AMSI VACATION RESEARCH SCHOLARSHIPS 2020–21

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Optimal Control of Translocation Strategies for Threatened Australian Mammals

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1 Abstract

Australian mammal populations are under significant threat from introduced predators such as feral cats and foxes (Radford et al). As a result, there have been great efforts to eradicate these species from fenced areas and islands across Australia and create 'havens' for threatened species (Legge et al.). In order to populate these havens with native species, individuals are translocated from established populations. Translocation strategies are dependent on population abundance in the source locations, which is governed by fluctuating rainfall, and accompanying vegetation growth. This project uses stochastic dynamic programming to provide a strategy for outlining the proportion of individuals for translocation that ensures the source population persists and success of expansion into other havens is likely. Using data from the Department of Biodiversity, Conservation and Attractions a model was produced to determine the relationship between rainfall, species abundance and species growth. From this, a transition matrix was built to house the probabilities associated with transitioning between states. A state is the composition of rainfall and abundance. The resulting optimal translocation strategies are highly dependent on abundance and further research is necessary to draw meaningful recommendations to ecologists.

2 Statement of Authorship

Michael Bode developed the concept of using stochastic dynamic programming. Montana Wickens analysed the data from the Department of Biodiversity, Conservation and Attractions. Bode wrote most of the psuedocode and Wickens developed it further. Wickens interpreted results. This report was written by Wickens.

3 Introduction

On two small islands off the coast of Western Australia, there live approximately 3200 burrowing bettongs (often referred to as boodies) (Sims). These boodies burrow in open spinifex and dune habitats, feasting on seeds, fruits, leaves, flowers and termites (Bamford). Since colonisation the boodie population has been in decline; their habitats were re-purposed for agriculture, their reputation was diminished to garden pests and they were introduced to foreign predators such as foxes and cats. By the 1960s, the populations on the mainland were extinct (Bamford). These macropods forage through the shrubs, mixing organic matter to encourage richness of the soil and burying combustible materials to decrease likelihood of fires (NSW Government). Alongside the decline of fire regimes performed by Indigenous Australians, the local extinction of many small Australian mammals has contributed to widespread soil deterioration. Luckily, some small populations of boodies have survived such as those on Bernier and Dorre islands. Goats were eradicated from Bernier island in 1984 these islands have since become a refuge for boodies as well as the Shark Bay bandicoot, banded hare-wallaby and rufous hare-wallaby (Veitch) (Shark Bay).

To further promote the boodie population, some of the boodies are translocated to other safe havens around the country. A safe haven may be a nature reserve, a wildlife zoo or another fenced or offshore area free from goats and cats. Requests for these translocations are frequent and not all can be completed for fear of harming the existing population. It is well-known that boodie populations fluctuate with rainfall. Rainfall brings a lush habitat and more food. If the population were more predictable, these translocations may be increased to periods of high rainfall when the population is sure to boom (AWC).

Stochastic dynamic programming will be implemented to create a decision matrix, enabling ecologists to observe the state of the population (past 12 months of rainfall and current population abundance) and allow for a certain proportion of animals to be translocated that year. The program will use Bellman's equation to optimise the "value" of decisions and account for the subsequent decision problem based on the initial decision. The value associated with a decision is some variant of the following equation:

$$V(\text{Population}) = C(\text{Harvest}) + V(\text{Population} : \text{Harvest})$$

where harvest is the term used to refer to animals that will be removed from the population via translocation programs.

4 Population Model

The aim of this project has always been to use stochastic dynamic programming to analyse the dynamics of the boodie populations and suggest a harvest limit, i.e. 'If there are less than 1000 animals on the island, no harvesting can occur this year'.

Thanks to population monitoring conducted over the past 10 years we have been able to retrieve estimates of the boodie populations on the islands with error bars. We have also retrieved the rainfall data from Carnarvon weather station (approx. 100km east of the islands) dating back to the 1940s.

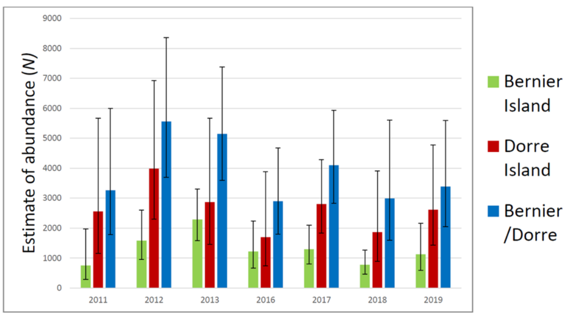

Figure 1: Abundance estimates for boodies Bernier (green) and Dorre (blue) Islands.

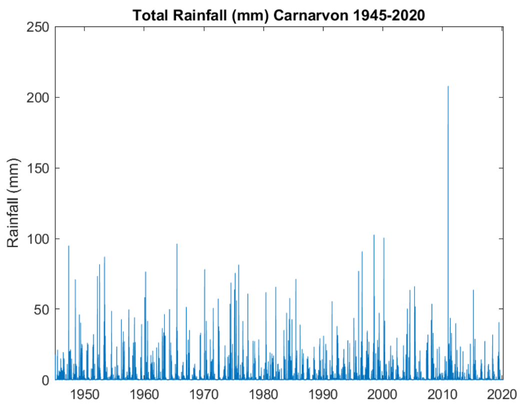

Figure 2: Rainfall data recorded at Carnarvon Airport between January 1945 and April 2020.

We hoped that with this information we could build a transition matrix which tells us the likelihood of moving between states each year. So, if there were 2000 animals on the island and 350mm of rainfall in the past year we could create a probability distribution function for the number of animals in the following year.

The first problem was that we only had population data for 7 years, but this problem could not be resolved. So we assumed normal distributions around each data point with the standard deviation as shown in the report and sampled from the distribution to simulate probable data points. This same technique also gave us the probable recruitment each year (by sampling from the next year's distribution).

Then, using the rainfall data, we wished to fit a curve to the data. The model chosen for the data is:

$$z = a + be^{-cx} + dy^2 \tag{1}$$

where z is the recruitment, x is the current stock and y is the rainfall. One paper suggested boodie populations are most correlated with the rainfall over the previous two years. But we weren't sure if this was also true for our fit - could we get a better fit using only the previous 12 months rainfall or (with the side effect of an additional parameter) should we treat this year's and last year's rainfall separately?

So for each option,

i) the past two year's rainfall with distinct parameters ,

ii) the past two year's rainfall with the same parameter,

iii) only the rainfall from the current year, and

iv) only the rainfall from last year,

we used the data as described above and found the best fit. Then we used the best fit to predict new data and calculated the correlations between the two.

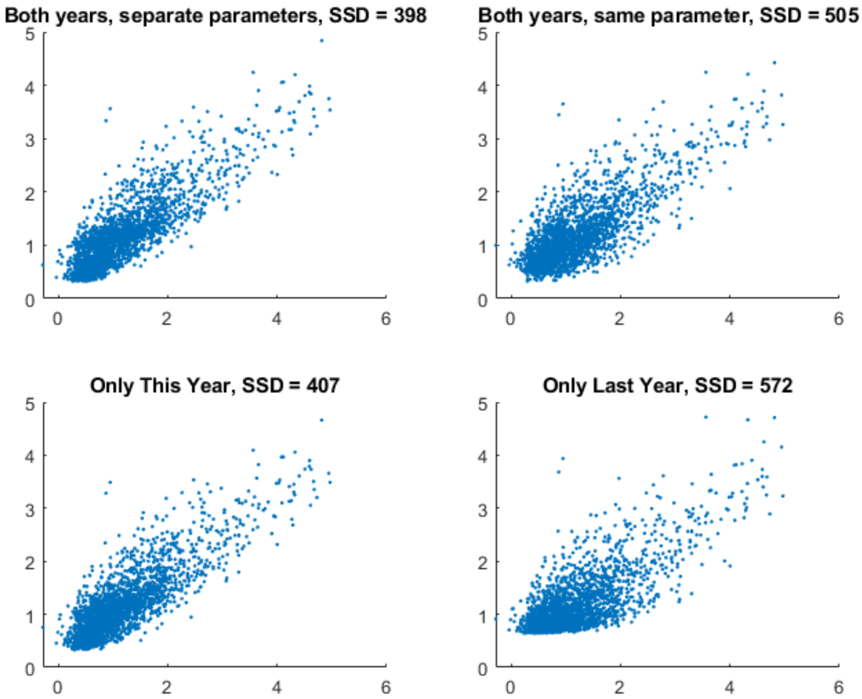

Figure 3: SSD values using rainfall data in different ways

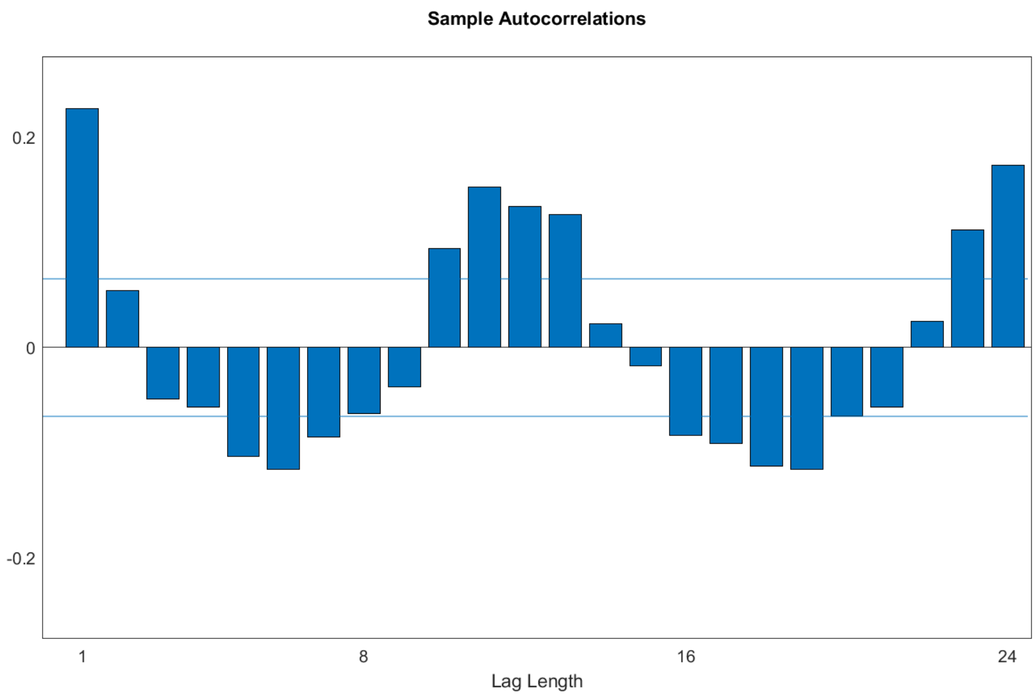

Figure 4: Aside from seasonal (twelve month and 6 month) correlations we see no significant correlations between years.

The best SSD values arise from using both years with separate parameters and using only the current year's rainfall. For the sake of parsimony we have chosen to use only the current year's rainfall data. So now we have the data we will use to fit the curve to. Using Matlab's curve fitting toolbox, the best values for a, b, c and d and their respective 95% confidence intervals were found. The resulting curve looks something like the one below.

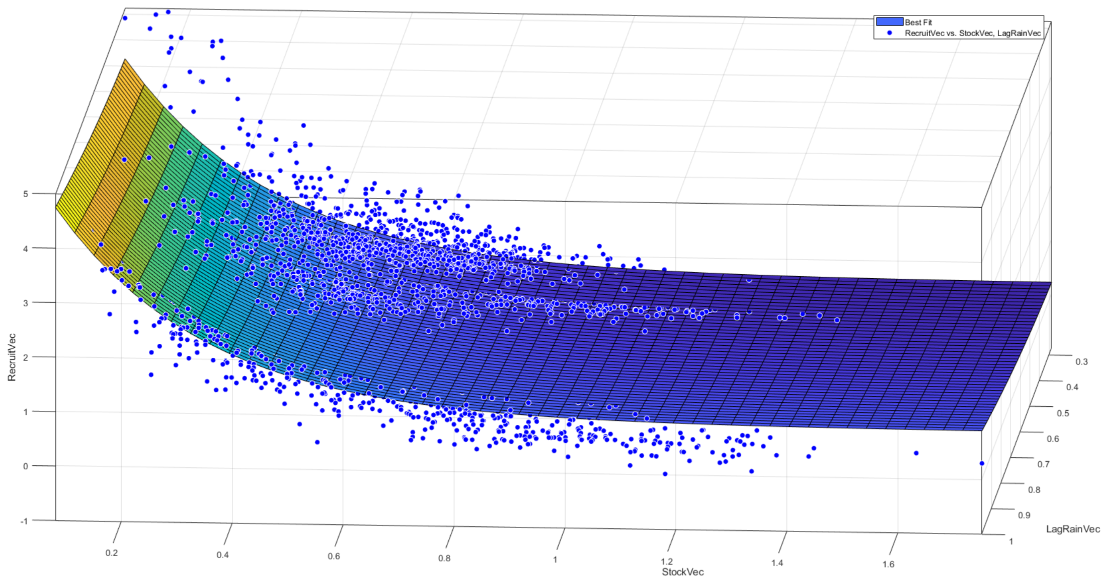

Figure 5: $a = 0.1533$, $b = 5.192$, $c = 3.67$, $d = 0.741$.

Sometimes our best fit curve has a negative value for 'a', meaning that in the case that our distribution sampling retrieves a large stock value and small rainfall value it it often the case that the proportional recruitment is negative. For now, we can just ignore these values but fixing this problem would require us to change the model. This could be explored further in future research.

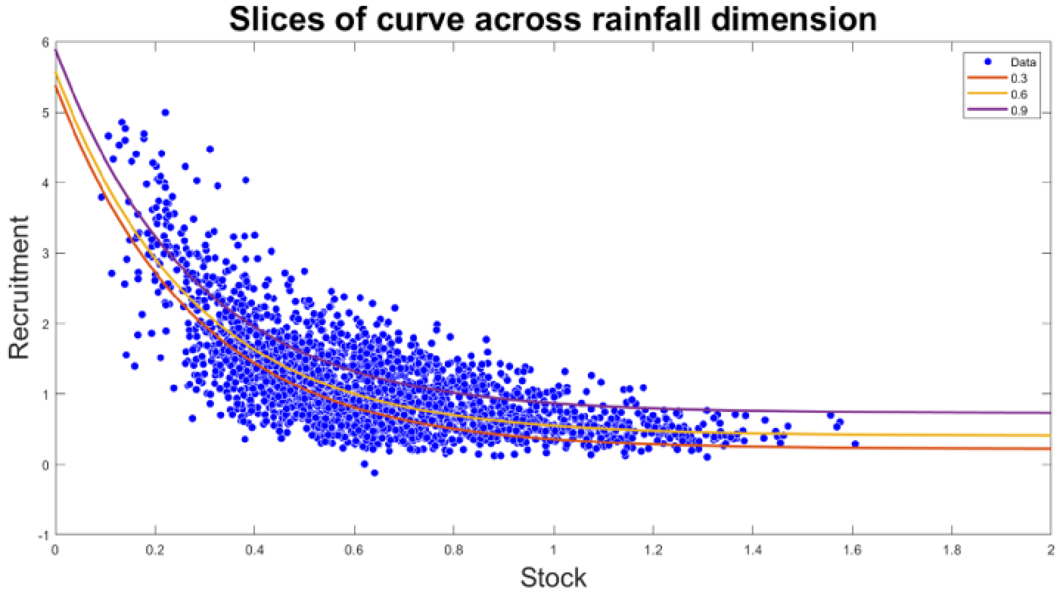

Figure 6: Slices of the best fit curve when rainfall is 30%, 60% and 90% of maximum observed.

5 Transition Matrix

Now, using the best fit we can predict the proportional recruitment given a particular rainfall and current stock level. So we iteratively draw our 'best fit curve' from the distribution of parameters (assume normal again) and keep track of how often a certain state (defined by stock and rainfall) is reached from any other given state. Then convert this spread of transitions into probabilities and we have the transition matrix.

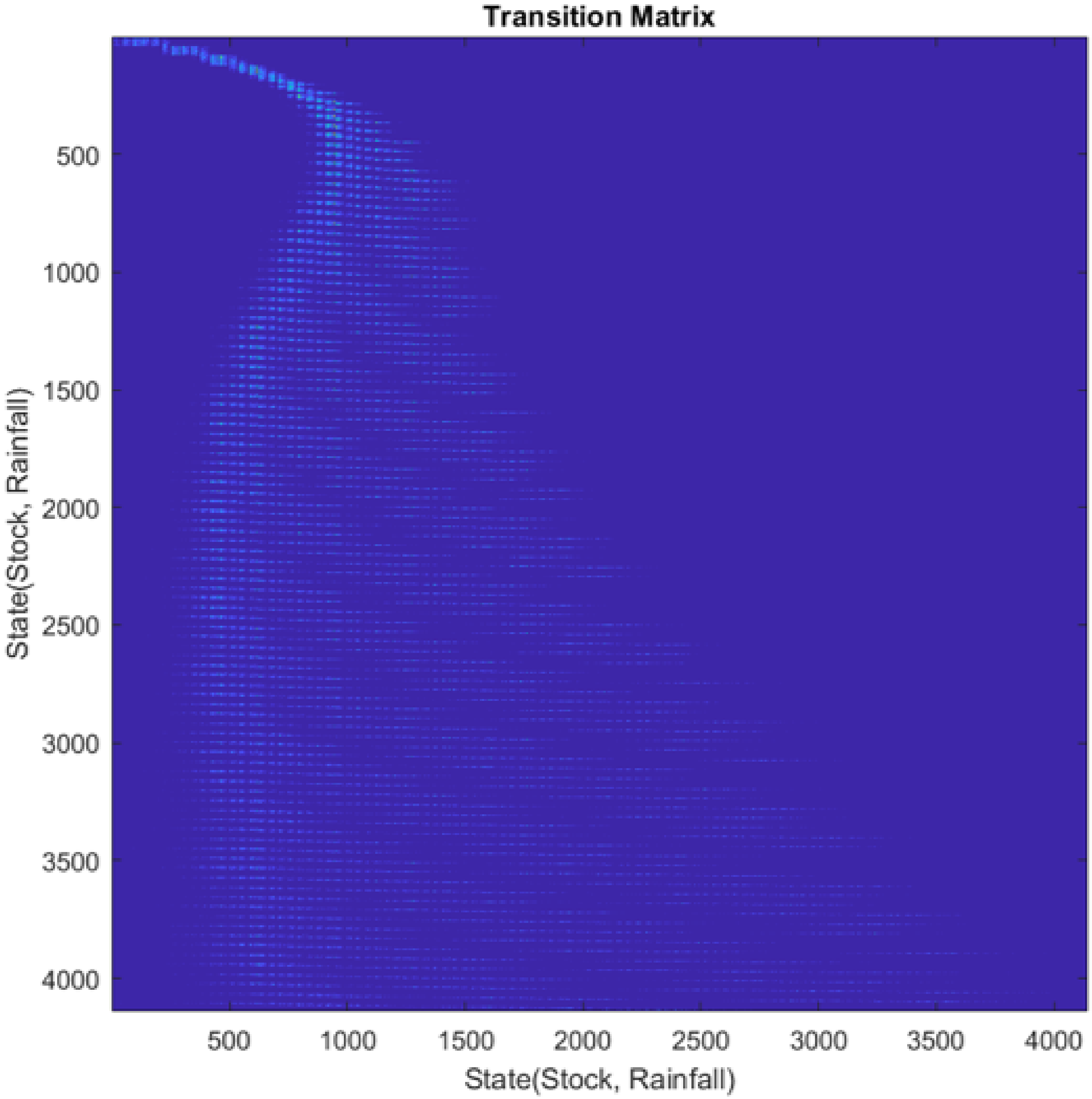

Figure 7: Transition matrix for likelihood of moving between states. Lighter colours mean the current state (vertical axis) is more likely to transition to that future state (horizontal axis).

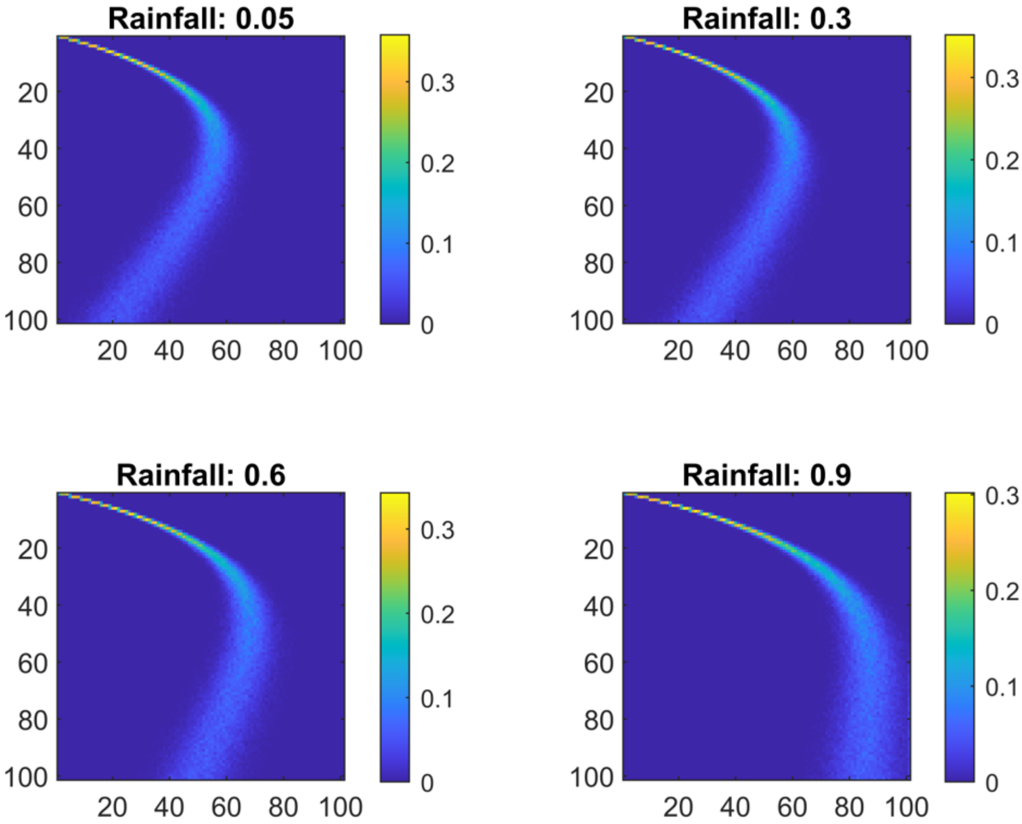

Figure 8: Transition matrices extracted from Figure 7 according to rainfall.

The above images are interpreted as the current state along the vertical x axis and the next state along the horizontal axis. My interpretation of this is that for low abundances the rainfall does not have a significant effect on the growth. But for abundances of 0.5 and higher, more rainfall seems to increase the likelihood that the population will remain high. Low rainfall maps both high and low abundances to low abundances.

Now we wish to verify these calculations by simulating some populations. We can compare the trajectory made by the transition matrix with the trajectory made with the best fit curve and look at the histogram of relative abundance on the right. From figure 9 we see that the histograms match quite well. We also included a trajectory to show what 70% harvest looks like using the transition matrices with an action.

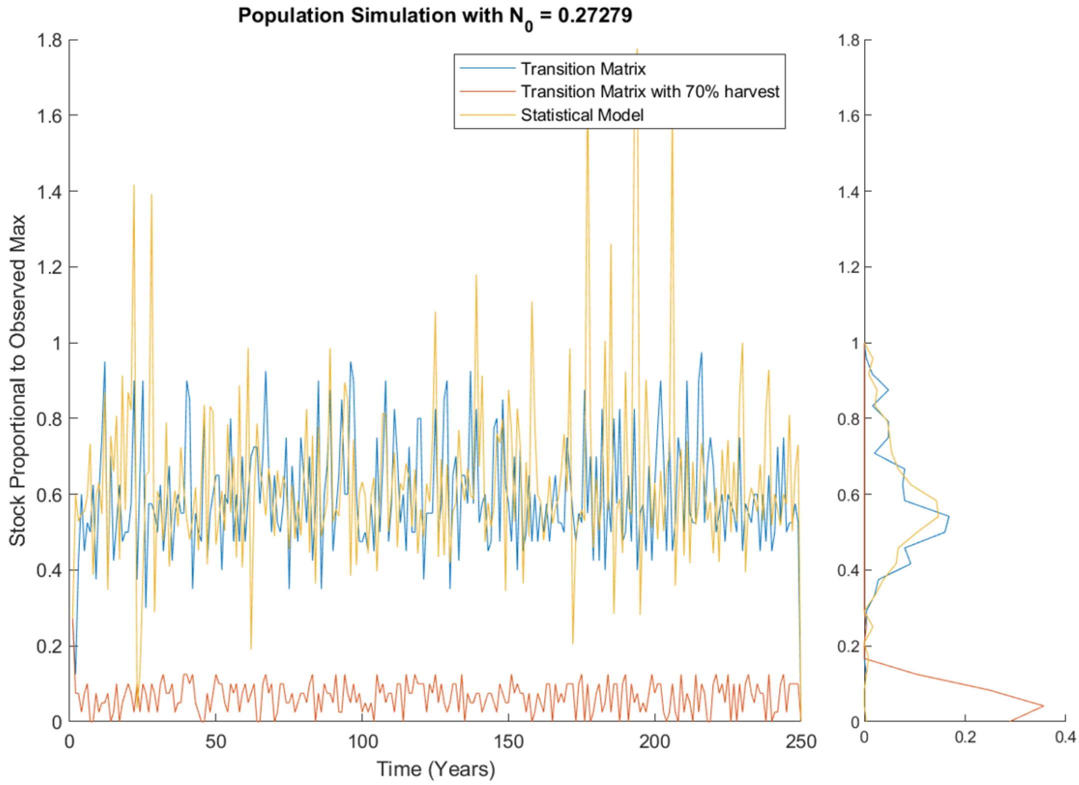

Figure 9: Population simulation over 250 years using both the transition matrix and statistical model (which draw from the curve of best fit). Similar histograms on the right hand side verify our method.

6 Stochastic Dynamic Programming

Now we have all our transition matrices we can run the stochastic dynamic program using a backwards iteration of Bellman's equation:

$$V(Time, State) = \underset{Actions}{max}\,\{Short\ Term\ Contribution + Value\ of\ Next\ State\}.$$

We assign a value to harvesting individuals of the population, a value to the remaining population and a discount rate to specify how much we care about the future. For each action, we require a new transition matrix. One that uses the probabilities in Figure 7 and then applies an action of harvest. The figure below shows what the new transition matrices look like.

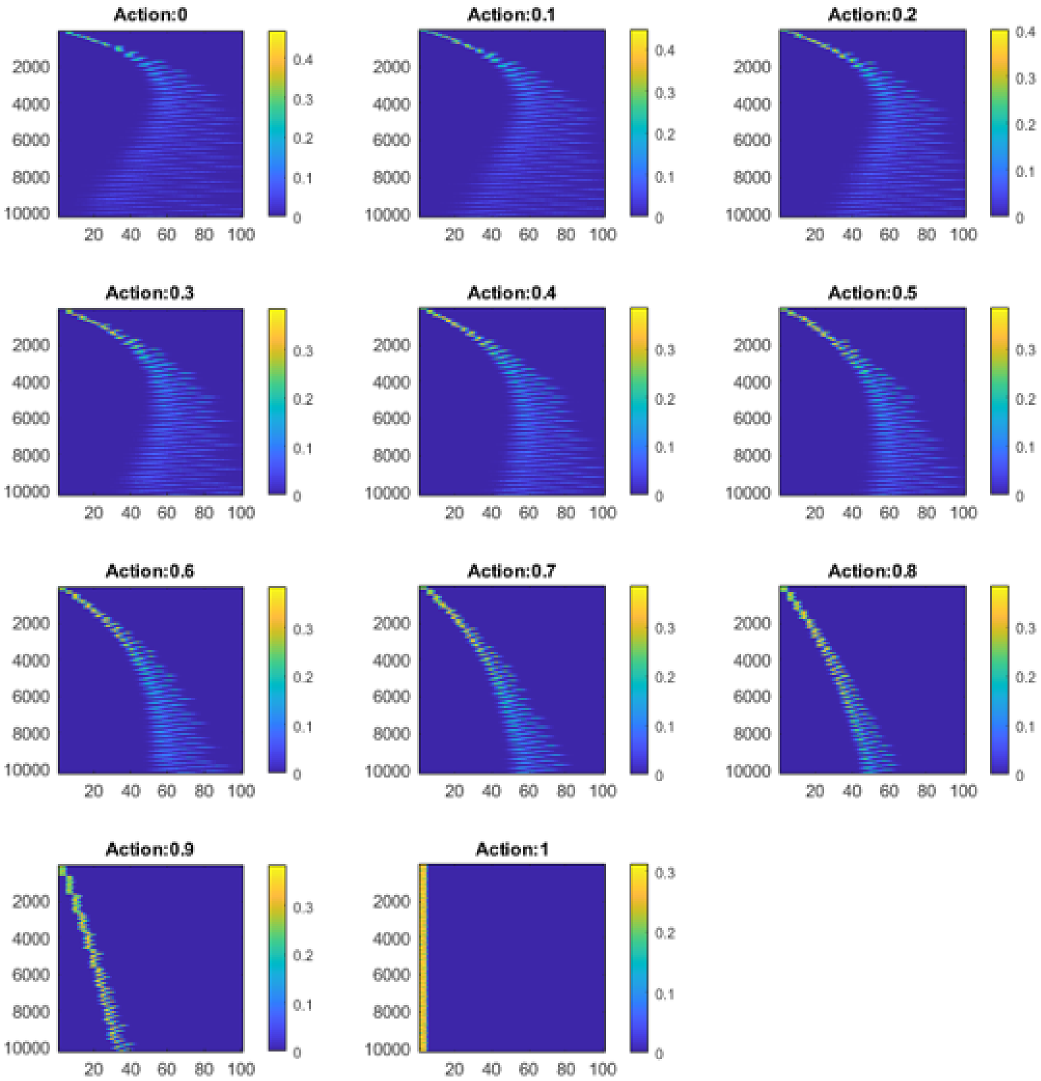

Figure 10: Transition matrices after action of 'harvest' at different proportions.

So we see that when no action is taken, i.e. all the boodies are left on the island, we maintain the original transition matrix. Also note that we are no longer mapping to a state describing rainfall and abundance but instead only abundance. When we set the action to 0.5 this simulates removing 50% of the boodies. When we set the action to 1, we are removing all the boodies off the islands, hence a strong probability of extremely low abundance.

7 Discussion

The stochastic dynamic programming was implemented with a best guess as to how to value 'harvesting' the boodies. We started with a discount rate of 0.2, harvest value of 0.1, and population value of 2. So we value 1 harvested boodie as much as 20 on the island and we care about boodies this year 5 times as much as boodies next year. Figure 11 shows the corresponding solution.

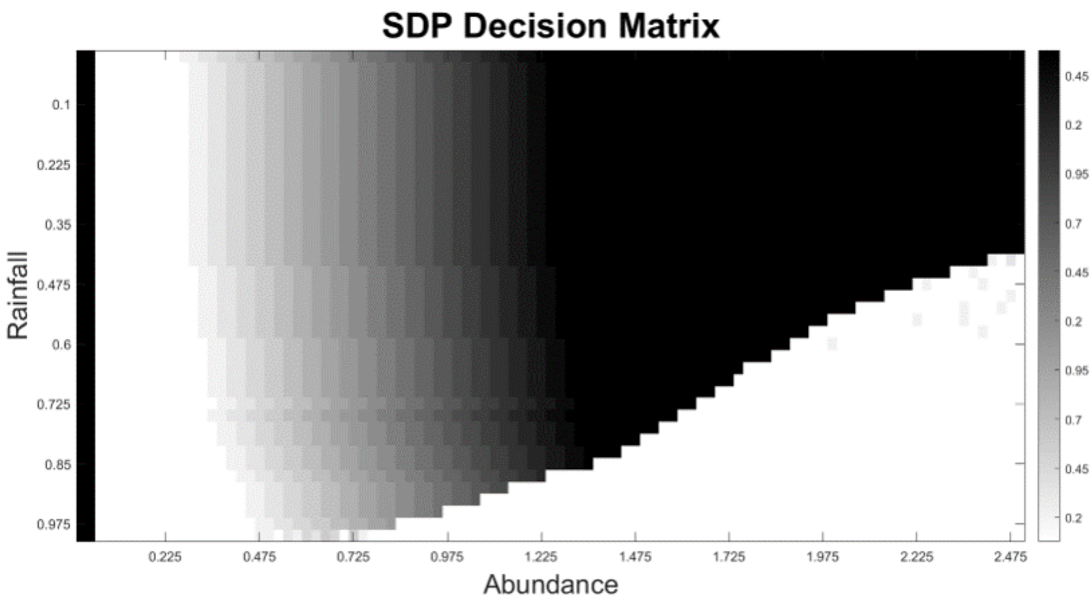

Figure 11: Solution to stochastic dynamic program when we value 1 harvested boodie as much as 20 on the island and we care about boodies this year 5 times as much as boodies next year.

This solution can be read like a manual as to how to control the population so to optimise abundance on the island and the quantity of harvests. We see that an abundance of 72.5% and rainfall of 50 % corresponds to the action of 0.3 (or 30%) harvest.

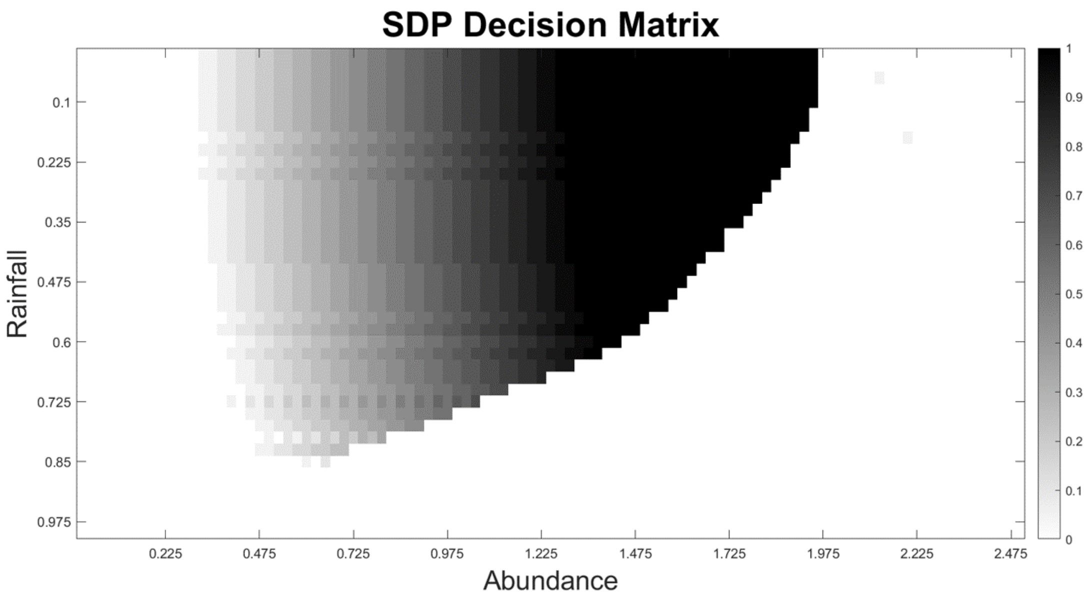

Figure 12: Solution to stochastic dynamic program when no value is attributed to harvesting and we care about boodies this year 5 times as much as boodies next year. The optimal action for most states is no action.

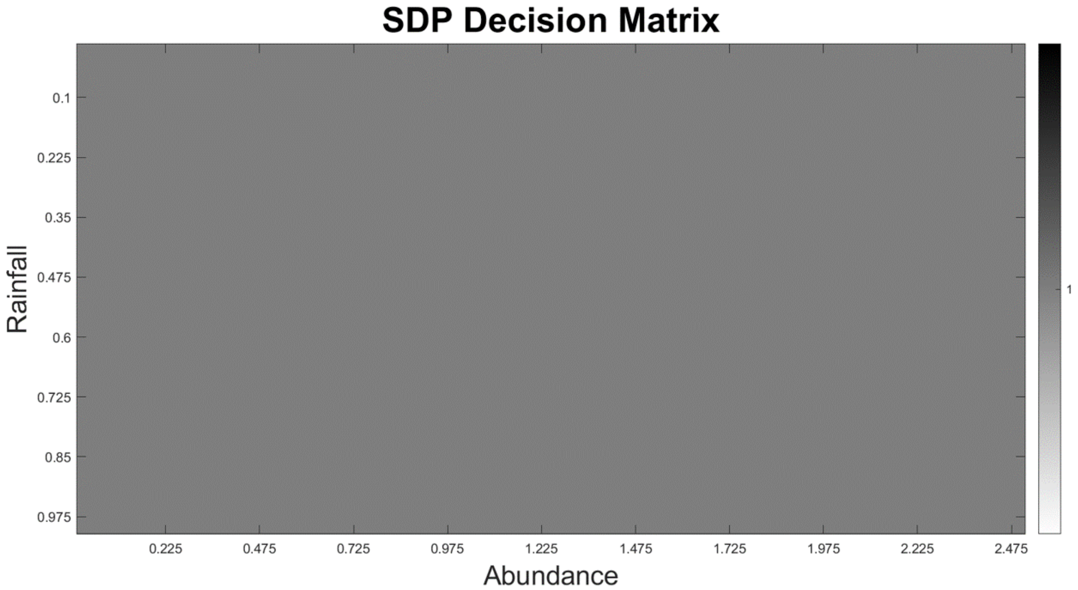

Figure 13: Solution to stochastic dynamic program with no discounting i.e. we only care about this year. The optimal action is always 100% harvest.

8 Conclusion

There are so many adaptations to this research I would love to keep exploring. Foremost, we need more data. Simulating data from the confidence intervals can only tell us so much. I think it is a stretch to infer too much from this simulated data. I also want to improve the statistical best fit, perhaps the mixture of polynomial and exponential isn't appropriate, perhaps the method of fitting could also be improved. The transition matrix is very impressive and it does make a lot of sense, i just wish we had some more data to verify it with. The dynamic programming worked a charm but it is imperative to discuss the harvest and discounting parameters with ecologists before making any recommendations to the translocation teams.

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