ABCZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Faculty of Tropical AgriSciences

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Investigating the use of AI-based image identification to monitor wild cryptic lizards: The shore skink, Oligosoma smithi, as a case study.

MASTER'S THESIS

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Author: Pauline Raphanaud

Chief supervisor: Doc. Francisco Ceacero Herrador, Ph.D.

Second (specialist) supervisor: Doc. Marleen Baling, Ph.D.

Declaration

I hereby declare that I have done this thesis entitled "*Investigating the use of AI-based image identification to monitor wild cryptic lizards: The shore skink, Oligosoma smithi, as a case study*." independently, all texts in this thesis are original, and all the sources have been quoted and acknowledged by means of complete references and according to Citation rules of the FTA.

In Angers, Wednesday 10th of August 2022

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Pauline Raphanaud

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Abstract

Biodiversity conservation increase through the last decades, but is facing massive threats, mainly by habitat modification. Reptiles (*Sauropsidae*, excluding *Aves*) are strongly linked to their habitat, and have less movement capacity compared to many other animal taxa such as birds or mammals. Therefore, monitoring reptile populations is a viable method to monitor habitat changes. But reptiles also suffer from of lack of knowledge on their basic ecology, such as movement or even population estimation. This due to less attractive image to the public, and a difficulty of trapping and identifying. Trapping small lizards for Capture-Marking-Recapture surveys requires an investment of time and money, for often poor results, due to trapping rate of the target specie. Using artificial intelligence software to identify individuals by their natural marking is preventing induced harm to the animal by marking and allow researchers to process bigger databases for a reduced time of analyses. In this master's thesis, we investigated the use of IBEIS, an artificial intelligence software based on image identification, to monitor the Shore skink, *Oligosoma smithi*, as a case study.

We used dorsal pictures of the skinks, among a database of 391 pictures of skinks captured in the pitfall traps of 3 grids in the Tāwharanui Open Sanctuary, with survey sessions were conducted bet November 2006 to May 2008. We identified 10 recapture events with IBEIS, and using SECR 1.4 App, we found out an estimated population of 6864 individuals, with around 820 individual per hectare on our study site. Despite a strong original database, recaptures did not occur frequently, thus we cannot use these estimations as solid proof, but are anyway a first step into understanding the unknown movements of this species. From our results, we think this low recapture rate is not due to IBEIS, but a high density of animal. To have a better understanding of these animals, a survey should be conducted with new technologies we dispose, like camera trapping and AI, following individuals without survey interruptions over year.

Key words: Artificial Intelligence, Monitoring, Recapture, Photo-identification, Lizard

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List of the abbreviations used in the thesis

- I3S: Interactive Individual Identification System
- IBEIS: Image Based Ecological Information System
- LT: Long-term grid
- LTc: Number of capture event in the Long-term grid
- SECR: Spatially Explicit Capture-Recapture
- ST: Short-term grid
- STc: Number of capture event in the Short-term grid
- SVL: Snout-Vent Length
- UC: Uncontrolled grid
- UCc: Number of capture event in the Uncontrolled grid

1. Chapter 1: Introduction and Literature Review

1.1. Conservation in herpetology

1.1.1. Conservation status of lizards globally

New Zealand ecosystem, unlike most of the other world's ecosystems, is not ruled by the mammal's taxa. This special evolution is mainly explained because of the split with the supercontinent Gondwana 85 million years ago (Craig et al. 2000) and thus, with almost every non-aquatic fauna, leading to a high degree of endemism of the island's biodiversity (Wallis & Trewick 2009). Within the reptile (*Sauropsida* taxa, excluding the *Aves*), we observed the emergence of unique reptiles, such as geckos, skinks, marine snakes, and the unique tuatara's species (van Winkel et al. 2018).

Nowadays, as consequence of past and current human activities and its effects on the climate, reptiles, as almost all world's living organisms, are endangered. According to the Global Reptile Assessment published on the IUCN Red List of Threatened Species, more than one in five of the world's reptiles are facing the danger of extinction (Böhm et al. 2013; Cox et al. 2022). Even if 12% of described reptile species are considered "Data deficient", the major threats of decline and extinction are habitat loss, degradation or pollution, but also pet trading, invasive species, climate change, and disease (Brian D. Todd, John D. Wilson 2010). New Zealand, despite its geographic distance from the other continents, does not escaping these threats because of globalisation. Studies have shown that island are vulnerable to climate change, where a population can be destroyed by a catastrophic weather event such as a hurricane (van den Burg et al. 2022), invasive species, even with species considered as non-competitive with the native ones (Wairepo 2015), or large-scale habitat destruction, like wetland drainage, deforestation, ecosystem degradation and pollution. To monitor these changes on the ecosystem, it is common to use animal populations as sentinels: where some species can be greatly affected by small changes, studying population dynamics could help us to evaluate the impact of an activity. Herpetological fauna is becoming more common to use as bioindicators (Silva et al. 2020), as most of reptile species have low movement, migration is quite slow and thus, a slight change in the environment directly affect the population health and abundance(Schaumburg et al. 2012; Zocche et al. 2013), which is perfect for monitoring studies. Indeed, many parameters that directly affects their survival can be measured, such as the development rate, thermal tolerance, acclimatization, or stress effects... Leading many species to be very good bioindicators.

For this thesis, we will focus on Lepidosauria's taxa, hereafter called "lizard", as a measurement for status of bioindicators, estimation of the population density, size, and abundance (Krebs 2014), behaviour, or population movement generally requires capture and recapture methods (Powell et al. 2000). These Capture-Marking-Recapture (CMR) methods are most useful when it is difficult to count all the individuals in a population individually, and therefore a statistical estimate is required. It can also be used to obtain other demographic parameters such as birth rate, mortality rate or survival rate. Moreover, data quality is often good, because of the amount of data collected per individual is often high (a lot of measures can be recorded easily) and allow to compare the individual with itself across, with the population... But these methods are not compatible with a large population, and should be limited to a defined area, assuming that the population is stable. The fact that lizards do not have big population movement is a non-negligeable point for CMR methods, as they require closed populations. In animal conservation, the prediction of animal movement is an essential part to evaluate the management and its effectiveness on protected species and habitats (Patterson et al. 2008). But lizards are less easy animals than mammals or birds to monitor, and we are facing limited survey methods (Greenberg et al. 1994; Ali et al. 2018) to estimate their presence.

1.1.2. Field monitoring methods used for lizards

Currently, many capture and tagging methods exist on fauna, which can be separated into two groups: Invasive and non-invasive. Invasive methods could be summed up as methods that require animal handling, or temporary capture even without handling (e.g., pitfall traps). The most common capture techniques of capture are basking traps, drift fences, pitfall traps, funnel traps, and sticky traps (C. Kenneth Dodd 2016). They are keeping the animal locked alone, or with other individuals or species, to a place that require human intervention to release the individual. In addition to detection methods, we can add the marking methods considered invasive, like the bee-tag, and marking paint, which have extremely limited application because of the natural shedding process of reptiles. For reptiles, it poses severe outcomes in terms of monitoring, because shedding event of an individual for a monitoring is impossible to predict. Thus, monitoring with these marking methods is under a huge bias, animal shed at least twice within year, preventing long-term monitoring, as the tagging method is more likely to disappear the longer the individual has been captured. It involves an incapacity of monitoring individual across years, and even between seasons. Indeed, the tag might disappear on its next capture, leading to consider this individual as a new capture and not a recapture, biasing the population size estimation, for instance. Other techniques, such as such as scale clipping or burning, toe clipping, PIT-tagging under the skin (Bloch & Irschick 2005) are even more stressful for the individual.

But many of these captures and tagging methods are not applicable for lizards, especially for small skinks. Indeed, a frequent problem with monitoring lizards is the fact they are smaller, leaving fewer hints of their presence, most of them are not making noise for reproduction or communication, their catch rate is often low, and many methods are inducing high-stress levels, which could affect individual fitness. Furthermore, trap efficiency varies a lot regarding the target species, for instance, pitfall traps are much more suitable for skinks than geckos (Greenberg et al. 1994). The induced stress increases the risks of drowning, being predated after release, thirst, hunger even more in neonates, and lower or higher body temperature (Moore et al. 1991; Martínez Silvestre 2014). Such stressful experiences induce bias, making the individuals trap-shy, making them avoid the area of capture in the future. Another bias is that the farther the animal is from a trap, the less likely it is to get captured, and increasing trap density for such small animals would too much disturb the environment (Wilson & Mcmahon 2006).

Non-invasive methods such as identifying an individual by its natural shape, and body pattern, by looking for individuals on basking areas, or eye catching, are stress-free but often prevent the identification because of the distance between the observer and the target, which often flee as soon as the observer is getting closer. A solution to these problems is to use camera traps, as used for large mammals, such as MammalWeb (https://www.mammalweb.org/en/) a citizen-science project on which citizen help to recognize mammal species within the amount of camera trap pictures of researchers. We can see how mainstream camera trap has been accessible these years to users (Green et al. 2020). Critterpic® tool is a tunnel with a bait and a camera on top (Sanders et al. n.d.), is a novel method of non-invasive and stress-free way of taking standardised dorsal pictures of the fauna. Indeed, do we really need to identify an individual right on the field? Camera trapping is doing the same function as invasive CMR methods. The problem with identifying individuals by their natural shapes or pattern is that features can vary from quite simple to extremely complex, mixing colour and shapes. Image handling can be feasible by an observed if the images total < 50 but if there are > 100 pictures, individual identification can be labour-intensive, and the errors of identification may increase if it was done by the human eye only. In B. Calmanovici study (Calmanovici et al. 2018), manual identification was around four times slower rather than using an automated software utilising artificial intelligence, here I3S. From here, we can introduce an innovative approach, the use of artificial intelligence, helping to identify multiple species (Matthé et al. 2017) or individuals within large dataset (Kelly 2001).

1.1.3. Importance of monitoring at an individual level

The CMR monitoring methods allow for the estimation of abundance and density of a population. Many methods exist, depending on data collected. All these methods are based on the total amount of individual captured, the number and the frequency of recaptures across the different survey sessions (Lettink & Armstrong 2003). But these estimations require assumptions, such as a closed population, without death, birth, or emigration, which is almost impossible in wild and natural fieldwork reality. But we can approach these assumptions as close as possible by well-designed protocols, with suitable survey methods and calculations. Lizard, even if the population is not perfectly fitting these assumptions, usually have a small dispersion rate (Perry 2007), thus having a population almost closed. These estimations also require a certain frequency of capture rate to be accurate (Powell et al. 2000; Krebs 2014). Indeed, by studying animals at the individual level, it also helps to understand population dynamics, its stability, like by looking at resource partitioning, unequal sharing among the individual within the same species. But also understand important ecological phenomena, like contest, scramble competition, population stability, animal dispersion into the suboptimal habitat, and physiological parameters that affect body size (DeAngelis & Rose 2018)**.** For instance, within the population of the Bark anole, *Anolis distichus*, it has been shown that some males and female do share some food type intake, but females tend to predate larger prey but feed less often (Schoener 1968). Another example, within the European jay (*Garrulus glandarius*) Swedish population, resource partitioning and behaviour has been studied by measuring individual bill growth (Andrén 1990).

Increasing our understanding of population dynamics is leading to being able to predict more precisely population behaviour by creating models, and for instance, readjust our conservation methods for the management of a protected area (DeAngelis & Rose 2018)**.** It is a necessity to know better a population nowadays, because our increasing databases, our increasing calculation power due to better programs and more powerful computers gives us the tools to conduce deeper analysis on populations. Studying behaviour and demography leads to studying more specific subjects like studying movement: Allowing individual-based predictions of animal movement with new mathematical techniques (Patterson et al. 2008), studying dispersal... Indeed, some populations never crosser invisible barriers, and mathematical predictions can show population movement within a population (Morales & Ellner 2002). By making more realistic models, we can bottom-up the approaches to understand the parts of a system, where the parts are the individuals, and the system is the population (Grimm 1999) and thus reinforcing our understanding of species and their relation to their environment**.**

In conservation biology, these models are widely used in invasion biology for instance, by not only having data on density and abundance, but also the population dynamic, like its movement types (Wilson et al. 2009)**.** By getting population general behaviour, a study showed that unusual changes in population behaviour of four large mammals' species in a closed area without predators can be linked to poaching events (de Knegt et al. 2021)**,** and implications for management and rapid actions against poaching can be deployed. Despite all these benefits, the actual state of art showed poor communication of new methods between researchers of different fields of study, like conservation biology and computer science, and a clear deficit in standardised methods, preventing the spread of these new techniques (DeAngelis & Rose 2018)**.**

1.2. Artificial intelligence in herpetology

1.2.1. Brief history of artificial intelligence, its current and most common use

The first known artificial intelligence program appeared between 1964 and 1966, developed by Joseph Weizenbaum: a simple program that tried to create a conversation with a human (Haenlein & Kaplan 2019). It took time for researchers and the public to develop interest in this field, likely due to the difficulty of access to computers. Since then, several methods have shown up, like the famous tree-search method, a method used by IBM artificial intelligence “Deep Blue” (Campbell et al. 2002) to play chess, which won in 1997 against the world chess master Gary Kasparov, which was a major event in artificial intelligence history. Other methods were developed, such as statistical analysis, or artificial neuron networks (Hebb 1949). This last technique, now a lot used in our current artificial intelligence, took time to emerge, because of the limited power of computers, despite an extremely powerful method. In 2015, Google helped to bring back this technology with AlphaGo, a deep-learning program that plays Go (Silver et al. 2016), a similar but more complex game than chess. We now see this technology used in many powerful companies such as Facebook with photo-recognition, big companies’ management evaluation and improvement, prediction of the economy, medicine. The application of artificial intelligence is slowly gaining momentum in the field of conservation ecology.

Artificial intelligence (AI) is introducing an innovative approach for research and data analysis, and despite its application to many fields has increased across the years, its use in ecology remains low (Galaz et al. 2021) with sparse applications. Artificial intelligence software developed and being developed are not using a single technique such as the neuron network but are all using different techniques. Indeed, process and code are still debated in the scientific community, regarding what kind of artificial intelligence technique, such as neural network or heuristics, would make the program to an application more efficient (Liu et al. 2018). The most common applications of artificial intelligence in ecology are identification of species or individuals from a targeted species, species description, population counting, population estimate, or behaviour recording (Gore et al. 2016; Weinstein 2018; Christin et al. 2019). Software that uses AI are identify species or individuals using at position of spots and patterns, but also their colours and shapes (Gore et al. 2016; Cheema & Anand 2017). Such software has been assessed on many different taxa such as cetaceans, lizards, giraffes, cheetahs, sea turtles (Kelly 2001; Speed et al. 2007; Sacchi et al. 2010; Bolger et al. 2012; Calmanovici et al. 2018), and even jellyfish (Martin-Abadal et al. 2020). We also saw the emergence of public use for image recognition AI, with citizen science being increasingly becoming the source of data collected by researchers over this past year. As a result, citizen science can generate large datasets for analysis, a conjugating human and machine viewpoints (McClure et al. 2020).

There is several software with AI application are now publicly available. For example, the well-known Google Lens, which, from a picture of a backpack can give the brand, its volume, and a link to online-shops where you can buy it, is the most public wide spreading photo-identification artificial intelligence. But more specific applications have been developed, such as the most famous artificial intelligence plant identifier PlantNet (Bilyk et al. 2020). This artificial intelligence, from a single picture of a leaf, can give you the specie name, is not always accurate, but manage to at least propose related plant to ease the identification. Regarding wild organisms, Google Lens tends to not but perfectly accurate too, but is also useful by at least guide you to a similar organism, and then save you time in identification. But we also can go into more specifics, like the different Wildbook (Berger-Wolf et al. 2017) proposed, the where public can upload their pictures on given servers, and the artificial intelligence is identifying species or individuals. Researchers mostly use it to gain time, on data processing part, having a bigger dataset for the same survey effort. Some other applications, which can be downloaded from mobile stores, have the same application, like ObsIdentify for wild biodiversity specie identification (Schermer & Hogeweg 2018), or MedusApp for species identification, abundance, toxicity, and directions in stinging cases (Blasco Talaván et al. 2016).

1.2.2. Application to identifying individuals for population monitoring

The study of individuals within a population (e.g., behavioural) requires the reliably of the researcher to identify individuals over time. The identification of individual using their natural colour patterning started between 1965 and 1985 (reference). It was first developed and used with large mammals with a long lifespan, such as zebras (*Equus burchelli*), giraffes (*Giraffa camelopardalis*), African elephants (*Loxodonta africana*), lions (*Panthera leo*), chimpanzees (*Pan troglodytes*), wild dogs (*Lycaon pictus*), and many cetacean species (Kelly 2001). Indeed, even from the seventies, researchers already saw that number of pictures for a survey could increase quickly, and thus would require increased time to process. These innovative programs were there to just help researcher to process the data to then analyse results, like estimating population size. The idea to use artificial intelligence software emerged c. 1990 in cetaceans' studies (Guo et al. 2020), which commonly acquire large datasets or images over time for individual identification. For instance, Tri-AI was developed to identify distinct species and their individual among a big dataset, of 102399 pictures for 41 different primates' species. The studies showed automatizing the process with the help of AI would allow to research to save time and thus, money.

In other non-charismatic taxa under the public eye, such as lizards (Gonzalez et al. 2016)**,** we observed a lower percentage of artificial intelligence software developed to for those species' groups. Lacking interest on these taxa reflects our vision in ecology, still too focused on large and visible species, whereas smaller and "invisible" animal are as important in our world, by their ecosystem services. Indeed, roles of small predators, such as Diptera, Coleoptera, and dragonfly larvae has shown an impact on mosquitoes' larvae, and thus on mosquitoes' population (Shaalan & Canyon 2009), which could play a role on mosquitoes-transmitted diseases. Amphibian taxa, which represent 41% of IUCN RedList threatened species, is still poorly studied (Titley et al. 2017) regarding other more charismatic taxa (such as mammals) and no conservation plan are taken to preserve populations and their habitats (Bishop et al. 2013). But these low studies numbers have led researchers to invent methods to identify individual with artificial intelligence help (Moore et al. 1991; Bloch & Irschick 2005; Konstanze Gebauer 2012), and few studies emerged, trying to use pre-existing programs. Successful results were published, identifying individuals by using the size of pectoral scales as fingerprints of the European lizards *Lacerta bilineata* and *Podarcis muralis* (Sacchi et al. 2010)**.**

Using artificial intelligence to process the entire or a part of the data from the field is requiring the same survey effort as processing the data by a human. But the extraction and analysis, even with learning the software operations, is a massive time gain (Dunbar et al. 2014) reducing cost and human-induced mistakes. Indeed, Sears et al. (Sears 1990) demonstrated the decreasing effectiveness and increasing mistakes of a person after 2 hours of work, induced by fatigue. A study on cheetahs, without calculation well explained the problem: Training a person takes hours, matching a picture can reach one hour with mistakes risks, whereas the software is analysing a picture within 5 minutes. Another study on large mammals (wildebeest, impalas, gazelles, reedbucks) showed that the amount of time saved is up to 9 years, with a technician working 40 hours a week on a dataset of 3,2 million images (Norouzzadeh et al. 2018)**.** This huge database is not surprising, with the increasing accessibility of camera trapping devices (Green et al. 2020), artificial intelligence can reduce the amount of data that is going to be used in a study, or human manipulation (Swinnen et al. 2014; Lizard 2018)**.** In 2015, a study even used a drone, a small flying device, to capture pictures of wildlife: It showed that wildlife and environment disturbance was lower than if humans were sent on the field, even without interaction with targeted species (Gonzalez et al. 2016)**.**

1.2.3. Non-exhaustive artificial intelligence software overview

We present here a non-exhaustive list of individual recognition artificial intelligence programs currently used in ecology, which has all been considered in the data processing of this master’s thesis.

One of the most famous programs is Hotspotter (Crall et al. 2013), which is used to compare an image to an existing database of images. The programme compares features (describe what specific features) of the animal, and scores by matching possible matches between the new pictures and some of the database. Then the user requires to manually review the matches and decide to accept or reject the non-match or match between proposed pictures. Another programme, Image Based Ecological Information

System (Reijns 2015), hereafter IBEIS, uses the same algorithm as Hotspotter (Oddone 2016) but it integrates more tools into its interface, like image analysis. A programme called Wildbook (Berger-Wolf et al. 2017), similarly uses the IBEIS (and thus Hotspotter) algorithm, but it is readily available online website and uses citizen science as part of their data-gathering. Wildbook is now a service proposed and developed with Microsoft® (David W. Kimiti, Timothy Kaaria, Edwin Kisio, Ian Lemaiyan, Saibala Gilisho, Francis Kobia 2018).

Interactive Individual Identification System, commonly named I3S (Hartog & Reijns 2014), is a pixel-based recognition program, or pattern recognition. It was developed for identification of sea turtles, but has shown extended application to other species, from whale sharks (Speed et al. 2007) to the Mosor rock lizards (Lizard 2018). It comes with four variations, regarding what features we are planning to use for our species (Calmanovici et al. 2018). I3S Classic can be used for similar shapes for a same pattern, like a body part which is not curved and thus, does not twist the pattern, remaining stable over the different individual pictures. If the pattern is too unequal, it is better to look at I3S Spot. I3S Contour would be used to look at an edge, like a dorsal fin of a whale's tail, and I3S Pattern+ is concerning features hard to classify in the 3 other categories. All these declinations of I3S are based on the same pattern: the user is defining three reference points defined on the animal, like the right arm, left arm, and the tail base (Sacchi, Roberto & Scali, Stefano & Mangiacotti, Marco & Sannolo, Marco & Zuffi 2016). A more updated version of the programme, I3S Straighten (Reijns 2015), was developed to correct body deformation, like newt bending their body while handling. Body deformation can strongly lower software ability to match images of individuals, leading to false-negative results. The correction by I3S Straighten has shown that the error rate decreased significantly (Rosa et al. 2021). For this programme, identifiable images were best to acquire from ensuring animal body position, background, light reflection on the animal's body are standardised. However, such quality images can be hard to achieve in the field.

Other algorithms available are based on I3S code, such as Wild-ID (Bolger et al. 2012), mainly used for giraffes, but showed reliable results for other animals, such as on Ocelot (*Leopardus pardalis*) and Jaguars (*Panthera onca*) (Nipko et al. 2020). Aphis software (Óscar et al. 2015) is also using the I3S algorithm, trying to match a database picture to the new picture proposed for identification, thus is not a potential software for our study, our database being too large (Gatto et al. 2018). Mydas (Carter et al. 2014), using the neuronal network technique, is only used for sea turtles for now, but might be usable for other species. It looks in its database for a matching picture with over 95% of similarity.

We decided to use IBEIS software, mainly because of the satisfactory results of preliminary tests we conduced. Indeed, this software was easier to manage, and the automatic process of individual identification was what we were looking for. Also, because of the software was evaluated by enough researchers before compared to other software, with good results. The software is also free, guaranteeing the access to the public, compared to other paying software.

1.3. A case study, the Shore skink, *Oligosoma smithi*

We used the Shore skink, *Oligosoma smithi* (Gray,1845), in this master's thesis as a case study. This species is endemic from the North Island of New Zealand (van Winkel et al. 2018), widely abundant from Gisborne region to Aupouri Peninsula's east coast, including offshore islands. The species is restricted to coastal areas, within dunes and rocky shorelines. This diurnal specie is active from spring (October) for mating season, laying 4-6 eggs that hatch in January-February, living between 10 to 15 years. It mainly feeds on invertebrates but is also able to feed on fruits such as berries and has been observed scavenging on bird and fish carrion. Coloration of this species is quite diverse (Figure 1), dorsal surface is going from pale creamy white to grey shades, brown, green, gold, and shiny black. Pattern can be absent, spotted (distinctive dense speckling), lined (mid-dorsal line) or a mix between these three categories (Baling 2007; Baling et al. 2016). This skink is capable of autotomy, the tail regrowing only once, often with a distinct colour a pattern (sleeker).

The specie is considered as Least Concern (LC) by the IUCN Red List of Threatened Species (Hitchmough 2021), mostly because of its high abundance. Indeed, the populations tends to be quite high in predator-free area, but conservation in New Zealand continue to deal with invasive animal species, such as mammals like cats, possums, or mice (Craig et al. 2000) or biological-close species, like the invasive

Australian skink, the Rainbow skink, *Lampropholis delicata* (Chapple et al. 2014). Even though Shore skinks can live with invasive predators, they are known for their rapid response to the predator removal. Indeed, it has been observed a population increase up to 3600% after 9 years of mammal pest eradication and thus, represent a viable candidate as bioindicator species (Towns 1994; Towns et al. 2001).

Figure 1: The Shore skink, Oligosoma smithi

2. Thesis aims, objectives, and structure

The aim of this master's thesis was to extract information from a recapture study conducted 15 years ago, by identifying new individuals with the artificial-intelligence software IBEIS. With the new data generated, we aimed to estimate basic information on the Shore skink population of this part of the Tāwharanui Open Sanctuary, such as population density and movement.

The objectives of this master's thesis are 1) to test the feasibility of an AI-integrated software, IBEIS, to identify individuals across time (within a survey session, between seasons, and between years); and 2) to determine the population status and movement of a New Zealand skink population using capture-recapture from IBEIS.

Here, we will evaluate the feasibility of IBEIS to identify individuals from a small, cryptic but highly variable skink species in New Zealand. The shore skink (*Oligosoma smithi*) species shows a wide range of coloration and diverse dorsal patterns (Baling 2007; Kraus 2010) and would be suitable for identification using artificial intelligence. Photographic individual identification on the small-scaled skink (*O. microlepis*), a closely related species, has already been done by eye (Konstanze Gebauer 2012). Therefore, individual recognition may be possible by the dorsal pattern of the shore skink. There is an existing image dataset on a population of the shore skink (*Oligosoma smithi*) that was used in this thesis (Baling et al. 2016, 2020, M. Baling unpublished data). The use of artificial intelligence on such cryptic species will help to better understand the species' biology and increase our knowledge of such understudied animals.

This master's thesis is composed of four parts. The first Chapter introduces the various concepts and software pertinent to this thesis and includes the aims and objectives of the thesis. Chapter two the thesis aims and objectives, chapter 3 is the methods used, chapter 4 showing the results, and chapter 5 is discussing on the results. Chapter 6 is concluding this master's thesis, where we provide an objective eye on this study, and suggest recommendations some future research directions.

3. Methods

3.1. The study site: Tāwharanui Open Sanctuary

The species studied is the Shore skink (*Oligosoma smithi*, Gray 1845), a skink from the North Island of New Zealand (*Figure 1*). We used for study site a portion of the Tāwharanui Open Sanctuary beach (*Figure 2*) also used by C. Wedding for his master's thesis (Wedding 2008). It is divided into three zones: Short-Term, Long-Term, and Uncontrolled (Here after ST, LT, and UC), corresponding to the different zones for monitoring the impacts of the invasive mouse (*Mus musculus*) on New Zealand skinks. Each area consists of 28 meshes, with each pitfall trap spaced 20 metres vertically and 25 metres horizontally (*Figure 3*). LT grid is the only one within the predator-free area of the sanctuary, ST and UC being the other side of the predator-proof fence. The data were provided by Ph.D. M. Baling and included for each individual captured at a given time a dorsal and ventral photo, measurements such as size, weight, pregnancy, tail loss and regrowing, if the individual has already been caught, substrate type and vegetation cover in the square metre in the capture grid. Data were collected from November 2006 to May 2008, in the months of November, December, February, March, May and August. Each capture session lasted 7 days and was grouped into clusters, from A to I and declined in number for every survey session (*Table 1*). Standardised dorsal pictures were taken, of the skink and its habitat background (1 x 1 meter), with an Olympus mju 770SW (Olympus, Japan). Each dorsal and habitat background photograph involved a grey photographic standard (QPcard 101, Sweden) with 18% reflectance. Each photo was given a unique number including capture date, sex, and capture number in the session, starting from zero at the beginning of each session. We only used dorsal photo for identification because ventral pictures are not showing any mark, scales are too blurry or the belly too shiny to be suitable for artificial intelligence identification. These ventral pictures are anyway good to be used as support for individual identification, some individuals occasionally have scars or belly pigmentation.

The visual database included 499 photos, which were manually sorted to exclude juveniles, leaving 391 photos for analysis. 8 events of recapture have occurred, but the individual identification was impossible. This is because juveniles have thinner bodies and change colouration and pattern as they grow. The use of artificial intelligence could have been interesting to test, however it would have taken more time for this thesis, so we limit ourselves to data where we are sure it is usable. For population estimation, because of the multiple survey sessions, we will use Schnabel method.

Figure 2: Photograph of Ocean Beach dunes at Tāwharanui Open Sanctuary showing the three grids from the left: long term control (LT), short term control (ST) and uncontrolled (UC). Photograph by Chris Wedding

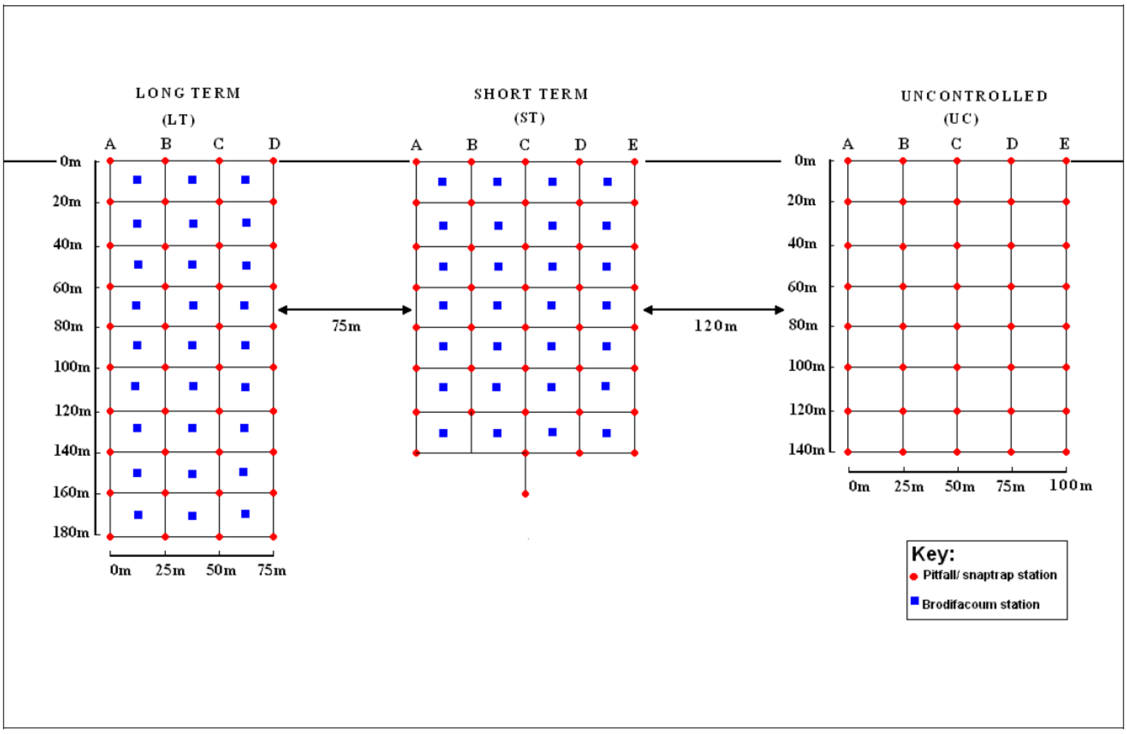

Figure 3: Diagrammatic layout of grid, including pitfall traps and brodifacoum bait stations, at Ocean Beach, Tāwharanui Open Sanctuary. 71n with author's permission and Copyright Act 1994 (New Zealand)

Table 1: Planning of survey sessions

Survey sessions year	*CODE*	*No of catch per survey session*	*Date*	*No of catch this day*	*Recapture events numbers*
2006	**A**	**24**	06/11/2006	24	
	B	**33**			
	B1		13/11/2006	8	
	B2		14/11/2006	12	
	B3		15/11/2006	3	1
	B4		16/11/2006	10	
	C	**10**			
	C1		10/12/2006	7	
	C2		14/12/2006	3	
	D	**119**			
2007	D1	20	24/02/2007	20	2
	D2	32	25/02/2007	32	
	D3	18	26/02/2007	18	
	D4	20	27/02/2007	20	4
	D5	17	28/02/2007	17	3 and 5
	D6	12	01/03/2007	12	
	E	**67**			
	E1	7	07/03/2007	7	
	E2	10	09/03/2007	10	
	E3	4	11/03/2007	4	
	E4	2	15/03/2007	2	
	E5	20	17/05/2007	20	
	E6	5	18/05/2007	5	
	E7	19	19/05/2007	19	
	F	**27**			
	F1	8	17/08/2007	8	
	F2	6	18/08/2007	6	
	F3	13	19/08/2007	13	
	G	**63**			
	G1	28	18/11/2007	28	
	G2	24	19/11/2007	24	
	G3	11	20/11/2007	11	8 and 9
2008	**H**	**36**			
	H1	14	9/02/2007	14	7
	H2	9	10/02/2007	9	6 and 10
	H3	13	11/02/2007	13	
	I	**12**	2/05/2008	12	

3.2. Image Based Ecological Information System software

The software Image Based Ecological Information System software, IBEIS, is based artificial neuron network based. Basically, once you introduced a picture in the software, you should indicate the software the area of interest, which is determined by yourself. In our study, we tried to include every part of the skink. Then, the software is processing the picture, comparing it to its database, by detect and describing the repeatable features, here the dorsal pattern of our skink. Then IBEIS is comparing it to the queries description of nearest neighbours by kd-tree in its database and ranking it with a score. For georeferenced data, spatial analyses can be done, and IBEIS is also comparing with spatial data. Then the user must check the results: when the database is still small and the software not so much trained, the software always quotes “Unknown” instead of “True” or “False”, but the more analyses are made, the more the soft is choosing a positive or negative results, with less and less need from the user to review the results. In our experience, when we reached this threshold, we still checked the “True” matches manually, to be sure that the event is not “False positive”. Pictures have been added survey by survey, to train the software step by step. At the ended, we compared all pictures of the database between each other, to see if with training, that IBEIS is finding new recaptures events.

IBEIS was chosen for this master's thesis experiment. IBEIS was chosen over other software because of its ease of installation, although it must be used on a Linux computer and not Windows or IOS, its user-friendly interface and the numerous actions proposed, but mainly because of its effectiveness, as proven by scientific studies (Wedding et al. 2010; Parham 2015; Parham & Stewart 2016; David W. Kimiti, Timothy Kaaria, Edwin Kisio, Ian Lemaiyan, Saibala Gilisho, Francis Kobia 2018). The limitations of this software are almost same as the other software: the photos must have a minimum quality and be identifiable even by a human being. The need to have Linux or to create a virtual machine may also restrain some people. Also, the software was sometimes crashing but is automatically saving your progression, so it’s a big plus.

3.3. Population abundance and density: SECR App 1.4

To conduce our analyses of our data obtained with IBEIS, we choose to use the web interface of Spatially Explicit Capture-Recapture (Efford 2022) (hereafter SECR) of an R package. This website helped to represent animal captures and movement from its first capture other(s) recapture(s). This software provided population abundance and density estimation on site, and individual detection probability. We removed 13 data from individuals captured outside the 3 grids LT, ST, and UC. Indeed, the software needs standardised entries to work properly, thus we needed data from individual only inside our trapping area. From the 10 recapture events we obtained with IBEIS, we had to remove one of them because the individual has been hand-caught once, we are then using only 9 recapture events.

We used a halfnormal detection function, with a binomial distribution of *N*, with a buffer of 25 meter for the habitat mask. We choose 25 meters of buffer because of two reasons: First, the author of a lot of bibliography of SECR program made population analysis on a specie of the same genus, the Speckled skink *Oligosoma infrapunctatum* (Efford 2019). Second, a individual focused survey (Germano 2007) was conducted with telemetry on another species of the same genus, the Otago skink, *Oligoma otagense*. It showed a movement range between 0 and 50 meters a day per individual, with a mean of 12 meters. We conducted the analysis on the 3 grids at the same time, but also for each grid individually to look at differences between the 3 locations.

4. Results

4.1. IBEIS

IBEIS worked very well towards the middle of the analysis: at the beginning human help was needed to tell IBEIS, for each photo categorised as "Unknown", whether it was a recapture or not. Subsequently, the software proposed fewer and fewer "Unknown" events and the results categorised as such were often very similar. The software understood that the background of the photo was not to be identified, nor the observers' fingers, but the individual (*Figure 4*).

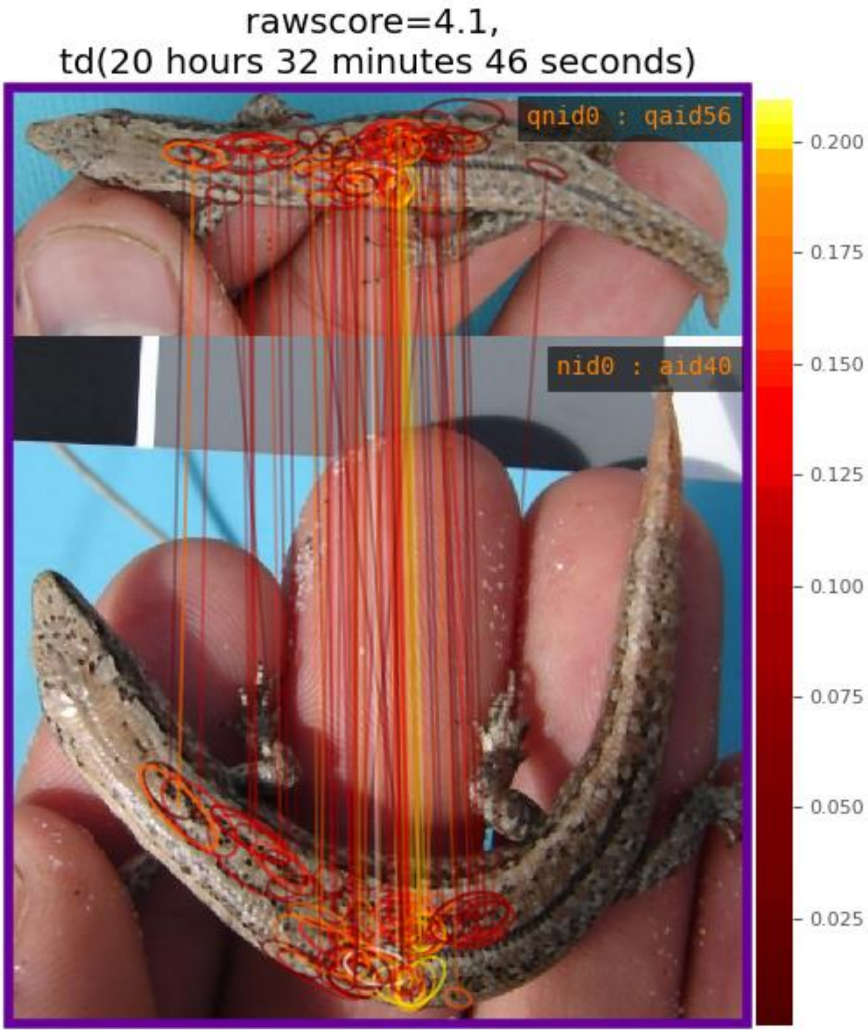

Figure 4: Example of IBEIS analyse on one of our recapture events.

Of the 391 images, we were able to identify 381 different individuals, 10 individuals having been recaptured (*Table 2* and *Annex 1*). The use of ventral photos was useful, saving time but not necessary, on one female individual, N°2 having a scar on the neck. Of the 8 individuals already identified as recaptured, 2 were found by IBEIS, N°8 and N°9, and recovered the photo of their first capture. At the end of the analysis, we ran IBEIS again with all the photos, to see if the software could identify new recaptures with training, but this was not the case. No individual was recaptured after 4 months, for reasons that we will detail in the discussion. IBEIS did not created false-positive results (marking a possible match as "True" whereas it is not) but did one false-false result (Recapture 5). We identified this false-false match as a recapture event because the matching score that IBEIS indicate for each event (True, unknown, and false) was very high compared to other false and unknown events.

The abundance estimate for the 3 sites was calculated using the Schnabel (1938) method, and is 7153.1 individuals estimated, with a standard error of less than 1, of 4.42085E-05. This estimate is however not usable due to the low number of recaptures events but can be used for future consideration.

Table 2: Synthetic table of obtained data: for the "Sex" column, "M" stands for male and "F" for female

Recapture event	Name on the first catch	Name on the second catch	Sex	Trap ID of the first catch	Trap ID of the second catch	Distance (in meters) between the two-trap locations	Time delta (in days)	Body Condition Index (BCI) delta
1	061113tawhs D06m	061115tawhs D05m	M	**NONE**	3C1	**NONE**	2	0,00
2	061115tawhs D06f	070224tawhs D03m	M	3C1	3C2	20	101	0,01
3	070224tawhs D11m	070228tawhs D04m	M	3A4	3A4	0	4	0,02
4	070224tawhs D15m	070227tawhs D08m	M	2E5	2E5	0	3	0,00
5	070227tawhs D17f	070228tawhs D12f	F	1D2	1D2	0	1	0,00
6	071118tawhs D03f	080210tawhs D04f	F	1A7	1C1	130	76	0,00
7	071118tawhs D08f	080209tawhs D03f	F	1B2	1B2	0	83	0,01
8	071119tawhs D10f	071120tawhs D09f	F	2A2	2A2	0	1	**NONE**
9	071119tawhs D15f	071120tawhs D06f	F	1D4	1D4	0	1	**NONE**
10	071119tawhs D29f	080210tawhs D03f	F	1A5	1A5	0	83	**NONE**

4.2. SECR 1.4

We generated with SECR a map of individual catch and the 9 recapture events we observed with IBEIS, making a synthetic map of individual movement (*Figure 5*). The animal moved in average 25,9 meters away from their first capture trap, with a maximum range of 103 meter away, but the median move is of 0 meter. Indeed, 5 individuals were recaptured on the same trap. Frequency of distance between the first capture and the recapture has been compiled on the *Figure 6*.

We obtained an estimate of 6864 individuals on site, which is different from the total of the 3 grids analysed separately, of 7648 individuals. We obtained an estimate of 2310 individual for LT, 3450 for ST and 1888 for UC. The density of individuals on the entire site is of 820 individuals per hectares, showed with individual abundance estimation on the *Figure 7*. SECR estimated that the probability pç(×) of an individual at a given point × to be captured at least once, is p(×) =0,01.

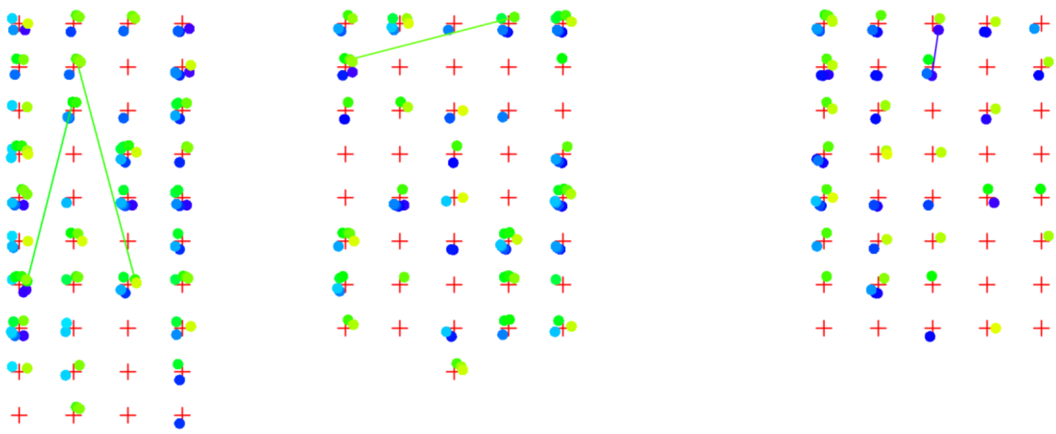

Figure 5: Individual capture and recapture (obtained with IBEIS) from november 2006 to may 2008

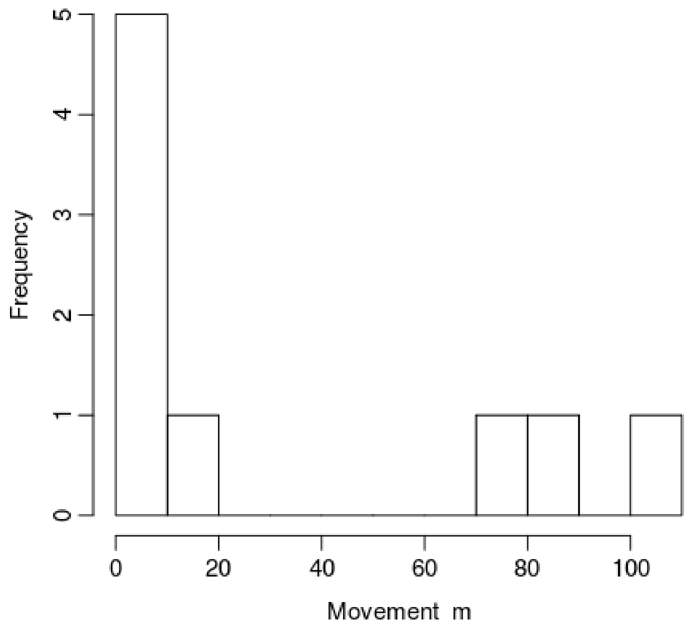

Figure 6: Frequency of distance moved by the 9 individuals recaptured. 5 where recaptured on the same trap, resulting of a movement of 0 meter. Individual number 12 moved of 20m; 217 of 83,8m; 242 of 103m; 270 of 77,6m.

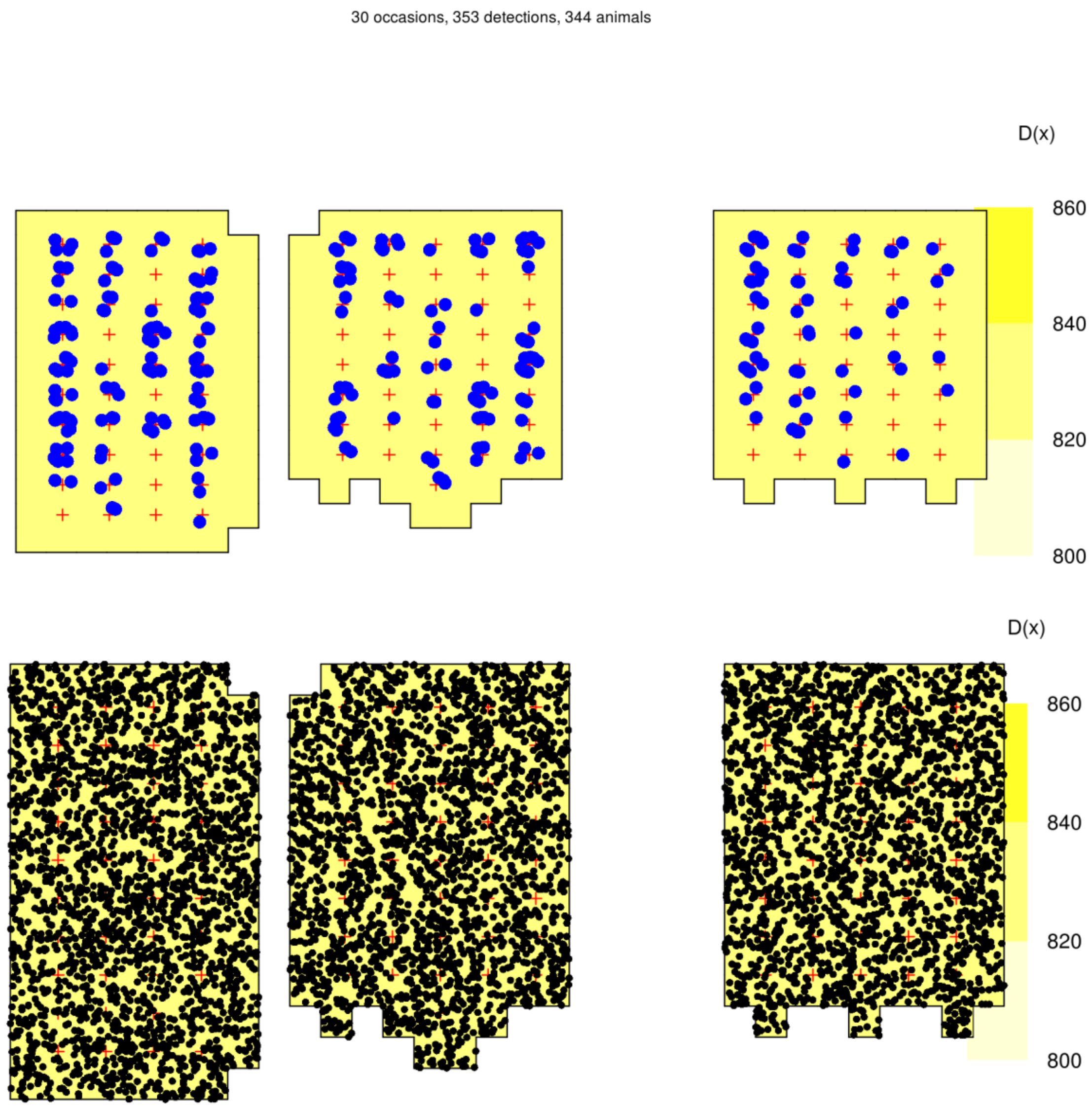

Figure 7: Individual density and abundance estimation on the three grids (from the right to the left) LT, SH, and UC. Capture and recapture events are symbolised as large blue dots, crosses are the pitfall trap, and small black dots are the random individuals estimated, on a random position. D (×) is the same on all our grids, equal to 820 individuals per hectare

5. Discussion

5.1. Artificial intelligences and IBEIS

5.1.1. I3S and other software considerations

Other software than IBEIS were considered for processing the data but were not selected, they are presented below. At the beginning of this master's thesis, it was planned to compare the efficiency of the two most promising software, IBEIS and I3S Pattern+, but technical and temporal constraints forced us to reshape the plan.

5.1.1.1. I3S Pattern+ and I3S Straighten

I3S seemed to be a prime candidate, and moreover it was a different method than IBEIS to analyse the picture: a pixel-based recognition program. After a discussion with the I3S development team and its extensions, we chose I3S Pattern+, as the Shore skink has quite complex patterns. The first test was not conclusive: The three reference points to be placed on the animal (*Figure 9*) include areas of the photo, which the software also analyses and thus distorts the whole analysis. We therefore used the I3S Straighten (Rosa et al. 2021) software. This software allows the body of the animal to be aligned along an axis, reducing the sections of the photo that do not contain our subject. This software has been tested on the belly of newts, presenting the same problems related to the deformation of the body by animals of this shape. The problem with this software is that some places, and therefore patterns, are more or less distorted in the original photo, and adding additional photo editing also generates errors. However, the study mentioned earlier shows a beneficial effect of I3S Straighten on the recognition rate of the software.

Figure 8: The three reference points, always (1) Right arm, (2) Left arm, and (3) tail top.

We tried, with 32 photos processed with I3S Straighten. The problem is the complexity of the dorsal patterns and the reflections, sometimes obscuring up to a quarter of the animal's back (*Figure 10*). Indeed, it is not possible to choose the colours used as foreground and background, as the light modifies the perceived colours to a great extent, and a brown dorsal pattern will be either background or foreground depending on its position and the brightness. It should be noted that these photos were taken with a conscious effort to standardise and work on the exposure, but not enough to compare with the results with I3S Pattern+. We did however try to separate the body of the animal into two parts, "upper back" and "lower back", but despite slightly better results, this was not conclusive and therefore required twice as much processing time, in addition to the problem of I3S "working directories". We spent about 70 hours on this AI option, for 30 individuals processed (out of 391) to try and fix the problems encountered, but without success.

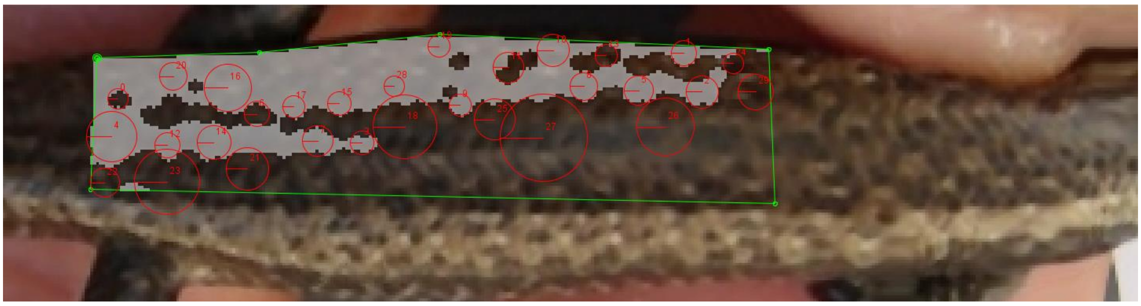

Figure 9: Example of an individual identification try with I3S Pattern+. Even by segmenting animal's body, the software manages to identify a part of the pattern, but clearly not enough to be a base for any study.

The combination of these light-related problems, the sometimes-bizarre correction of I3S Straighten, the wide colour palette that cannot be simply classified as foreground or background, the amount of manipulation time required, and the poor results meant that we did not retain I3S for this experiment.

5.1.1.2. Other software

Other software, such as those mentioned in the introduction, were to be considered during our choice. However, these programs were quickly discarded. First, Google Lens and other such software are simply not suitable for this kind of study and their program is not Open Access. We considered using Hotspotter as well as Wild-Me, but these programs are in fact relatives of IBEIS, IBEIS being more powerful and more accomplished. Wild-Me is also the algorithm on which Wildbook is built, an option, like Wild-ID, that is subject to a charge. In our view of sharing and accessibility of knowledge to as many people as possible, we wanted to keep the software free. Finally, APHIS, AmphIdent and Mydas are not very well-developed software at the moment, and IBEIS has already shown superior results, so we preferred not to include them.

5.1.2. General discussion on IBEIS results

5.1.2.1. IBEIS results

Compared to the tests conducted with I3S, IBEIS is clearly different: first, I3S works by pixel-based recognition, and IBEIS by neuron network. These differences at the very heart of the two software are a first step in explaining why their respective analyses were so different. On the other hand, IBEIS has such an efficient system that truly little training was needed, and from the beginning the algorithm understood that the background was not to be considered, as well as the observers' fingers, present on all the photos but in different but always similar configurations, which could have made IBEIS very confused about what to analyse. Another good point is the ability of IBEIS to consider the coloration, but to bypass the reflections on the body of the darkest individuals. Indeed, IBEIS could have totally mistaken these highlights for dorsal patterns, but this was not the case. There were a few instances where IBEIS occasionally confused skinks' legs and fingers with other body parts, but these did not weigh heavily in the balance of the final score. This is interesting because it allowed us to see the mistakes the software can make in its analysis (*Figure 11*). We can see that many back patterns are used for identification, and that some errors do not prevent the software from identifying recaptures.

Figure 10: Match of IBEIS, identified as Unknown. The fingers of the right leg have been used in the identification, even if the picture is not in a good quality enough to see anything. It is of course an error of IBEIS. Despite this error, the score was low, and allow the researchers to decide in a brief time if the proposed match is true or false.

The last point, which is very surprising and interesting when studying animals capable of autotomy, is that the software was able to identify a recapture of an individual, even though it had quite different tails (*Figure 12*). Indeed, individual G049, recapture 10, was captured for the first time shortly after losing its tail. When it was recaptured, about 3 months later, it had grown back, with a vastly different colour and no pattern. Between moulting, which severely limits all methods of marking reptile skin, and autotomy, which can result in the loss of a potentially useful area for individual identification, this kind of IBEIS capability is a powerful addition to research including CMR methods with artificial intelligence.

Figure 11: Individual G049, recapture N°10.

An interesting point is the false-false event, indeed, even if IBEIS was not able to indicate a recapture event, the scoring of each proposed match is an excellent tool for the observer to assist the artificial intelligence, its attention being drawn by an exceedingly high score despite an event automatically classified as negative. We have not been able to identify why IBEIS did not identify this match as a recapture, perhaps due to the slightly different brightness from one photo to another, but IBEIS has demonstrated several times that this parameter does not seem to bother it in its analyses. This also poses the problem of standardisation: despite the effort by the people who collected and manipulated the scintillations, many reflections and differences in colourimetry can be observed in the dataset. M. Baling, the main handler, used these data to study the importance of camouflage (and thus pattern as well as colour) in this species (Baling 2007; Baling et al. 2016), testifying to the great attention paid to this parameter when taking the photos. Critterpic® (Brorman 2022), as stated in our introduction, with a bait inside the tunnel, could allow back photos of Shore skink to be taken, without light faults, and without the need for handling, removing all the stress that handling can cause the individual. This would be another step towards a more respectful and less invasive animal ethic.

In any case, it is certain that, like Calmanovici (Calmanovici et al. 2018), the use of artificial intelligence software has saved a lot of time, even including the phase of getting used to the software. With a database of almost 400 images like ours, as well as the complex patterns of our skins, the identification of a single individual would be much more time consuming and error prone. According to our estimates, at one hour per individual, we would have needed about 48 days (based on 8 hours per day), whereas with IBEIS, including the software installation time, the results were created in 4 days.

5.1.2.2. Discussion on IBEIS results

We did not recapture many individuals according to IBEIS, despite a rather high population density, according to M. Baling. Only 10 individuals were recaptured, the events having been verified manually. We manually estimated the number of individuals on these 3 sites was 7153,1. However, the sparse number of recaptures clearly prevents us from using this estimate seriously, but rather to use it as an indication in future studies, for example.

The reasons for this sparse number of recaptures are unknown at present, but we can offer several explanations. One of the simplest explanations is that IBEIS is simply not efficient enough, and therefore has not been able to identify other recapture events. The skink population density could also be extremely high, making recaptures unlikely. This could also be explained by trap avoidance behaviour, being human structures, the animals might be more inclined to dodge these points specifically. Another behavioural change, as mentioned in the introduction to this master's thesis, is that individuals may have been traumatised by capture and handling, making them trap-shy; still present at the site but avoiding the traps. The low recapture rate could also be explained by the high mobility of the animal, which is said to be a long-distance animal. This point could be studied, it could be a behaviour of search of food or partner... Given that we know truly little about the behaviour of these animals. The animals could also be subject to a high mortality rate, either naturally or due to the stress of handling. Such high mortality would imply that the species would need a high rate of reproductive success to maintain its numbers. Recaptured individuals identified by IBEIS were usually recaptured within the week of the first capture and have never been recaptured after 4 months of interval. For a species living between 10 and 15 years, this result is quite concerning, and this master's thesis can only make hypothesis on the reasons of their absence.

To conclude, the use of artificial intelligence, even if it has not been developed for the species we want to identify, seems to work. The time saving is huge, and can allow for a larger collection of photos, allowing for more data to be collected for a much-reduced analysis time. With larger datasets, the accuracy of the analyses will be better, and will advance our knowledge of species that we still have little knowledge of.

5.2. Discussion SECR 1.4

Our understanding of the Shore skink (*Oligosoma smithi*) remains poor with this study, recapture events not being high enough to use data for more precise population abundance and estimation. On the other hand, only one study has been found during our scientific literature review on population estimation or movement on this species, and does not really focus on movement but more into behavioural measurement of diving or sprint speed (Hoskins et al. 2017). Few studies on the same genus have been conducted, such as population response to agricultural or weather changes on the Grand skink *Oligosoma grande* and Otago skink *O. otagense* (Whitaker n.d.; Coddington & Cree 1997), population survey on *O. tamakae* (Lettink. et al. 2010), population densities of the Cryptic skink *O. inconspicuum,* McCann's skink *O. maccanni,* and a rare subspecies, the Southern grass skink *O. aff. Clade 5 polychroma* under different predator management regimes(Wilson et al. 2017), or long-term CMR survey on the Small-scaled skink *O. microlepsis* (Konstanze Gebauer 2012). These studies are helpful to better understand our species but does not replace studies on the target species. Indeed, even if the genus is the same, each species has a different ecology.

Total abundance calculated for all our 3 grids (N=6864) differs from the addition of the calculated abundance of the 3 grids separately (LT=2310; ST=3450; UC= 1888; total=7648). It might be explained because on the 9 recapture events used for analyses, 4 events were in LT, and 2 were within the ST and UC grids. Analyses were biased, half of the recaptures happened in LT but with a high capture event number (LTc=162), inducing lower density, ST having sparse number of recapture and medium capture event number (STc=136), and UC having a sparse number of recapture and low capture event number (UCc=97). On the other hand, these separated analyses showed the higher population abundance in ST grids, which is surprising, ST and UC grid being outside of the predator-free area. We expected a higher population within the area predator-free. Analyses on the 3 grids at the same did not showed any differences of population abundance and densities within the total area, so we cannot confirm that there is a difference of population between these 3 grids. We also could see those individuals within the predator proof area (LT) where more likely to move in higher distance from their first capture trap, but this result is not scientifically proved, as our recapture database being too small to conduct any statistical analyses.

Our low recapture rate with IBEIS has many hypothetical reasons, and SECR estimated a high population density, which matches with one of the hypothetical reasons we advanced, and M. Baling field experience. Another explanation would be that the Shore skink is a specie that moves a lot, involving animal going outside of study site. This explanation is unlikely to be true: Even if the specie is not the same, J. Germano (Germano 2007) estimated a maximum of 50 meters moved per day by the Otago skink, *Oligosoma otagense*, but with a mean of 12 meters a day. Moreover, many of our recaptured skink do not move from their previous capture place, and the few one recaptured somewhere else did not move that far (103 meter maximum), within 3 months between captures.

SECR is a great tool to conducted quick analyses and population estimate. Despite our very low number of recapture event discovered by IBEIS software (=10), we managed to obtain a population estimation on our study site, and its density, even with a high relative standard error. With these small results, we did not try to estimate population home range, it would have been useless waste of time for totally unusable results.

6. Conclusions

Scientific literature on the Shore skink remains quite sparse, and inexistant when it comes to movement or abundance. This master's thesis showed that with easy access existing tools, such as IBEIS and SECR App 1.4, data processing on animal survey might take less time and being more accurate. Indeed, IBEIS showed its ability to correctly identify most of the recapture events, and as much software developed for individual or species identification and recognition, is a promising tool for researchers. To increase the knowledge on the Shore skink, such as more precise movement, population abundance and density, it would be interesting to conduced new surveys, including the availability of easy data processing with IBEIS. An idea would be to conduced surveys as J. Germano did on the Otago skink (Germano 2007) with telemetry, to ensure a high catch rate. Maximum and average dispersion for the specie would be an extremely interesting data, with implications for research and conservation plans.

It would be interesting to conduce survey over time with standardised camera traps, such as Critterpic® for instance. Standardised dorsal pictures, frequently collected by research over years would help to know individual dispersion, partially removing the effect of a high population with IBEIS quick identification of individuals, an even distinct species.

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Annexe 1: Pictures of the recaptured individuals (8 pages)

Recapture event number	Identification code	Picture and name of the individual on its first catch Picture and name of the individual on its recapture
1	B001	061113tawhsD06m 
1	B001	061115tawhsD05m 

Recapture event number	Identification code	Picture and name of the individual on its first catch Picture and name of the individual on its recapture
2	B025	061115tawhsD06f 
2	B025	070224tawhsD03m 
3	D012	070224tawhsD11m 
3	D012	070228tawhsD04m 

Recapture event number	Identification code	Picture and name of the individual on its first catch Picture and name of the individual on its recapture
4	D005	070224tawhsD15m 
4	D005	070227tawhsD08m 

Recapture event number	Identification code	Picture and name of the individual on its first catch Picture and name of the individual on its recapture
5	D084	070227tawhsD17f 
5	D084	070228tawhsD12f 

Recapture event number	Identification code	Picture and name of the individual on its first catch Picture and name of the individual on its recapture
6	G025	071118tawhsD03f 
6	G025	080210tawhsD04f 

Recapture event number	Identification code	Picture and name of the individual on its first catch Picture and name of the individual on its recapture
7	G022	071118tawhsD08f 
7	G022	080209tawhsD03f 

Recapture event number	Identification code	Picture and name of the individual on its first catch Picture and name of the individual on its recapture
8	G037	071119tawhsD10f 
8	G037	071120tawhsD09f 
9	G031	071119tawhsD15f 
9	G031	071120tawhsD06f 

Recapture event number	Identification code	Picture and name of the individual on its first catch Picture and name of the individual on its recapture
10	G049	071119tawhsD29f 
10	G049	080210tawhsD03f