | Sex | Movement Prob. |
|:---:|:---:|:---:|:---:|
| M1 | 1 | Male | 78 |
| M3 | 1 | Male | 65 |
| M4 | 1 | Male | 88 |
| M5 | 1 | Male | 83 |
| M6 | 1 | Male | 86 |
| F1 | 1 | Female | 77 |
| F2 | 1 | Female | 76 |
| F3 | 1 | Female | 88 |
| F4 | 1 | Female | 92 |
| F5 | 1 | Female | 91 |
| F6 | 2 | Female | 92 |
| F8 | 2 | Female | 93 |
| F9 | 2 | Female | 95 |
| F10 | 2 | Female | 83 |
| F12 | 2 | Female | 82 |
| F14 | 2 | Female | 87 |
| F15 | 2 | Female | 63 |
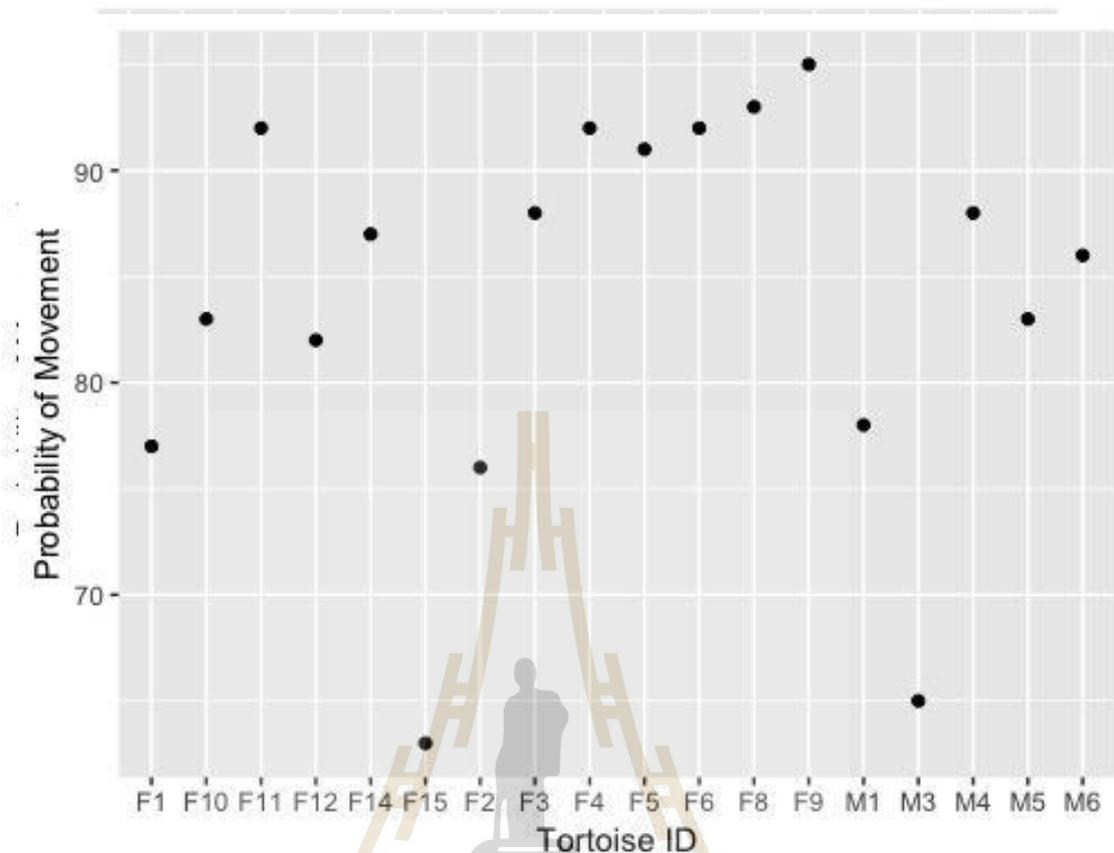
**Figure 4.5** Null movement probabilities of each study animal.

When I looked at the seasonal variation in movement probability, including the Tortoise ID covariate, there are significant differences in the movement probability between the seasons. The Wet season has a significantly higher movement probability of 0.98 over the 0.72 and 0.73 for the Cold and Dry seasons respectively. I confirmed this with a Kruskal-Wallis test (chi-squared = 67.142, df = 2, p-value = 2.632e-15) and further pairwise Wilcox test to differentiate season-season differences. Wet season is significantly different in probability from Cold season (p<0.001) and Dry season (p<0.001) with the Dry and Cold seasons not varying significantly from one another (p=0.57).

**4.1.2.2 Movement Probabilities with Rain**

I hypothesised that rainfall would produce an increase in movement probability and mean daily displacement (MDD). I modelled the effect of the covariates Rain_24hrs and Rainfall on the response variable Moved (y/n). Rainfall (in mm) is the amount of rain that had fallen since the last datapoint for an individual. Rain_24hrs is a binary variable to indicate whether it had rained since the last datapoint. The Rain_24hrs model created movement probabilities of 0.79 in absence of rain and 0.91 if rain had occurred, suggesting a significant difference. The Rainfall model provided a starting probability of 0.82 with a 0.006 increase in probability as rainfall increases each mm. This was not deemed significant in the model and model selection identified Rain_24hrs better with an AIC score 33.2 points lower.
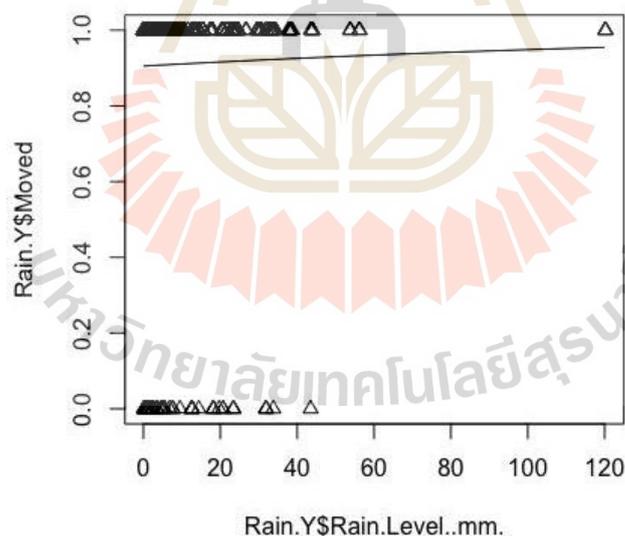


**Figure 4.6** Plot of probability of movement according to increasing rainfall (mm).

To further investigate the effect of Rainfall on movement probability I created a new dataframe Rain.Y to only use positive rain data. A new model, using the Rain.Y dataframe, resulted in a non significant increase of probability as rainfall

increased (in mm), with probabilities varying from 0.905 to 0.954 within the range of rainfall recorded.

### 4.1.2.3 Movement Probabilities all Covariates

Using the function Dredge within the package MuMIn all of the measured covariates were modelled against the response Moved in a GLM (table 3.2). Month, Season, Habitat Type, Humidity, and Tortoise ID were found in the top 30 models with a delta AICc <4.2 (0-30). I found Sample, Max.Temp and Sex to not negatively or positively affect the models, being found in half of the top 30 models. Any collinear or dependent covariates (Season < Month) had the weaker covariate removed before I selected the final models to assess. The best models within the top 10 comprising a delta AICc <2.2 all contained Habitat Type, Humidity, Month and Tortoise ID, with Max. Temp, Rain_24hrs, Rainfall, Sample and Sex all appearing sporadically (table 4.4). I discovered that interactions between Habitat Type and Tortoise ID reduced model AIC by 3.7 points. Resulting in the best model for predicting whether a tortoise is likely to move being: *Moved ~ Habitat Type x Tortoise ID, Month, Max.Temp and Humidity*.

**Table 4.4** Dredge output for final selection of covariates in modelling movement probability. (*Int* = Intercept, *Hbt* = Habitat type, *Hum* = Humidity, *Mx. Tmp* = Max temperature, *Mth* = Month, *R. 24* = Rain since previous datapoint, *R. mm* = Rainfall amount in mm, *Smp* = Sample group, *Sex* = Sex, *Trt. ID* = Tortoise ID, *df* = Degrees of freedom, *lg LIK* = Log Likelihood, *AICc* = Corrected AIC, *delta* = delta AIC, *Wt* = Model weight).

| Int | Hbt | Hum | Mx. Tmp | Mth | R. 24 | R. mm | Smp | Sex | Trt. ID | df | lg LIK | AICc | delta | Wt |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -5.180 | + | 0.1142 | -0.0814 | + | | | | | + | 32 | -631.70 | 1328.5 | 0.0 | 0.127 |
| -5.180 | + | 0.1142 | -0.0814 | + | | | | + | + | 32 | -631.70 | 1328.5 | 0.0 | 0.127 |
| -5.231 | + | 0.1115 | -0.0757 | + | 0.1832 | | | | + | 33 | -631.20 | 1329.6 | 1.08 | 0.074 |
| -5.231 | + | 0.1115 | -0.0757 | + | 0.1832 | | | + | + | 33 | -631.20 | 1329.6 | 1.08 | 0.074 |
| -5.505 | + | 0.1159 | -0.0763 | + | | | + | | + | 33 | -631.21 | 1329.6 | 1.09 | 0.074 |
| -5.505 | + | 0.1159 | -0.0763 | + | | | + | + | + | 33 | -631.21 | 1329.6 | 1.09 | 0.074 |
| -5.105 | + | 0.1126 | -0.0808 | + | | 3.79 e-03 | | | + | 33 | -631.62 | 1330.4 | 1.91 | 0.049 |
| -5.105 | + | 0.1126 | -0.0808 | + | | 3.79 e-03 | | + | + | 33 | -631.62 | 1330.4 | 1.91 | 0.049 |
| -5.552 | + | 0.1132 | -0.0707 | + | 0.1808 | | + | | + | 34 | -630.73 | 1330.7 | 2.20 | 0.042 |
| -5.552 | + | 0.1132 | -0.0707 | + | 0.1808 | | + | + | + | 34 | -630.73 | 1330.7 | 2.20 | 0.042 |

### 4.1.3 Predictors of Movement Distances

#### 4.1.3.1 Predicting Movement Distances with Season

I made GLMs for MDD against Season using Inverse and Log links in a Gamma distribution, to see if the patterns in movement probability translated into movement distances. In both models the seasonal impact on MDD differed significantly. The Inverse link model was 13.8 AICc points lower (i.e better) than the Log link model. The Inverse link model estimated the Cold season MDD of 31.81m, the Dry season 56.04m and Wet season 46.41m. The Log link model estimated the Cold season MDD 33.73m, Dry season 55.13m and Wet season 48.35m. These are the estimated average MDDs for each season given the model fit to the data. The lower AICc score indicate better accuracy/fit of the Inverse link model. I also analysed the MDD against Season in a Kruskal-Wallis test. Resulting in a significant differences (chi-squared = 69.75, df = 2, p-value = 7.146e-16). Using a pairwise Wilcox test I identified significant decreases in MDD from the Dry to Col season (p<0.001) and Wet season (p<0.001).

#### 4.1.3.2 Predicting Movement Distance with Rainfall

To investigate the effect of rainfall on MDD for each individual I created a data frame with positive movement and rainfall data only and used a GLM with Gamma distribution and Inverse link (table 4.5). The inverse link having a lower AICc value to the log link equivalent.

**Table 4.5** Model output for GLM: MDD ~ Rainfall + Tortoise ID, family = Gamma (link = inverse). * = significant difference from default (*Rainfall.mm. for ID F1*).

| Coefficients | Estimate | Std. Error | t value | *P* value |
|---|---|---|---|---|
| (Intercept) | 1.590e-02 | 2.946e-03 | 5.399 | 8.94e-08 * |
| Rainfall.mm. | 1.498e-04 | 8.623e-05 | 1.737 | 0.082722 |
| F2 | 1.140e-02 | 6.060e-03 | 1.881 | 0.060370 |
| F3 | 3.92e-03 | 4.652e-03 | 0.856 | 0.392296 |
| F4 | 2.064e-03 | 4.468e-03 | 0.462 | 0.644147 |
| F5 | 3.390e-03 | 3.811e-03 | 0.889 | 0.374037 |
| F6 | 8.924e-03 | 5.822e-03 | 1.533 | 0.125714 |
| F8 | 1.673e-02 | 6.661e-03 | 2.512 | 0.012206 * |
| F9 | 1.290e-02 | 6.071e-03 | 2.152 | 0.033886 * |
| F10 | 4.169e-03 | 5.025e-03 | 0.830 | 0.406975 |
| F12 | 2.432e-02 | 8.577e-03 | 2.836 | 0.004693 * |
| F14 | 2.073e-02 | 7.932e-03 | 2.613 | 0.009140 * |
| F15 | 3.478e-02 | 1.047e-02 | 3.323 | 0.000932 * |
| M1 | 4.293e-04 | 4.260e-03 | 0.101 | 0.919760 |
| M3 | 5.042e-03 | 4.998e-03 | 1.009 | 0.313402 |
| M4 | 1.898e-04 | 4.284e-03 | 0.044 | 0.964664 |
| M5 | -7.400e-03 | 3.288e-03 | -2.251 | 0.024684 * |
| M6 | -3.665e-03 | 3.892e-03 | -0.942 | 0.346667 |

Null deviance: 1228.7 on 787 degrees of freedom

Residual deviance: 1092.9 on 770 degrees of freedom

**AIC: 7590.7**

The modelled estimates are transformed with the inverse link and so require back-transforming in order to understand the effect size in the original units meters/mm. The inverse link model gives an Intercept of 62.89m and a default slope of (0.99 x X)m. The default is the effect of rainfall on individual F1. The slope in this cases is a reduction in distance by 1 cm for each 1 mm of rainfall increase. Thus increases in rainfall appear to reduce the distance of movement in MDD but there are significant individual differences in effect.

### 4.1.3.3 Predicting Movement Distances with all Covariates

I used the dredge function again to create all possible combinations to find the best predictor covariates for MDD. I included covariates Month, Sample, Sex, Tortoise ID, Rainfall, Humidity, Max.Temp and Habitat Type. I ran two dredges to identify which link would also produce the best models, as previously the Inverse link fit the models better than the Log link with the Gamma distribution. I ran the dredges with a dataset of only positive move datapoints (Moved.Y) as I wanted to identify effects on movement distance. Inverse link models within the top 10 included Month, Tortoise ID and Rainfall consistently. Habitat Type was not included in any of the top models. The Log linked model set had consistent covariates Month, Tortoise ID, Habitat Type and Rainfall found in the top models (table 4.6). The best model within the Inverse link model set combined Tortoise ID, Sex, Month and Rain Level with a total AICc= 15861.9. The best model within the Log link model set combined Month, Rain Level, Tortoise ID, Sex and Habitat Type but had a higher AICc= 15884.8.

**Table 4.6** Dredge output for final selection of covariates modelled against MDD using Log Link. (*Int* = Intercept, *Hbt* = Habitat type, *Hum* = Humidity, *Mx. Tmp* = Max temperature, *Mth* = Month, *R. mm* = Rainfall amount in mm, *Smp* = Sample group, *Sex* = Sex, *Trt. ID* = Tortoise ID, *df* = Degrees of freedom, *lg LIK* = Log Likelihood, *AICc* = Corrected AIC, *delta* = delta AIC, *Wt* = Model weight)

| Int | Hbt | Hum | Mx. Tmp | Mth | R. mm | Smp | Sex | Trt. ID | df | lg LIK | AICc | delta | Wt |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4.190 | + | | + | | -0.0046 | | | + | 32 | -7909.74 | 15884.8 | 0.0 | 0.119 |
| 4.190 | + | | + | | -0.0046 | | + | + | 32 | -7909.74 | 15884.8 | 0.0 | 0.119 |
| 4.193 | + | | + | | -0.0046 | + | | + | 33 | -7909.60 | 15886.6 | 1.8 | 0.048 |
| 4.193 | + | | + | | -0.0046 | + | + | + | 33 | -7909.60 | 15886.6 | 1.8 | 0.048 |
| 4.230 | | | + | | -0.0049 | | | + | 30 | -7912.75 | 15886.6 | 1.85 | 0.047 |
| 4.230 | | | + | | -0.0049 | | + | + | 30 | -7912.75 | 15886.8 | 1.85 | 0.047 |
| 4.294 | + | -0.002 | + | | -0.0047 | | | + | 33 | -7909.70 | 15886.8 | 1.99 | 0.044 |
| 4.294 | + | -0.002 | + | | -0.0047 | | + | + | 33 | -7909.70 | 15886.8 | 1.99 | 0.044 |
| 4.141 | + | | + | | | | | + | 31 | -7911.78 | 15886.8 | 2.0 | 0.044 |
| 4.141 | + | | + | | | | + | + | 31 | -7911.78 | 15886.8 | 2.0 | 0.044 |

### 4.1.3.4 MDD Differences within Habitats and Samples

Using a Kruskal-Wallis test (because of the non-normal distributions in MDD) I calculated a significant difference within the habitat type MDD (chi-squared = 37.908, df = 2, p-value = 5.867e-09). A pairwise Wilcox test identified DEF as the

habitat type differing significantly from both DDF (p<0.001) and EDGE (p<0.05) habitats, although there was no significant difference in MDD between DDF and EDGE (p>0.1).

Despite not being a one of the key predictors within the dredge models to predict MDD there seemed to be differences in mean MDD between the sexes and sample years. Using a one-way Wilcox test with an alternative hypothesis of "greater" males had larger mean MDD but not significantly (W = 19 and p-value = 0.2684). Using a two-way Wilcox test to compare the MDD between the two sample years, there was a significant difference in the two samples (W = 59 and p-value = 0.002098), with a significant decrease in MDD in the second sample. Re-running the samples against each other in another two-way Wilcox test using only the females of each sample I still received a significant result (W = 31 and p-value = 0.0303).

### 4.1.4 Habitat Use

I analysed habitat use according to variations within the sexes, across the sample years, between individuals and within the seasons. When comparing the sexes, seasons and individuals I pooled the data for tortoise F5 from both sample years. I checked for significant between her habitat uses across the two years using a Pearson's chi-squared test which gave non-significant differences (X-squared = 3.5142, df = 2, p-value = 0.1725).

I ran a Kruskal-Wallis test against the proportional use of each habitat type by all individuals pooled together. This gave a response of no significant difference between the habitat types (chi-squared = 40.931, df = 35, p-value = 0.2263). Then I used a two-tailed Wilcox test to identify differences in the proportional use of DEF,

DDF and EDGE habitats between males and females. The Wilcox test return no significant differences between the sexes for DEF(W = 33.5, p-value = 0.7517), DDF (W = 33.5, p-value = 0.7508) or EDGE (W = 16.5, p-value = 0.1687). To corroborate this I also conducted a Pearson's chi-squared test with all habitats between the sexes (X-squared = 1.2647, df = 2, p-value = 0.5313). I assessed sample differences in habitat use to no significant differences (X-squared = 0.27571, df = 2, p-value = 0.8712). Finally I assessed habitat use between the seasons using the Pearson's chi-squared test resulting in a significant difference (X-squared = 40.847, df = 4, p-value = 2.891e-08). Looked in at differences in habitat use in a plot is is clear to see the disproportionate use across the seasons (figure 4.7)
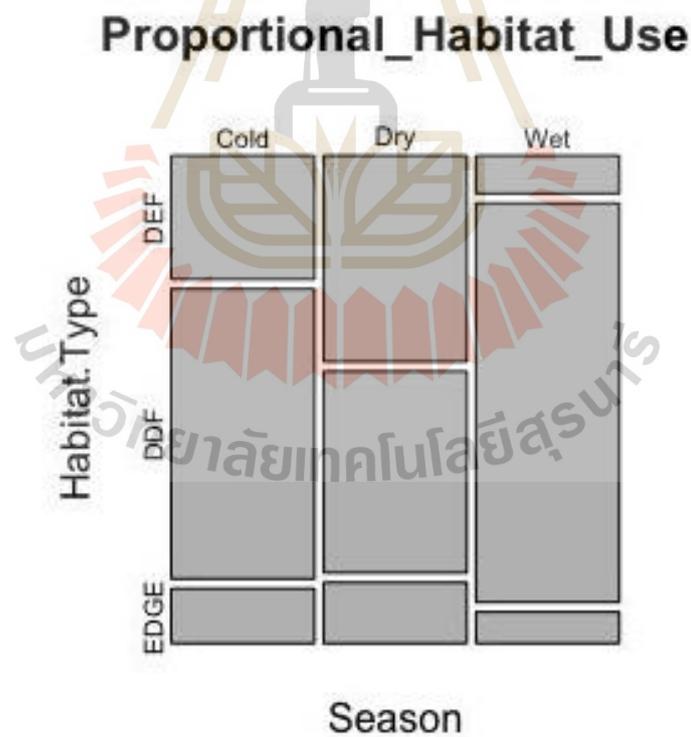


**Figure 4.7** Proportional use of DEF, DDF and EDGE habitats across seasons.

### 4.1.5 Variation in Morphology

Lengths, widths and weights were recorded for all tracked individuals along with 100 other encountered individuals within Sakaerat Biosphere Reserve. Modelling body mass against movement probability using a poisson distribution I saw a slight positive relationship. This relationship was not significant and the residuals were still non-normally distributed.

#### 4.1.5.1 Mass and Habitat Use

When I modelled mass against habitat use I saw a strong relationship, particularly between Mass and DEF.prop (proportional use of DEF). The gamma distribution (identity link) model indicating an almost significant (p=0.056) slope estimate of 33.02 (figure 4.8). Suggesting that for each kg in mass increased there is a 33% increase in proportional DEF use.
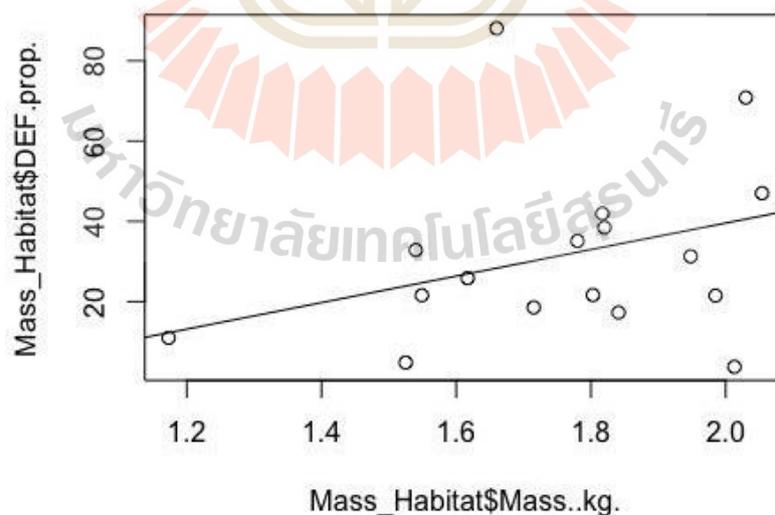


**Figure 4.8** Proportional use of DEF and body mass with GLM predicted fitted line.

The same model constructed for DDF proportional use suggested a negative association however this model was not significant (p=0.3245). Looking at the relationship between Mass and EDGE proportional use the slope was also far from significant (p=0.956).

### 4.1.5.2 Body Size and MDD

I created a model to assess the association between Mass, Body Length and /or Body Width with MDD, using Tortoise ID as a random effect to account for other individual specific variance. Body Length and Body Width were not used in the same models as they are strongly correlated with each other ($R^2$=0.8337). GLMs using Gamma distribution with Identity link were the best representation of the data. The best model with an AICc 7.4 points lower than the next model included Body Width and Mass against mean MDD suggesting Mass (p=0.0001) and Body Width (p=0.0026) significantly influenced mean MDD. The slopes indicated an increase of 11.45m in mean MDD for every 1 cm increase in Body Width with a reduction of 80.27m in mean MDD with 1 kg increase in mass.

**Table 4.7** Model output for GLM: mean MDD ~ Body Width + Body Mass, family = Gamma (link = identity). * = significant influence.

| Coefficients | Estimate | Std. Error | t value | *P* value |
|---|---|---|---|---|
| Intercept | -248.435 | 46.951 | -5.291 | 0.000114 * |
| Body Width cm | 11.454 | 2.183 | 5.248 | 0.000123 * |
| Body Mass kg | -80.278 | 22.029 | -3.644 | 0.002655 * |
| Null deviance: 3.5349 on 16 degrees of freedom | | | | |
| Residual deviance: 1.3745 on 14 degrees of freedom | | | | |
| **AIC: 134.23** | | | | |

### 4.1.5.3 Body Variation Between the Sexes

Using a Wilcox test on all adults processed I discerned that there was no significant difference in mass (p=0.611), length (p=0.490), width (p=0.512), carapace length (p=0.505) or carapace width (p=0.372) between sexes. I modelled the relationships between the sizes with sex, to identify whether there were different ratios in the length/width growth. Using Shapiro-Wilk normality tests and histograms I concluded that the covariates to be modelled were all within normal distribution and applicable for simple linear regression. The model outputs showed that Body Length was positively correlated with Width and Mass in both males and females with both covariates acting as significant predictors of Body Length at some point.

**Table 4.8** Outputs of linear models predicting relationship between body sizes.

| Model Formula | Slope | Coefficient p-value | Adj. R2 | F-Statistic and DF | Model p-value |
|---|---|---|---|---|---|
| Length(cm)~ Width(cm), Males | 1.205 | p<0.001 | 0.7009 | 90.05 on 1 & 37 | p<0.001 |
| Length(cm)~ Width(cm) + Weight(kg), Males | 0.129 / 4.954 | p=0.314 / p<0.001 | 0.918 | 215 on 2 & 36 | p<0.001 |
| Length(cm)~ Weight(kg), Males | 5.386 | p<0.001 | 0.918 | 428.5 on 1 & 37 | p<0.001 |
| Length(cm)~ Width(cm), Females | 1.553 | p<0.001 | 0.696 | 74.27 on 1 & 31 | p<0.001 |
| Length(cm)~ Width(cm) + Weight(kg), Females | 0.979 / 2.475 | p<0.001 / p<0.01 | 0.776 | 56.45 on 2 & 30 | p<0.001 |
| Length(cm)~ Weight(kg), Females | 4.726 | p<0.001 | 0.648 | 59.83 on 1 & 31 | p<0.001 |

The strength of the relationship between Body Length and Body Width in both sexes is almost identical with little difference in slopes (figure 4.9). A 1 cm increase in Body Width incurs a 1.2cm increase in Body Length in males, with a respective 1.5cm increase in females. Thus there does not seem to be any dimorphism in body size.
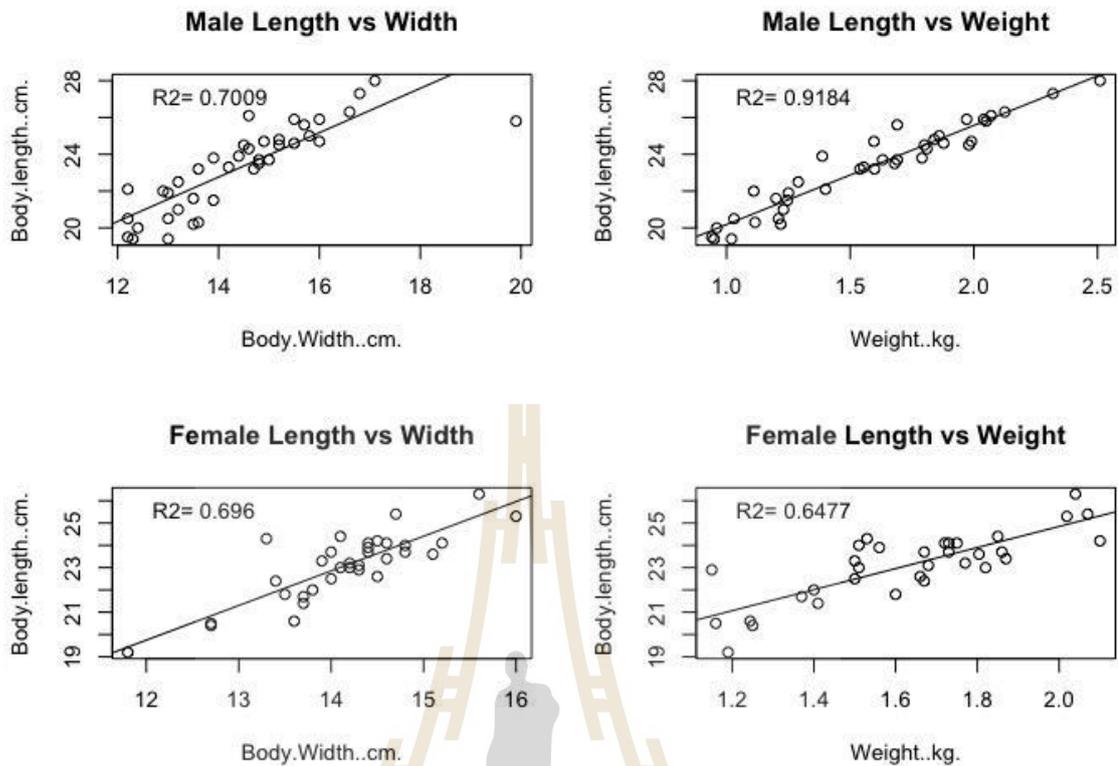
**Figure 4.9** Plots of the relationships between male and female body lengths (cm), widths (cm) and weights/mass (kg).

## 4.2 Discussion

### 4.2.1 Home Range Estimates

I tracked a total of 20 individual adult *I. elongata* between March 2016 and September 2018 with 3 individuals removed from the analysis because of limited tracking data. 1 male individual (M2) had severe burns to his carapace, tail and limbs so I decided to remove his transmitter and re-attach to another individual caught approximately one week later (M6). Individual F7 twice had malfunctions causing large gaps in tracking before eventual transmitter removal. Individual F13 was also only tracked consistently November - February until I lost her in the dense evergreen

forest of Sakaerat. I finally relocated her before she again moved out of telemetry range after 2 days without subsequent relocation.

My home range estimates varied greatly between individual, sample and sex with minimal significant differences. It is probable that the small sample sizes and large individual differences in home range sizes reduced the potential to reach significant difference between groups. The variation in the home range estimates within the different methods (MCP vs 95% KDE) is down to their assumptions in estimating home ranges. 100% MCPs outline the outermost location points (Row and Bluin-Demers, 2006). I used 100% of location points over 99% or 95% because I had already filtered out anomalous locations, potential errors and mistaken identities. KDE points are given weighting and collections of points around one area with overlapping boundaries are considered of higher importance (Row and Bluin-Demers, 2006). I set the boundaries of each points as the mean MDD for that individual, assuming that individual had the ability to move that distance (mean MDD) away from its last known location, before arriving at its next known location. The use of point weighting in 95% KDEs should incorporate most of the points which are around other points, eliminating outliers. Assuming outlying points are not location of resource use but transit points or one-off forays (Row and Bluin-Demers, 2006). The weighting means that 50% KDEs should be the densest 50% clusters of points. These clusters are occasionally connected to each other to form a "core" area of a home range, where the animal is likely to spend most of its time and/or has the most valuable resources (food, mates, shelter) (Row and Bluin-Demers, 2006). Sometimes however 50% clusters are spread apart and not connected (Downs and Horner, 2012). In these circumstances animals may have several sites of key resources (fruiting trees,

water sources, hunting grounds) which are frequently visited but interspersed with long interval movements between them. I noticed some such occurrences in the 50% KDEs of individuals F5 and F9. Both females tracked within the second sample year and had 50% KDE sizes not too dissimilar (4.8-3.1). However F5's 50% KDE is split between two hotspots within her range which is connected by a corridor. These corridors can be seen within the map which appear to show regular movements along a narrow section of forest adjacent to the SERS main road. F9 has a single 50% KDE range with further locations radiating outward from this point before returning back to this central 50%. F5's two 50% KDE hotspots are split with one in DDF and one in DEF, approximately 475m apart (centre to centre) with a gradient of EDGE forest and a stream bed between them. F9's single 50% hotspot cover a small portions of DEF, EDGE and DDF. Each individual appears to require DEF and DDF within their 50% KDEs indicating key resources within both habitats across an annual home range. I do not believe that competition is a determinant factor in home range size or shape. Over the two telemetered samples and through opportunistic discoveries I have seen many mating and passive cohabitation occasions and no aggression directed toward a conspecific.The only competitive behaviour documented is SERS was two male individuals (not during study period) observed fighting over a suspected female (Ward *et al*., 2018). This case is unusual with no such comparative *in situ* records from other researchers or literature. The overlap between tracked individuals is very large and again highlights an apparent lack of competition within individuals (figure 4.10).
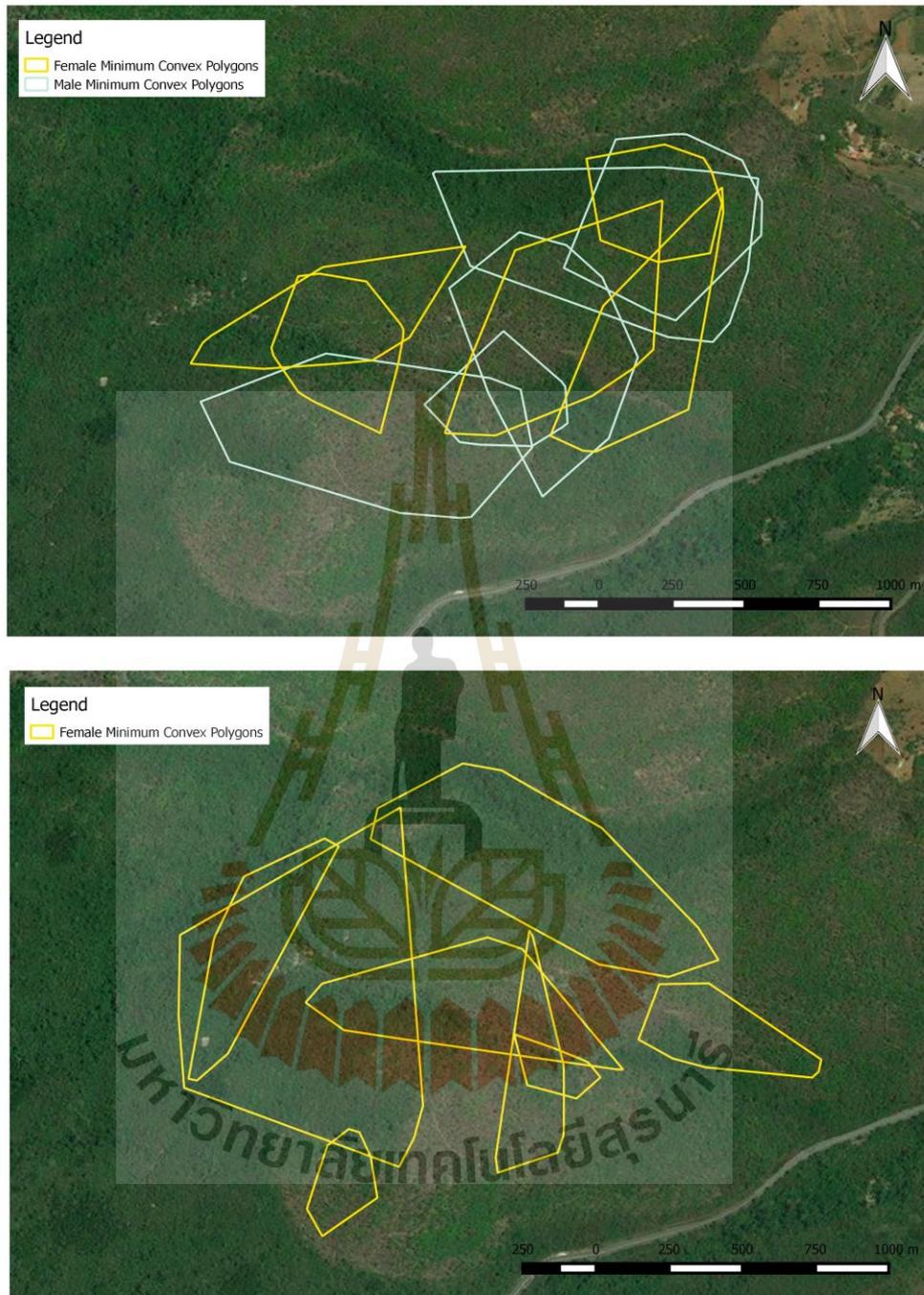
**Figure 4.10** Overlapping home range MCPs of telemetered tortoises from the first

sample (top) and second sample (bottom) groups.

### 4.2.2 Movement Models

#### 4.2.2.1 Movement Probabilities

Probabilities work along a logit scale which can be interpreted as ranging from 0-1 (0= not going to happen, 1= definitely going to happen, 0.01-0.99= increasing likeliness of happening) (Barros and Hirakata, 2003). Movement probabilities can be used as a proxy for activity in a species such as the *I. elongata,* which has a limited behavioural repertoire and prolonged sedentary periods. Tortoises do not move unless they choose to, to find food, mates or alternate shelters. Giving us a strong indication that changes in movement frequencies have good motivation.

Looking solely at movement occasions across the study period pooled together I received a null model probability of 0.84, or the naive probability (dividing the number of occasions moved by the number of datapoints e.g. 1667/1991 = 0.837). I tested whether the individual or sample year significantly affected movement probabilities using Wilcox tests to compare the differences in the groups with no significant variation in the movement probabilities of the individuals, samples or sex. Whilst there are differences in individual decisions to move or not, they are not great enough to suggest any individual's personality was drastically differently from their conspecifics. There are differences in null probability and anecdotally many (if not all) of the individuals in the study had distinct personalities in the way they interacted with the observers and patterns in their location selection. Because of this I decided to incorporate Tortoise ID in each predictive model when investigating the effect of other covariates on movement probability.

I modelled movement probability against seasons, with a significant difference (p<0.001) within the Season covariate and individual slope estimates for each season.

I converted these estimates (in log-odds) with the "plogis" function to identify each seasons specific probability as well as a Kruskal-Wallis and pairwise Wilcox test on the different seasons. These tests confirmed the wet season (August-October) had a significantly higher ($p<0.0001$) movement probability (0.98) than the cold (0.72) and dry (0.73) seasons. The wet season differs significantly from the cold (November-February) and dry seasons (March-July) in the amount of rainfall and occasions of rain it has (figure 3.2). The dry season also has some occasions of heavy rain between April and May with 4-6 weeks of intermittent rainfall which may explain the difference between the mean and range of rainfall for the dry season.

### 4.2.2.2 Movement Probabilities with Rain

With the wet season providing a significantly higher movement probability than the other two seasons I modelled rain and rainfall to identify whether this made the difference in movement probability. The GLMs suggested a significant rise in movement probability with occasions of rain, from 0.79 on rainless days to 0.91 on days where it rained, however no significant influence on movement probability in rainfall (mm). Looking critically at the model output it appears that the relationship is not linear but slightly curved. The rainfall slope (predicted probability increase of 0.006 per mm) implies that beyond 30mm of rainfall the probability of movement would be >100%. Looking at the predicted line in the probability plot (figure 4.6) and the predicted values from the model I also note that the prediction never reaches 1.00 (100%) instead climbing to 0.97 before retreating at higher rainfall amounts. I therefore cannot correctly predict the probability change or rate of change

along a linear expression, probably why the covariate was not significantly influential, and the output violates the linearity assumption of a GLM.

### 4.2.2.3 Movement Probabilities all Covariates

After identifying the best distribution to predict movement probabilities and the changes according to season and rainfall I decided to see which combination of covariates gave the best predictions of movement probability. I used the dredge function to find the best predictors out of the covariates recorded which gave me a table of the best combinations out of 2048 possible combinations of 12 covariates. The initial table however contained many covariates which were either co-correlated or dependencies on other covariates. Using the ranking of these variables in the dredged table with replacements of each co-correlated or dependent variable I was able to filter out the covariates that would invalidate the model. Max and Min temperature were co-correlated but Max Temp was used greater in the top models and so it used over Min Temp. Season and Month are also not suitable to be both used as Season is dependent on Month and so Month was used as the modelled covariate. The wet season was significantly different in rainfall to the cold season, but the 4-6 week period of heavy rainfall in the dry season caused non-significance in the difference of rainfall affect between the wet and dry seasons. For this reason using the Monthly differences is more precise and this showed in the models. I ran a second dredge omitting the Season and Min Temp creating a total of 512 models, identifying Habitat Type, Humidity, Month and Tortoise ID as consistently appearing in the top 10 models with Sex, Sample, Rainfall and Rain_24hrs sporadically appearing in the top models (delta AICc<2.2). The dredge function uses the additive properties of the

covariates which requires you to further investigate these top models for any interactive covariates which may improve the model fit. I noticed an interactive relationship between Habitat Type and Tortoise ID, in the top model (Moved ~ Habitat Type + Tortoise ID + Month + Max Temp + Humidity), improved the model fit and reduced the AIC score 3.7points. A model using Habitat Type and Tortoise ID as additive covariates is assuming that these covariates both play separate parts in explaining the variation found in the response variable. When I create an interaction between Habitat Type and Tortoise ID in a model I am now assuming that there are differences in the way each tortoise interacts with each habitat and that these differences will explain more of the variation seen in the response variable. I can corroborate this when I look at the coefficient breakdown within the model and compare how each individual tortoise varies in the movement probabilities in each habitat they use. I saw that some individuals had significantly higher and/or lower probabilities than the default individual in one habitat type. I concluded the best model using the data collected was; Moved ~ Habitat Type x Tortoise ID + Month + Max Temp + Humidity. This model did not create the highest probability, it is the combination of variables that best explains changes in movement probability seen within the data.

### 4.2.3 Predictors of Mean Daily Displacement (MDD)

I have already identified season as a significant predictor of movement probability (especially as a lone covariate) and so now I wanted to see if I could also use this to predict the observed MDD. I created two models using gamma distributions, one using a log link function and the other an inverse link. The inverse

link function better fit the model predictions to the data with an AICc score 13.8 points lower than the log link alternative. This model predicted that the cold season had the lowest MDD with the wet season increasing MDD by approximately 15m and dry season increasing the MDD a further 9.5m still. To gain further support in these model outputs being significant I ran the results through a Kruskal-Wallis test and post-hoc pairwise Wilcox test receiving a significant differences between each season. Whilst I had previously identified the wet season as having significantly larger probability of movement, and the wet season does have a significantly higher MDD than the cold season, we see that the MDD is still significantly lower than in the dry season. Ecologically however this may make sense regarding the species foraging techniques and dietary requirements. Through the tracking and observations of the individuals in this study I have recorded them feeding on many items including flowers, dried leaves, faeces, invertebrates, carrion, fungi and predominantly green leafy vegetation. I also had never recorded an individual seeking or being located near an open water source to drink from (except one individual that drowned), which suggests that the species may get most of its water requirements from its food. Within the wet season this green vegetation is sprouting and fresh shoots from many plant species will be newly available including fresh fungal bodies accessible to the low foraging tortoises (Tharapoom, 1996). With this widely available food and temporary water and mists across the forests, animals are likely to move regularly to utilise this resource but not needing to travel far to find this bountiful resources. In opposition, during the dry season the dipterocarp forest becomes very dry, water sources dry up and the small plants and shrubs become drier and desiccated. This requires individuals to travel farther to find necessary and limited resources, also punishing any individual

which travels excessively without having resources to support this engird expenditure. Another reason for the changes in movement probability may be because of the combination of humidity, temperature AND rainfall affecting the suitability for moving within the different forest types. Especially in the dipterocarp forest, where I recorded the majority of tortoise locations, the higher temperatures and reduced humidity and rainfall would create dangerous conditions. Moving regularly or being caught in the open or an unsuitable shelter would create further energy loss and bodily harm for an individual with limited supporting resources (Longshore, Jaeger and Sappington, 2003, Attum, Kramer and Baha El Din, 2013).

### 4.2.3.1 Predicting MDD with Rainfall

I created a model using the gamma distribution again with a log link and inverse link to predict MDD using the Rain Level and Tortoise ID covariate. In order to eliminate the problem of zero inflation which would cause confusion within the model and prevent accurate predictions I used a data frame including on positive rainfall values and added 1 to each MDD to give a minimum value of 1m. The inverse link again was the best when comparing the AICc scores of each model. Using the inverse link I received an intercept of 63m MDD for 0.1mm of rainfall, with a slope of 0.99. This slope however is a multiplicative slope, indicating that for each mm increase in rainfall you should multiply by 0.99 to get the equivalent change in MDD. Using the value of 0.99 we actually see that creates a negative relationship of a reduction in MDD by 1cm for each 1mm of rainfall. Unsurprisingly this influence of Rain Level was not considered significant in the model despite this model being the best. I further investigated whether the model for Rain Level and MDD was even

suitable by checking if the residual vs fitted values met the assumptions necessary for a GLM by using the plot function. The resulting linearity plot showed some equal spread of residuals around an almost 0 centred fitted line, however the spread was not even along the spread of predicted values (figure 4.11a). The normality plot also identified that there was a normal distribution across the positive theoretical quantiles however a lack of normality within the negative quantiles (figure 4.11b). These plots confirm that this model is not fitting within the assumptions of a GLM and its output not valid.
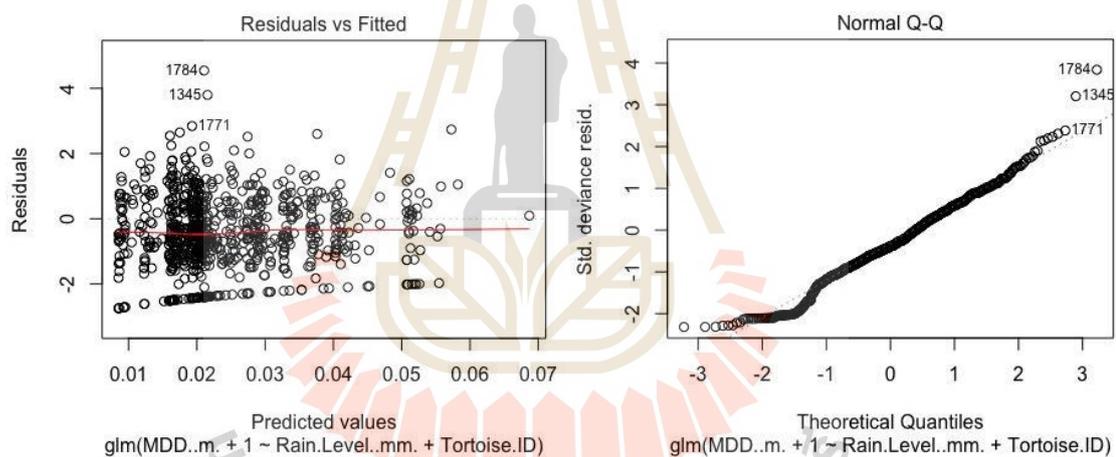


**Figure 4.11** Residuals vs Fitted plots to check for linearity (a= left) and normality (b= right) in the model predicted output.

### 4.2.3.2 Predicting MDD using all Covariates

I used the dredge function again and included the covariates Month, Sex, Sample, Tortoise ID, Rain Level, Humidity, Max Temp and Habitat Type to create 256 models. As the question revolved around predicting distances moved I

used a data frame constructed out of only positive moves and again ran a dredge for the gamma distribution with a log link and an inverse link. Despite the same covariates being used I noticed that the habitat type covariate was only influential within the log linked models and not within the inverse linked models. Other than Habitat Type the over covariates commonly found within the top models (dalta AICc<2.5) of the two dredges were identical (Month, Tortoise ID and Rain Level). It is unclear why Habitat Type was polarised in its apparent influence for MDD and further investigation into weather interactions using Habitat Type and other covariates were fruitless in creating better models in the inverse link group. When I again plotted the residual vs fitted outputs of the top models decided by the two dredges I found that both models looked acceptable in the linearity assumption however still had something to be desired within the normality assumption (figure 4.12). Both models seemed to fit these plots almost identically and using these visual diagnostic techniques could subjectively be passed as viable models but also rejected because of the lack of normality in fit. Model assumptions aside the suggestion of non-relevance for the habitat covariate casts doubt over the accuracy of the inverse link GLM. Models work only with data input into them and work only to try identify patterns in changes between covariates. A sense of responsibility is required by the modellers to understand when model outputs make biological sense and in this case it seems that the model is likely inaccurate (Bolker *et al*., 2008). With the further knowledge garnered to suggest that habitat types vary significantly in their mean MDD and the presence in other models suggesting significant influence (table 9), it is assumed that the present model is misrepresenting reality.
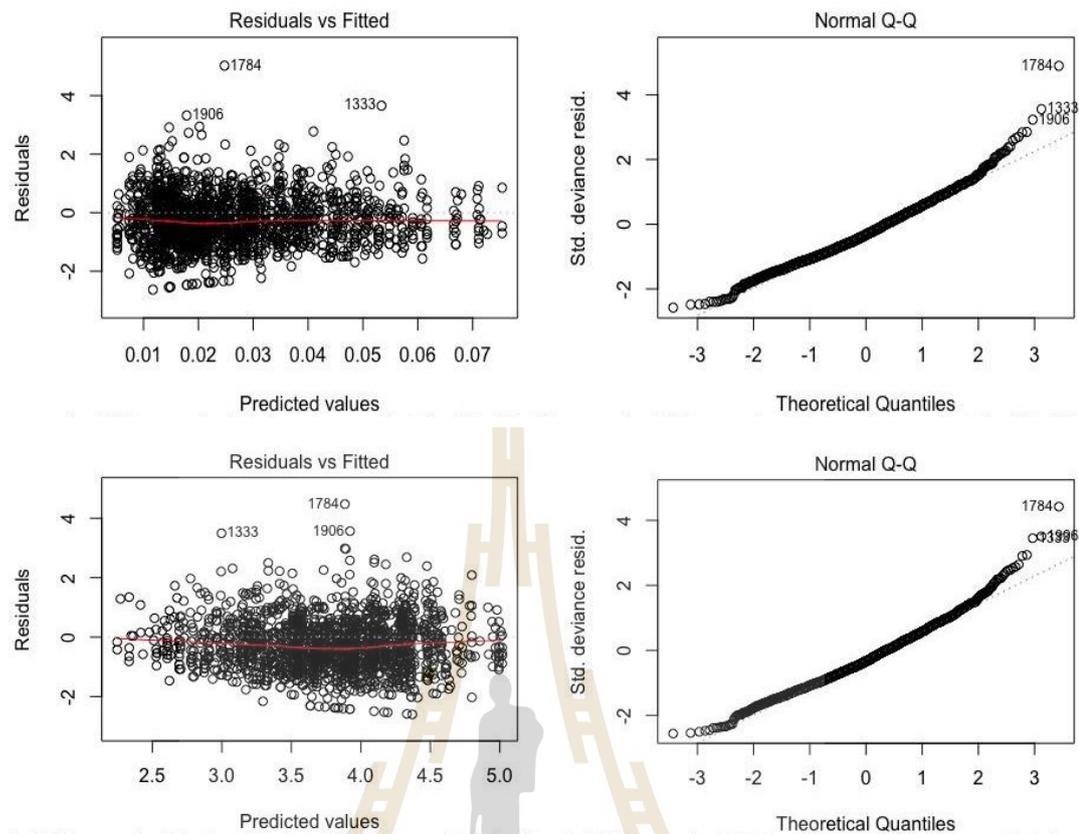
**Figure 4.12** Residuals vs Fitted plots to check for linearity (left) and normality (right) in the model predicted outputs of gamma distributed inverse link (top) and log link (bottom) models for predicting MDD against Tortoise ID, Month and Rain Level.

### 4.2.3.3 MDD Differences within Habitats and Samples

Alternatively to using models for MDD predictions I also wanted to calculate if there was a significant difference in MDD between the habitat types (despite the model inconsistencies) and the sample years using significance testing. The Kruskal-Wallis test identified there to be a significant difference with the pairwise Wilcox test indicating that the MDD was significantly lower in the DEF than

in either the DDF or EDGE habitats between the two, with no difference in the DDF or EDGE mean MDD. This may be because the DEF is a denser forest type with abundant food and shelter resources. In comparison the DDF is based predominantly on bamboo grasses and low understory heterogeneity. As I identified with the changes in habitat MDD in different seasons from the model above there is also a difference in habitat use within the seasons. The DEF typically has more movement probabilities with lower MDD because in the wet season there is a greater food and shelter resources than in the DDF requiring less movement distances to find said resources. Part of the difference in MDD between the habitats is also partially because of the use of the habitats at different times of year. Figure 4.7 illustrates that the DEF habitat type is used most often during the wet season and cold seasons, already identified as having the lowest MDD in the seasons.

Whilst there was no significant difference between the sexes there were significant differences between the MDD in females of sample 1 with sample 2. The second sample group of females had a significantly lower MDD however I am not sure why this might be. Comparing the rainfall, humidity and temperature differences there is no significant difference. There is a discrepancy between the tracking periods for each sample, with sample 1 tracked April - March and sample 2 tracked October / November - September. There is a distinct lack of wet season data from the second sample, however the wet season has been shown to have a lower MDD than the other seasons. I therefore feel that there is some other abiotic or most likely individual differences between the two samples which were not recorded or not recordable.

### 4.2.4 Habitat Use

I ran Kruskal-Wallis and Pearson's chi-squared tests to see if there were significant differences in habitat use as a whole, between the sexes, sample groups and seasons. The only significant differences were seen within the seasons as there was a switch in habitat use from DDF to DEF within the dry season. As I identified earlier this is most likely because the dry season has higher temperatures and lower humidity and rainfall which reduces the food and usable shelter sites in the DDF. The DEF is a more dense forest with more closed canopy and heterogenous understory providing higher humidity, more shade and more available food resources. In support of the theory that the habitat use change is driven by temperature and rain/humidity related factors, I have seen multiple occasions of animals moving from DEF into DDF during the dry season immediately after occasions of heavy rainfall. The frequency of DEF - DDF locations during the dry season without rain is 244 - 159 respectively, however when rain occurs this switches to 167 - 243 respectively corroborating this theory.

### 4.2.5 Variation in Morphology

#### 4.2.5.1 Mass and Habitat Use

There were clear relationships between mass and habitat use, as I identified that the larger mass individuals had higher proportions of their habitat use in DEF and a lower proportion of their habitat usage in DDF. However these models did not suggest significant influences on proportional habitat use relating to body mass. This is due to the small sample size of only 17 individuals and the locations their home ranges are found in. Many of the individuals were found with majority of

their range in DDF forest type with two individuals found almost exclusively in DEF forest.

### 4.2.5.2 Body Size and MDD

As with the habitat use I constructed models to identify whether body size (mass and carapace length) would correlate with the MDD observed. The GLMs constructed detailed a gamma distribution with identity link to be the best fitting model type and the best combination of size variables were Average Mass and Body Width. Both covariates were significantly influential with their coefficient slopes indicating that wider individuals had greater MDD yet heavier individuals reduced the MDD. Although this model was the best of the combinations (using the three covariates Body Lenght, Body Width and Average Mass) it is still using a sample size of 17 individuals and is representative only to the individuals modelled. It could make biological sense that heavier individuals moved less distances because they have more effort required to move greater mass. However the model does not fully make sense as I already discovered that Body Width (which is positively co-correlated with Body Length: $R^2 = 0.8337$) would be positively correlated with Mass (table 11). Logically indicating that if one of these variables was significantly positively correlated with MDD the other should never be significantly negatively correlated with MDD. I thereby conclude that this model, whilst significant as a model and with both covariates significant, is not biologically representative.

### 4.2.5.3 Body Variation Between Sexes

I finally tested for significant differences between the body size covariates in the different sexes. I had initially thought that there would be a discernible dimorphic difference in the body sizes of males to females and used a dataset of the all processed individuals from March 2016 until September 2018. Using this combined dataset of 72 adult individuals (39 females, 33 males) I concluded that there were no significant differences in any of the body measurements recorded. The adult individuals measured during this study duration averaged 1.6kg in mass and a straight body length of 23.2cm with the largest individual a male weighing 2.51kg at 28cm in length. These body sizes are lower than the average ranges mentioned by Ihlow *et al.* (2016) with only the largest individual reaching the straight body length of 28cm stated as the average size in the article.

### 4.2.6 Comparisons in Literature

Using other sources of literature and similar studies I assess whether my findings are outside of the known estimates or sit within what is expected. Many studies use radio-telemetry to study the movement patterns and home range sizes of tortoises including *I. elongata* (Tharapoom, 1996, Ihlow *et al.*, 2014, Som and Cottet, 2016). Tharapoom (1996) had previously conducted a masters study with *I. elongata* in Huai Kha Khaeng wildlife sanctuary, focusing on home range estimations and activity patterns and the *I. elongata* related to environmental conditions. The home range size estimates concluded an average MCP size of 22ha and 15ha for males and females respectively. According to Ihlow *et al.* (2016) the mean *I. elongata* home range sizes when compared with all known studies was between 5ha and 26ha for

which the present study fits well in the upper end of the average. Tharapoom (1996) identified no significant difference in activity between the sexes in the same manner that I did not find significant differences in the sexes between movement probabilities. Both studies identified activity changes between the seasons with peaks in the wet season.. My thought of the increased activity being related to increased food abundance was also shared by Tharapoom as his study documented more visible fungi and mushrooms being fed upon by forest tortoises during the wet season. The effect of temperature and humidity on activity however cannot be compared within the two studies as Tharapoom used tortoise location specific abiotic data, where as my present study used the same data collected from a static weather station.

Movement ecology studies looking similarly at the effects of abiotic factors as well as habitats as modelled predictors have also been conducted within other tortoise species (Longshore *et al*., 2003; Dabrik-Hamshare and Downs, 2017; Loehr, 2018). Loehr (2018) identified the speckled dwarf tortoises (*Chersobius signatus*) of South Africa as having seasonally dependant activity periods which also affected their habitat use. Although the habitats available for this species are limited their small size makes microhabitat a greater concern. This species lives on rocky outcrops with ephemeral resources a survival priority. The changes in seasonal temperatures and available basking or retreat locations were therefore essential in the annual survival of individuals (Loehr, 2018). Unlike *I .elongata* the *C. signatus* has a large seasonal temperature range of 3ºC to 31ºC within the winter active season. This range allows for less than one hour of optimal activity temperature for the species. The ranging of active temperatures in the larger *I. elongata* was much smaller and the diversity of habitat with available basking or shelter spots allowed for much longer periods of

activity. Elongated tortoises changed habitats with season changes, allowing for the continued use of food and shelter resources in a more favourable environment for the new season. This is not an applicable option for *C. signatus* which is restricted to the one habitat and limited shelter and food resources. Dabrik-Hamshare and Downs (2017) conducted a telemetry study on leopard tortoises *Stigmochelys pardalis*. Their focus was the home range sizes and effects of abiotic factors on the species ecology, similar to my own study, with the addition of GPS telemetry. All individuals were adults and there was no dimorphism with body sizes. Although not explicit in the movement patterns of the tortoises Dabrik-Hamshare and Downs do identify the seasonal changes in ranging behaviour and thus elucidate reduced movement occasions and distances during the cold season. One similarity within my study is the presence of large variations in home range estimations. Using 95% KDEs the leopard tortoises mean home range size varies between 40.53ha - 258.52ha. It is also noted that any variation in home range size between the sexes is not significant and that the large variation in ranging behaviour is likely a response in individual personality differences. These similarities between leopard tortoises and the *I. elongata* studied at SBR lend credence to the idea that non-significant differences with large variation is common among tortoises. It is discussed by Dabrik-Hamshare and Downs in relation to nomadic behaviour of individuals, which use space inconsistently and without strict ranges. This phenomena has been recorded within other species including the forest tortoise *Chelonoidis denticulata* (Guzman and Stevenson, 2008). According to Guzman and Stevenson (2008) this nomadic ranging behaviour should be expected as occasions of exploratory expansions of traditional core ranges increase the knowledge of the individual. These studies go further in supporting the findings of my study

however need to be taken cautiously. My study animals were a single population measured within one year each (except for F5). Many of the home range estimates and movement patterns could be influenced by such nomadic roaming as suggested by Guzman and Stevenson (2008), without multiple years of individual tracking we will never know. We must remember that the *C. signatus* and *S. pardalis* are species native to South Africa in areas with different climates and habitats available. These species differ greatly in size with *C. signatus* significantly smaller (approx. 140g) than *I. elongata* (1.2-2.8kg), which is significantly smaller than the *S. pardalis* (7.4-26kg). These size differences will have a substantial effect on the tortoises ability to cope with temperature variations and resource requirements. Making a direct comparison of the species irresponsible. Existing studies on species within similar habitats are not comparable because of methodological differences. Pedrono and Sarovy (2000) used radio telemetry to study movement patterns and estimate home ranges of the malagasy ploughshare tortoise (*Geochelone yniphora*). This species inhabits similar habitats to *I. elongata* and despite its larger size (4-10kg) is still considered a mid-sizes tortoise species. Pedrono and Sarovy (2000) however used translocated juvenile individuals from captive bred stock for their study and were not recording environmental variables. These are crucial differences to my present study which remove it from any comparative efforts.

# CHAPTER V

# CONCLUSION

With a total of 17 individuals tracked within their natural habitats and home ranges this study has created further evidence for the area usage and movement patterns of an endangered and under-studied species.

The home range sizes of the individuals studied varied widely from MCPs of 3.55ha to 70.97ha and 95% KDEs of 3.38ha to 54.30ha. However this large variation (including males and females) created means of 26.34ha and 23.76ha respectively which are within the currently known home range sizes for the species. I did notice that males had on average a larger mean home range size than comparable females (+11.10ha and +12.46ha respectively) but these differences, as with the individual home ranges, were not significantly different. I originally hypothesised that the home ranges would be between 20-40ha and that the male home ranges would be significantly larger. I can reject the null and confirm that home range sizes are within the hypothesised range however I cannot reject the null regarding the male to female difference. In my opinion given a larger sample size of males and females I would see a significant difference in the home ranges as has been suggested within the literature.

When I made the models to predict the movement patterns in relation to rainfall I saw that there were definitely effects on movement. Using the movement probability was my best modelling technique with the binomial distributions in Generalised Linear Models. I discovered that there was a clear significant increase in

the wet seasons as opposed to the dry and cold seasons. When I further looked into rainfall, the main difference between the seasons, as a predictor of movement probabilities I did see a significant increase in the movement after rain. Rainfall appears to be a major contributor to activity in this species. As described by the movement probabilities here and in the literature (Tharapoom, 1996, Ihlow *et al*., 2016), and with my own observations of increased feeding, mating and movement during the tracking. I also hypothesised that rain would particularly increase the MDD of the tracked individuals. The mean MDD between the seasons were significantly different with the wet season MDD, being significantly higher than cold season but significantly lower than the dry season. Later modelling the MDD I also noticed that rainfall did not significantly affect MDD at all. More to the point, the use of the MDD as a predictor with gamma distributed and inverse linked models, the best fitting models, was not a viable method of identifying the relationship. Plotting the linearity and normality of the model output visually identified there to be a break of the assumptions with the models being invalid. This unfortunately means that I cannot address the hypothesis of an increase in MDD with rainfall.

Using the GLMs again I identified the best combination of covariates to predict the movement probability of an individual included the habitat types interacting with the tortoise IDs, month, daily maximum temperature and daily humidity. When I used the interaction between habitat type and the individual it created the best models because the great differences in individual movement probability and individual habitat use are significantly different. This however is could also be reduced with a larger sample across more of the three predominant habitats to be representative of the Sakaerat population. It must also be considered

that these models are based on the covariates and data collected. Other covariates may play major roles in the decisions of how much and when the tortoises are active. Not to mention that the abiotic data being collected may not be under strict collection regimes. With each abiotic covariate being taken from a single static weather station which is not centred around the locations of the tortoises, and the weather data in the station collected manually at inconsistent times, we cannot confidently say that the abiotic data was accurate.

I can confirm that the tracking accuracies and data recorded regarding habitat use and locations is accurate as each track aimed to get visual confirmation of the individual. Using the habitat and location data I was able to run Pearson's chi-square and Kruskal-Wallis tests to identify significant differences in the MDD and seasonal proportional usage in the different habitats. The MDD was significantly lower in the DEF habitat than the other two habitats. In my opinion this difference was largely down to the variation in resource availability in the habitats. The DEF is a dense forest with higher annual average humidity and lower ground temperatures because of the canopy cover and shade provided by the dense evergreen trees with multiple stories. The different habitats were used disproportionately across the year as the wet season saw an increase in DDF use and a switch to DEF dominance with the dry season. As mentioned above the denser tree line, canopy cover and multiple stories proved the DEF with higher average humidity and lower temperatures. There is also considered to be a larger diversity of potential food sources for the tortoises within these evergreen forests (Tharapoom, 1996). Especially in the wet season, many of the food sources are either only apparent or predominantly apparent such as fungi, fresh shoots and new plant grown.

All together the data collected and the models constructed including the significance tests used to confirm differences illustrate a definitive seasonal variation in activity and habitat use. I am confident that the use of DEF habitat is influenced largely by rain and the season acts as a proxy for the changes in the rain. When I looked at occasions of rain in the dry season this confirmed that rain was the more influential than the season itself. Within the study animals I have tracked there were considerable, if not statistically significant, differences in individuals regarding their movement probabilities, MDD, body sizes and home range estimates. This species is a generalist with its diet and habitat and has observable personality differences which make it hard to find significant variations with small sample sizes. However the data collected further supports what is currently known. More importantly it supports previous studies and acts a a baseline for those studies which used translocated individuals that were the majority of studies in *I. elongata*.

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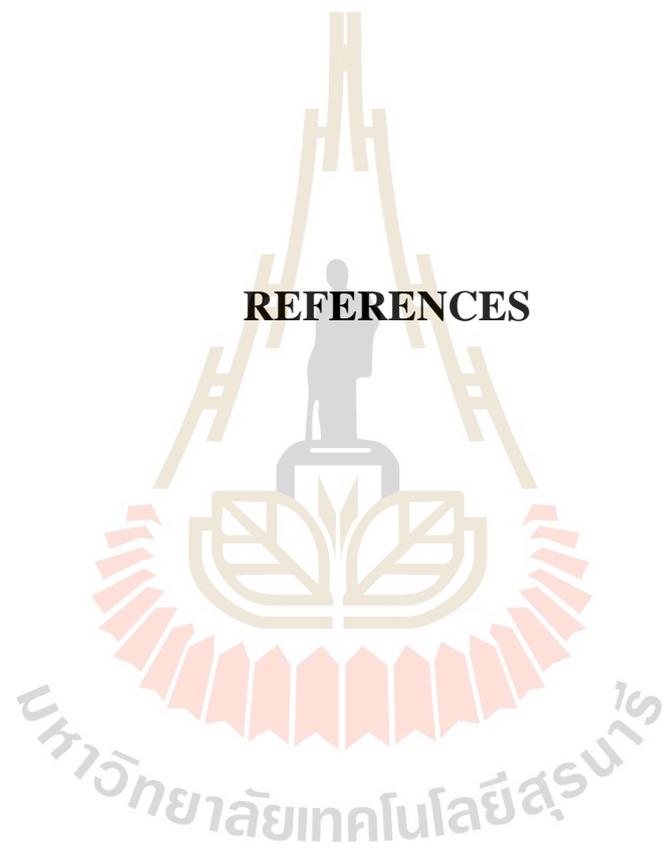
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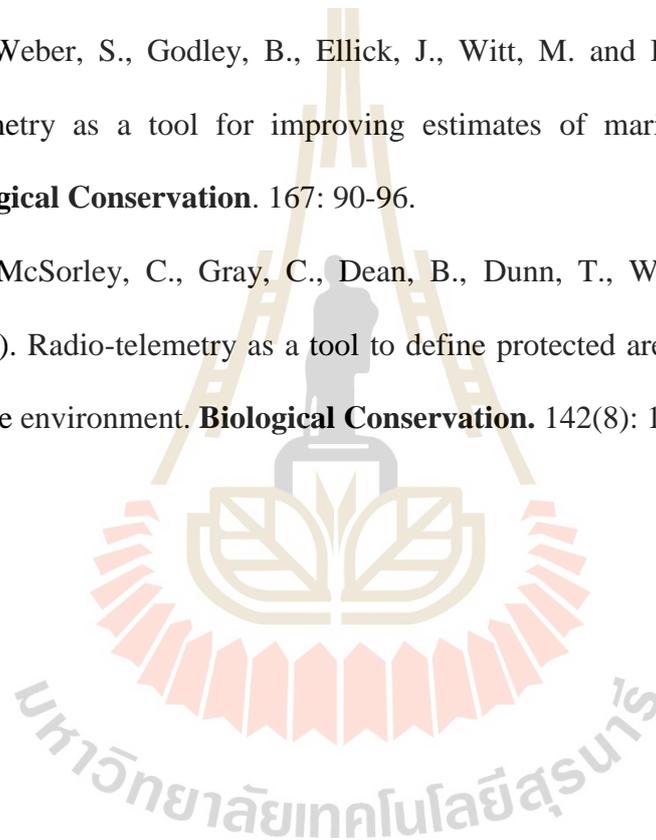
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