COMP90083 Computational Modelling and Simulation, 2024
Project 2 Report

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1 Introduction

Common Pool Resources (CPR) are resources that are difficult to restrict access to, and their use by one individual reduces the availability to others, either temporarily or permanently [1]. CPR include many essential resources such as fresh water, forests, and atmosphere. Although many CPR are renewable, they can be depleted if used unsustainably [2]. The unsustainable extraction is intensified by the tragedy of the commons (ToC) [3], where multiple rational and self-interested individuals accessing the same resource tend to extract as much as possible as quickly as they can, competing for the limited resource. However, individuals would often achieve better long-term returns if they cooperated and adopted a more sustainable approach to resource use.

Several studies have investigated CPR management, focusing on the emergence of the ToC [3] and factors that influence it [2, 4, 5]. Early research relied on experiments with human participants playing specially designed games [4], while recent work uses agent-based models (ABM) to simulate these games with computer-generated agents [2, 5]. Many studies emphasise modelling the ToC phenomenon and how different game setups affect sustainability and net profit, such as allowing agents to share information [2] or enabling communication to foster cooperation [5]. However, fewer studies focus on developing policies to enhance sustainability, despite earlier findings that external enforcement and peer punishment can foster cooperation [4]. This research aims to address this gap by designing an ABM to further examine the ToC and propose sustainable management strategies. Specifically, we focus on over-fishing, using the Whitetip Shark as our calibration example, which is a specie classified as threatened under the U.S. Endangered Species Act.

ABM has been widely applied to fisheries management, especially for small scale fisheries [6, 7]. Studies have examined the emergence of self governance under varying levels of cooperation and trust among fishers [6], as well as through collaboration and negative interference [8]. In the absence of policy intervention, self governance has been shown to promote more sustainable usage of the resources. Information sharing and collaborative organised harvesting have also been found to effectively improve fishers' yield and sustainable use of local resources [9]. Additionally, when incorporating dynamic short-term economic profitability in fishers' decision making, such as whether to fish and the target fish size, [7] shows that balanced harvesting naturally emerges. This results in catches that closely match the distribution of productivity across fish sizes, but overall fishing pressure must still be managed to prevent over-fishing. While most research has focused on emergence and equilibrium of agent behaviour, few studies have compared and evaluated the required conditions and effectiveness of regulations and policies related to over-fishing. This gap in research is what we aim to address.

The research question guiding this investigation is: **What strategies can facilitate more sustainable consumption of Whitetip Sharks as common-pool resources?** In this study, we implement and investigate four strategies aimed at the conservation and management of the Whitetip Shark. The parameters of our model are designed to be easily adjustable, allowing for application to the management of other species and common-pool resource scenarios.

2 Model Design

The environment is assumed to be constant, so the model has no **input data**.

2.1 Purpose

The model is designed to explore various management strategies aimed at preventing overfishing, with Whitetip Sharks serving as a calibration example. Specifically, the model investigates the optimal conditions and levels of enforcement that would enable the strategies to best support the sustainable harvest of Whitetip Shark as a common pool resource. In summary, four strategies will be evaluated along with null theory, with their main differences depicted in Figure 1 and motivations in section 3.1:

1. null theory (NULL): no conservation strategy implemented.

2. Local harvesting (LH): enforcing fishers to travel within the row they were initially located in.
3. Communication to maintain minimum shark population (COMM): cooperative fishers communicate and aim to maintain a minimum shark population.
4. Minimum length limit (LEN): prohibiting harvesting sharks below a certain length threshold.
5. Consumption constraint (NUM): limiting the amount of monthly shark harvest per fisher.

2.2 Entities, state variables, and scales

The model has three kinds of entities: fishers, sharks, and global observer.

Fishers are characterized by their location (x and y coordinates indicating the patch they are on), returns (the total number of sharks harvested, the number of sharks harvested in the current time step), and sustainability-related metrics (the number of time steps with sharks harvested, and the average value of the time steps with sharks harvested). For strategy implementation, fishers also store their initial y-coordinate when simulation begins, as well as whether they are cooperative.

Sharks are characterized by their location (x and y coordinates indicating the patch they are on), gender, age in months, number of offsprings produced at one time, age to become mature, and the number of time steps since the last time they produced offsprings.

Global observer tracks different aspects of the simulation for auditing purposes, namely the current year and month, the initial shark population, and months of reproduction.

There are also several **model parameters**: shark life expectancy in months, maximum shark capacity per patch, three von Bertalanffy growth function parameters to estimate sharks' length from age, length offset for female sharks, chance of shark being captured by each agent on the same patch, number of fishers, and initial population of sharks per patch. Moreover, model parameters related to strategy implementation include: *max-monthly-harvest*, *force-local-harvesting*, *min-harvest-len*, *detection-comm*, *coop-not-share-sharks*, and *cooperate-ratio*.

Simulations end when either all sharks are exhausted, or a maximum of 600 time steps (each representing a month so equivalent to 50 years) is reached. The grid landscape has 3×7 patches, each representing a broad region where Whitetip Sharks are available and may correspond to large areas such as $10 \times 10 km^2$. The harvesters are capable of travelling to any region in one time step.

2.3 Process overview and scheduling

The processes in the model are scheduled as follows at each time step: (1) update-year-and-age (2) fisher-move (3) fisher-harvest (4) reproduce (5) update-graphs. Process details are in section 2.6.

2.4 Design concepts

The **basic principles** of the model focus on conservation and management strategies aimed at preventing overfishing, and the over-exploitation of resources in general. Shark harvesting by fishers is modeled as an **adaptive behavior**, which includes compliance with management policies and collaboration with other agents sharing the same patch. These behaviors are implicitly assumed to facilitate the agents' **objectives** of maximizing sustainability and optimizing long-term returns from harvesting sharks. The trend in the shark population **emerges** from the model, whether it continues to increase, decrease, or converge. **Sensing** and **interaction** between sharks and fishers are summarized in Table 1. **Stochasticity** plays a role in generating diversity among agents and in the processes within the model. For sharks, this includes mating times, biological characteristics (such as gender, age of maturity, and the number of offspring per reproduction), and the population initialization (age, and time since last reproduction). For fishers, it includes their initial position, decisions on new patches to move to (in some strategies), and their cooperativeness. The capture of sharks also occurs stochastically. System behaviors are **observed** by tracking fishers' returns and shark population dynamics at each time step throughout the simulation. There is no **learning**, **prediction**, and **collectives**.

2.5 Initialization

Some **model parameters** are **adjustable**: strategy related (*max-monthly-harvest*, *force-local-harvesting*, *min-harvest-len*, *detection-comm*, and *cooperate-ratio*), *initial-shark-per-patch*, *chance-captured*.

Some **model parameters** are **fixed**: number of fishers is 20, shark life expectancy in months is 192 (16 years), maximum shark capacity per patch is 300, we use Von Bertalanffy growth function

Table 1: Sensing and interaction between agents.

Agent	Fisher	Shark
Fisher	In COMM, fishers can **sense** others on the same patch to determine their harvest limit through implicit communication. Fishers do not directly **interact**, but implicit competition arises as harvested sharks are no longer available to others.	Fishers can **sense** shark availability or population (only for COMM) on a patch, but cannot sense the individual sharks. They only **interact** with and harvest the sharks on the same patch as them that are stochastically captured by them.
Shark	Sharks do not **sense** fishers. They **interact** with fishers on the same patch when they are stochastically captured by them.	Female sharks can **sense** presence of mature males on same patch for reproduction, and they **interact** with (reproduce) pups.

parameters from [10] such that the shark length is evaluated as $325.4 \times (1 - e^{-0.075 \times (age+3.342)})$, female sharks are generally larger than male sharks [11] and a length offset by +10 is used.

Fisher state variables are initialized as follows: randomly allocated to a patch with initial y-coordinate stored; return and sustainability variables are 0; under COMM (*detection-comm* is true), *cooperative?* is stochastically assigned based on *cooperate-ratio*, otherwise *cooperative?* is false.

Shark state variables are initialized as follows: *is-female?* is randomly assigned; *initial-shark-per-patch* of sharks are created on each patch, which initializes their location; their age randomly initialized between 1 to 16 years old; sharks give birth on alternate years with an average of 6 litters [12], thus offspring-rate is randomly initialized between 2 and 10; *mature-age-in-months* randomly initialized between 6 to 9 years old [13]; *last-time-reproduce* randomly initialized between -6 to -30.

2.6 Submodels

2.6.1 update-year-and-age

Time is tracked by incrementing the month parameter each time step, and if it reaches 13, reset it to 1 and increment the year parameter. Additionally, shark age is tracked by incrementing their *age-in-months*, and checking for life expectancy to determine removal. The submodel is also responsible for shark color and size change in response to gender and age: immature sharks are grey and size 0.05, while mature (reproductive) sharks have size 0.1 and coloured pink for females and blue for males.

2.6.2 fisher-move

Fishers move to a new patch if they successfully found one. A submodel ***find-next-patch*** is responsible for finding a target patch, where the identification of possible and target destinations depends on the active strategy. For possible destinations: under LH strategy (*force-local-harvesting* is true), possible destinations are restricted to patches with available sharks that are on the same row as the fisher's initial row; otherwise, possible targets are any patch with available sharks. For the final target destination: under COMM strategy (*detection-comm* is true), the possible destinations with maximum sharks is returned; otherwise, a randomly chosen patch from the possible destinations is returned.

2.6.3 fisher-harvest

An additional submodel, ***sharks-be-harvested***, captures the logic of sharks being harvested by fishers. For each shark exceeding the *min-harvest-len* (relevant to the LEN strategy, set to 0 when inactive), it iterates through fishers on the same patch whose *monthly-shark-harvested* has not reached their *harvest-limit*. The shark is captured by the fisher with a probability of *chance-captured*, and the iteration stops if it is captured or all fishers have been considered. Upon capture, the shark dies, and the fisher's parameters (*total-shark-harvested* and *monthly-shark-harvested*) are incremented. This requires asynchronous updates as sharks harvested by one would be unavailable to others.

fisher-harvest is responsible for checking the harvest-limit, and updating sustainability-related metrics. Prior to the ***sharks-be-harvested*** where sharks are harvested, the fishers reset their *monthly-shark-harvested* to 0, and check their *harvest-limit* for the current month. In most scenarios, *harvest-limit* is equivalent to the *max-monthly-harvest* (relevant to NUM strategy, set to 100 when not active). However, if COMM strategy is active, cooperative fishers calculates their *harvest-limit* as

$$(N_{shark} - \textit{coop-not-share-sharks})/N_{fisher} \tag{1}$$

where N_{shark} and N_{fisher} are the number of sharks and fishers on their same patch. Non-cooperative fishers simply have a *harvest-limit* of 10000. After the shark harvesting, sustainability metrics for each fisher (*num-ticks-with-rewards* and *avg-ticks-with-rewards*) are updated.

Figure 1 depicts the process of fishers moving and harvesting for each strategy.

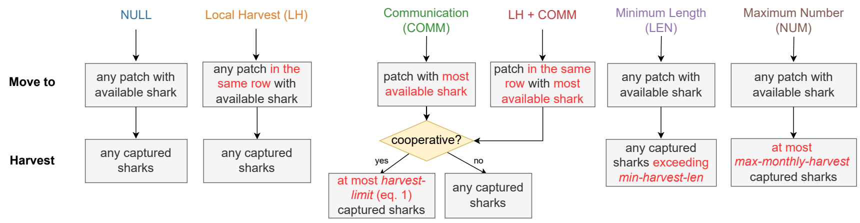


Figure 1: Movement and harvest behaviour of agents under different strategies.

2.6.4 reproduce

The breeding season of sharks is early summer [14], which is controlled in this model via $heat\text{-}level = (10 - |month - 10|)/11.11 + 0.1$. For each patch where the shark population has not reached *patch-max-shark* and there is at least one mature male shark, each of the mature female shark who has not reproduced in the last 2 years would reproduce *offspring-rate* offsprings with a probability given by *heat-level*. This would reset their *last-time-reproduce* to the current time step, and append the current month into the global variable *reproduce-month* for auditing purpose. New-born shark has the same initialization process described in 2.5, except their *age-in-months* is 0, and *last-time-reproduce* is -24.

2.6.5 update-graphs

Three visualisation graphs are updated: LPI (Living Planet Index), reproduction, harvest.

- ***update-LPI-graph***: a line graph with x = $\frac{ticks}{12}$ (time in years), and $y = \frac{\#Sharks}{initial\ shark\ population}$.
- ***update-reproduction-graph***: a histogram counting the reproductions by month.
- ***update-harvest-graph***: a line graph with x = $\frac{ticks}{12}$, and y = average *monthly-shark-harvested*.

3 Methods

3.1 Conservation Strategies

To address our research question, we have designed four conservation strategies, most of which were motivated by common management policies in fishery.

1. Local harvesting (LH): Each fisher is assigned a designated area for fishing to distribute fishing pressure more evenly across the ocean and promote sharks' sustainability.
2. Communication to maintain minimum shark population (COMM): Inspired by [5], we try to enable communication among fishers to foster cooperation and promote sustainable CPR.

   Incorporating a strong assumption that fishers can perfectly sense the number of sharks in every location, fishers, who are self-interested, will go to the location with the highest shark population and harvest as many as they can to maximise their returns, leading to all fishers moving together and creating a game environment. Under this game setting, a portion of fishers, determined by *cooperate-ratio*, will cooperate; they will share the sharks and maintain a minimum shark population in the location (*coop-not-share-sharks*) to prevent the depletion of sharks. For other not cooperating (defect) fishers, they will harvest as many sharks as possible. For this strategy, we are not only interested in its efficacy in promoting sustainability but also in what portion of cooperating fishers is required to achieve sustainable fishing.
3. Minimum length limit (LEN): Protecting small fish is a common practice in fishery as small and young fish have higher reproductive values and allowing them to grow and reproduce can sustain the fishery over time. Thus, we incorporate this policy and employ the Von Bertalanffy growth function [10] to estimate the shark length by their age.
4. Consumption constraint (NUM): Limiting the amount of fish each fisher can harvest can reduce the rate of shark consumption. We expect that a sustainable outcome requires a balance between the consumption and reproduction of sharks, which can be explicitly adjusted by this strategy.

3.2 Measurement of Strategy Performance

To investigate the effectiveness of the four strategies, we implement them individually on the calibrated model under null theory and evaluate their performance. To capture their performance under different levels of policy enforcement, experiments are conducted using different strategy parameters as shown in table 2, each of which will undergo 20 repetitions to mitigate stochasticity.

Let N be the number of fishers, and r_t^i be the amount of sharks harvested by fisher i at time step $t \in [1, T]$, where the simulation lasts for T time steps. Evaluation is performed using the following metrics recorded over time at the first month of every year, and at end of the simulation:

- Number of sharks remaining
- Return (mean monthly-shark-harvested across fishers): $r_t = \frac{1}{N} \sum_{i=1}^{N} r_t^i$
- Sustainability [15] (key metric): $E = \frac{1}{N} \sum_{i=1}^{N} t^i$, where $t^i = \mathbb{E}[t | r_t^i > 0]$ is the average time steps at which reward is received by agent i. This metric considers the duration of the simulation, also the returns and equality among fishers, making it our key metric to answer our question.
- Number of patches with sharks remaining: to examine the distribution of the shark population.

Having chosen the best levels of policy enforcement for each strategy, they are pooled and compared against the null theory to address our research question.

3.3 Model Calibration

Before any strategy implementation, the uncertain but important parameters are calibrated to create a structurally realistic model that captures the characteristic structures and behaviours of the actual system. We selected three significant patterns of the Whitetip Shark biological system for calibration.

1. Decreasing shark population: Due to overfishing and international shark fin trade, Whtietip Sharks have experienced significant population declines throughout a majority of its global range. However, there is no global population size estimate available for them [12] and we could only estimate the decline from past data. From 1992 to 2000, the Whitetip Shark population in the Northwest Atlantic declined by an estimated 70% [16]. Therefore, based on this 70% decline within 10 years, we will calibrate two uncertain parameters affecting the shark population over the simulation the most: the initial shark population and the chance of sharks being captured.
2. Seasonality of mating: Whitetip Sharks in the Northwest Atlantic Ocean generally breed biennially during early summer [14]. To reflect this, we introduced the heat level in the ***reproduce*** process to adjust the chance of reproduction depending on the current month using a linear function, such that sharks exhibit the highest reproduction probability between May and June.
3. Sexual dimorphism in length: Literature reveals that female sharks typically grow larger than male sharks [11], in which males maturing at 175 to 198 cm and reaching at least 245 cm, females maturing at about 180 to 200 cm and reaching at least 270 cm. Therefore, we decided to introduce a +10 offset to the length of female sharks as mentioned in section 2.5.

Considering the interactions between patterns, we will base on the calibration result from Pattern 1 to calibrate using Pattern 2, and then examine whether Pattern 1 still holds.

3.4 Model Parametrisation

Some parameters are determined according to the empirical information from existing literature, further aligning the model to the real Whitetip Shark biological system.

1. Life expectancy of sharks: 16 years, estimated by taking the average of the observed maximum ages over different regions; 12 to 18 years in the North Pacific and Western and Central Pacific, respectively, and 13 to 19 years in the South Atlantic [12].
2. Offspring rate of female sharks: uniformly distributed between 2 and 10, as the litter size ranges from 1 to 14 with an average of 6 [12]. We narrowed the range to better align with the average.
3. Mature age of sharks: uniformly distributed between 6 to 9 years old, as female Whitetip Sharks reach maturity between 6 and 9 years of age [13].
4. Reproduction frequency of sharks: 24 months, as the reproductive cycle of Whitetip Shark is thought to be biennial [13].
5. Parameters in the Von Bertalanffy growth function: we adopt parameters from [10] such that the shark length is evaluated from age as $325.4 \times (1 - e^{-0.075 \times (age + 3.342)})$

3.5 Model Assumptions

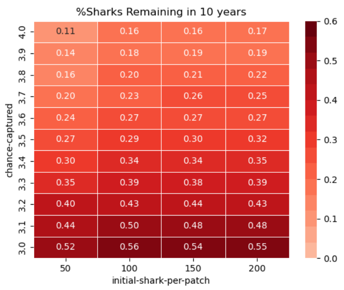
Parameters lacking empirical data and not calibrated are determined by assumptions. The model assumes (1) a fixed 20 fishers, who are initialized in random locations, (2) a maximum capacity of 300 sharks per patch, and that (3) cooperative fishers in COMM aim to maintain 30 sharks at minimum per patch. Some other assumptions include the age and gender distribution initialized, and sharks have an equal chance of being captured by any fisher.

3.6 Sensitivity Analysis

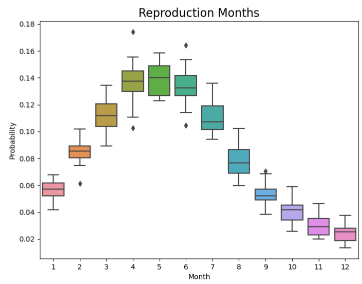
To evaluate the robustness of the strategy comparison result in sustainability, which is our key metric, local sensitivity analysis of all parameters, including those believed to be critical: ***fishers-num*** and ***initial-shark-per-patch***, will be conducted. Each parameter will be shifted by $\pm 15\%$ to the reference value. We will run 30 simulations for each parameter variation using random seed 1 to 30 to mitigate stochasticity. To quantify sensitivity, we measure $\bar{S} = \frac{|S^+|+|S^-|}{2}$, where $|S^+|$ and $|S^-|$ are the average absolute upper and lower sensitivity over 30 simulations respectively.

4 Results and Discussion

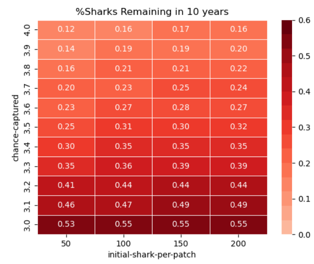
4.1 Model Calibration



(a) Pattern 1 calibration result.



(b) Pattern 2 calibration result.



(c) Pattern 1 calibration result after pattern 2 calibration.

Figure 2: Calibration results.

From Figure 2a, using grid search over ***chance-captured*** and ***initial-shark-per-patch*** and balancing computational cost, the two parameters were decided to be 3.5% and 100, respectively, which resulted in 29% of sharks remaining in 10 years with a standard deviation of 0.037 under null theory, aligning with Pattern 1. Based on this calibration result, we tuned the heat-level linear function of reproduction and obtained the heat-level function in section 2.6.4 to demonstrate Pattern 2, as seen in Figure 2b. Finally, considering the potential impact of the change in the heat-level function on the shark population, as seen from Figure 2c, we reran the grid search and confirmed that Pattern 1 still held under the calibrated parameters set, leading to 31% of sharks remained in 10 years.

4.2 Optimal Level of Enforcement of Each Strategy

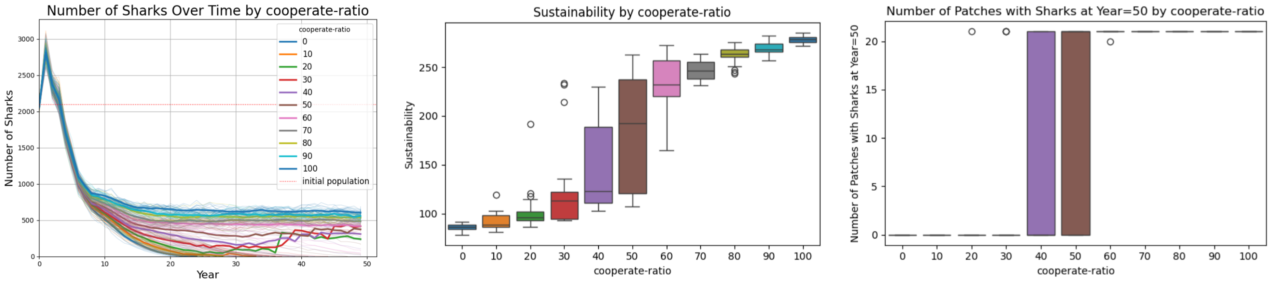
The optimal scenario or enforcement level per strategy is summarised in Table 2 and discussed below. Note that Local Harvesting (LH) is simply active or inactive, with no varying levels of enforcement.

4.2.1 Communication to Maintain Minimum Shark Population (COMM)

As demonstrated in Figure 3b, the more cooperating fishers the more sustainable it is. Thus, the best ***cooperate-ratio*** was decided to be **100**, although this is not realistic. It is worth mentioning that starting from 40 ***cooperate-ratio***, it demonstrated signs of sustainability despite the high variability, as seen from both Figures 3b and 3c. Sustainability finally became stable when 60% of the fishers were cooperating. This reveals that at least a majority of fishers have to cooperate in order to achieve a confident outcome of sustainable and fair fishing.

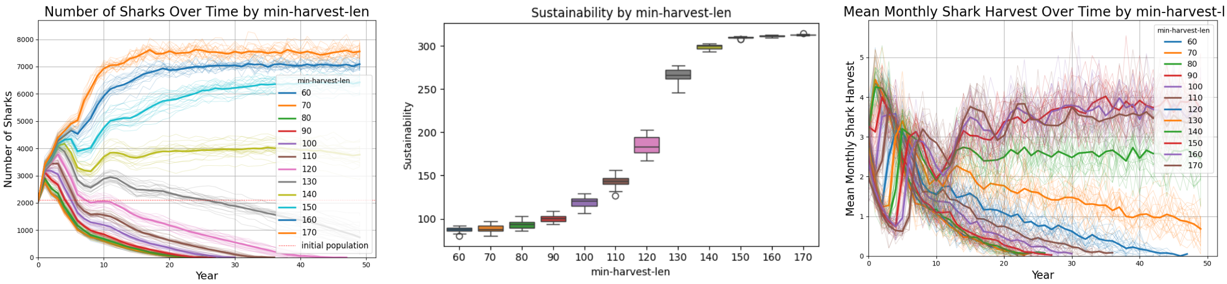
4.2.2 Minimum Length Limit (LEN)

It is hypothesized that the stricter the minimum length limit, the more sustainability we can achieve, and our results support this. Therefore, from the perspective of sustainability, the ideal ***min-harvest-***



(a) Number of sharks over time. (b) Sustainability in year 50. (c) #patches with sharks in year 50.

Figure 3: Results of COMM in different levels of enforcement.

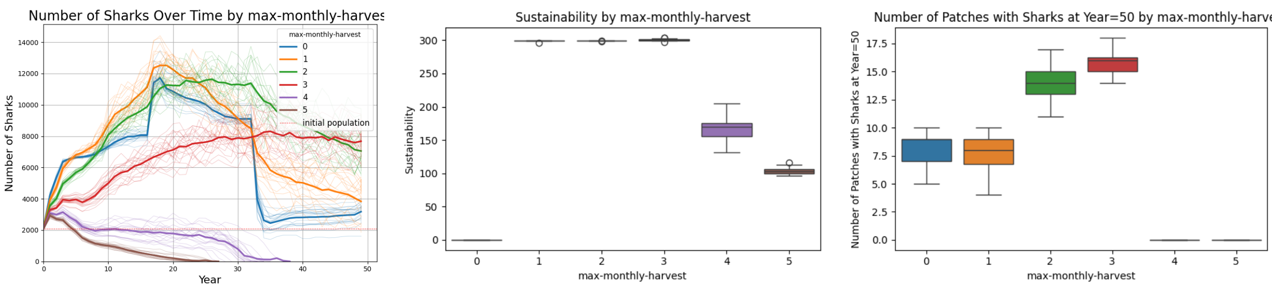


(a) Number of sharks over time. (b) Sustainability in year 50. (c) Return over time.

Figure 4: Results of LEN in different levels of enforcement.

len would be the strictest limit **170**. However, this harsh minimum length restriction would limit the sharks that fishers can harvest and hence, induce fewer returns for them, as shown in Figure 4c, where 170 was only the third highest mean return for fishers in year 50. In fact, from Figure 4a, 140 could already offer a stable shark population over the next 50 years. Furthermore, 150 not only provided the highest mean returns for fishers but also maintained a high and confident sustainability score, achieving a mutually beneficial outcome for fishers and sustainable fishing.

4.2.3 Consumption Constraint (NUM)



(a) Number of sharks over time. (b) Sustainability in year 50. (c) #patches with sharks in year 50.

Figure 5: Results of NUM in different levels of enforcement.

Unexpectedly, stricter consumption constraints (lower ***max-monthly-harvest***) on fishers did not imply a larger remaining shark population over the simulation, as revealed in Figure 5a. An interesting emergence of the model is noted: when every fisher could only harvest two or fewer sharks every month, the shark population would experience a relatively profound increase and decrease around year 18 and year 33, respectively. The duration between these changes was 15 years, which is approximately the life expectancy of sharks (16). This phenomenon was the most significant when no fishers were allowed to harvest at all (***max-monthly-harvest=0***). We attribute this to the maximum capacity of patches being filled up quickly near year 18 due to over-reproduction; If the patch population is capped, most mature sharks cannot reproduce, hindering the age diversity of the population. This will result in a large number of sharks dying out at the same time after 16 years of life expectancy.

On the other hand, when every fisher was allowed to harvest three sharks at maximum every month (***max-monthly-harvest=3***), the shark population was robust to the patch capacity thanks to the balance between consumption and reproduction, leading to a relatively diverse age distribution within sharks and thus, a stable population over 50 years. Reaching the highest sustainability score also, as shown in Figure 5b, it was decided to be the best level of enforcement for NUM.

Table 2: Experimented parameter values for each strategy. Best scenarios are in bold.

Strategy	**Parameter**
LH	force-local-harvest: **True**
COMM	cooperate-ratio: {0, 10, 20, ..., 90, **100**}
LH+COMM	force-local-harvest: **True** cooperate-ratio: {0, 10, 20, ..., 90, **100**}
LEN	min-harvest-len: {70, 80, 90, ..., 160, **170**}
NUM	max-monthly-harvest: {0, 1, 2, **3**, 4, 5}

4.3 Comparison of Strategies

A comparison is made between the strategies using the optimal parameter values identified in section 4.2 and summarised in Table 2. The evaluation focuses on sustainability while considering fishers' returns to explore trade-offs between sustainability and returns.

From Figure 6b, three top-performing strategies can be identified: COMM, LEN, and NUM. The high sustainability measurements indicate that the fishers are capable of receiving rewards over a long period under the three strategies. However, as compared to LEN and NUM, the COMM strategy shows a notably lower number of sharks with a small variance in Figure 6a. The low shark population may be due to agents only ensuring that there is an agreed-upon minimal number of sharks to be maintained, whereas the small variation is because, with 100% cooperative fishers, such a minimal amount is almost guaranteed. Moreover, NUM will incur local shark exhaustion in some patches as seen from Figure 6c, similar to LH, because this strategy does not prevent fishers from over-harvesting a particular region; it only restricts the number of sharks each fisher can harvest every month.

LH only exhibits slightly higher sustainability than the NULL theory, but the number of sharks remaining is much higher. Analysis of model behaviour reveals a common scenario: some rows can have fewer fishers initialized, allowing for population growth in those areas. Yet, sharks exhaust quickly in other rows with more fishers, resulting in low average sustainability since most fishers receive no rewards. Additionally, Figure 6c shows simulations with sharks depletion under LH. This suggests that the effectiveness of enforcing local harvesting depends heavily on the regional fishing pressure, and more intervention is likely required. Thus, we attempted to combine it with COMM (LH+COMM) as fisher cooperation within a fixed local region is more feasible in the real world.

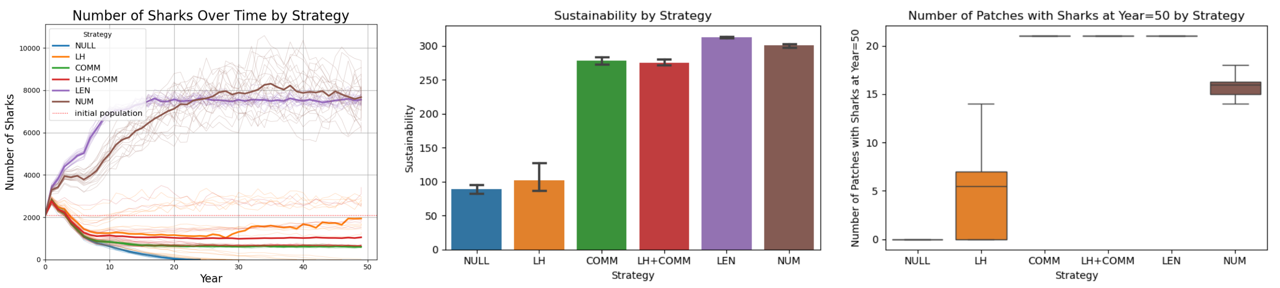
Performing as anticipated, LH+COMM can mitigate the drawbacks of LH while promoting equality among fishers in different rows by preventing shark depletion in any row. Figure 6a reveals that it also attains a higher number of sharks over time compared to COMM. As a result, the sustainability has improved significantly compared to LH.

In terms of the fishers' returns, in Figure 7a, LEN and NUM remain to be high-achieving. Particularly, LEN has a slightly better mean return because, under NUM, every fisher can only harvest three sharks at maximum every month. However, this consumption constraint provides a rather stable return for fishers over time, as seen from Figure 7b. In contrast, we can observe that LEN demonstrates more fluctuations in returns over time compared to others and is gaining stability as the simulation progresses. Since the length of sharks is correlated to their age, this is likely due to the improving age diversity within the shark population as the simulation goes on.

The COMM strategy has a much lower return, again because only a minimal amount of sharks remains. While the sharks do not become exhausted, their population and the return of the fishers are relatively constant at a low level. LH strategy performs better than COMM for returns despite their lower performance for sustainability. A possible reason is that LH has high variability and incurs many depletions, leading to lower sustainability; but on average, the number of sharks remaining is higher, leading to a higher average return as in Figure 7b.

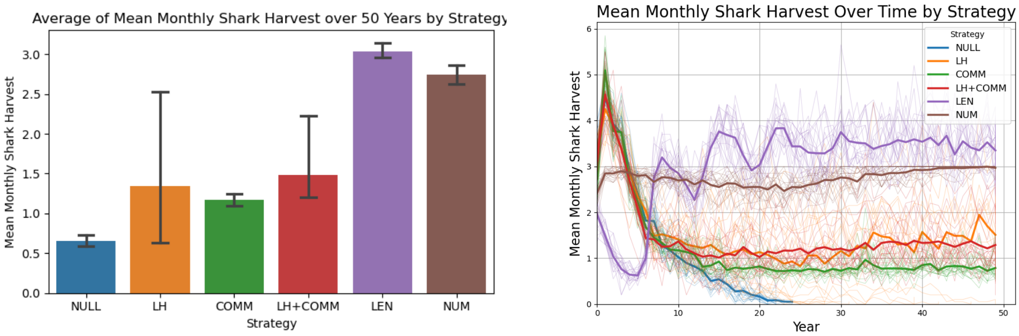
Hence, LEN (Minimum Length Limit) is found to be the best-performing strategy in both sustainability and returns, outperforming those of the null theory by 3 times and 6 times, respectively.

Not to be overlooked, in Figure 6a, across all scenarios including the null theory, where sharks are likely to extinct within 25 years, an initial increase in the shark population is consistently observed thanks to the reproduction of initial mature sharks. This effect fades out over time as the population of initial mature sharks gradually dies out, contributing fewer newborns to the total population.



(a) Number of sharks over time. (b) Sustainability in year 50. (c) # patches with sharks in year 50.

Figure 6: Sustainability comparison of the strategies under best scenarios.



(a) Average of return in January of 50 years. (b) Return over time.

Figure 7: Return comparison of the strategies under best scenarios.

4.4 Sensitivity Analysis

Table 3: Sensitivity analysis parameters and their $\bar{S}$ across different strategies.

Parameter	Value (±15%)	NULL	LH	COMM	LH+COMM	LEN	NUM
fishers-num	20 (17, 23)	**2.6130**	**2.2002**	0.2220	0.0538	0.0406	**0.7007**
initial-shark-per-patch	100 (85, 115)	0.3913	0.3260	0.0457	0.0539	0.0599	0.0680
chance-captured	0.035 (0.02975, 0.04025)	**2.4721**	**2.0360**	0.0600	0.0094	0.0077	0.0585
patch-max-shark	300 (255, 345)	0	0.0206	0	0.0035	0.0201	0.0065
reproduction freq. in months	24 (20.4, 27.6)	0.4530	0.5842	0.0890	0.0283	0.0259	0.0068
life-expectancy-in-months	192 (163.2, 220.8)	0.6609	0.6116	0.0382	0.0345	0.0722	**1.2032**
offspring-rate	2-10 (1-9, 4-12)	0.5737	0.3360	0.1091	0.0138	0.0255	0.1508
mature-age-in-months	72-108 (48-84, 96-132)	**1.3528**	**1.0194**	0.1286	0.0927	0.0385	**0.7992**
asymp-size	325.40 (276.59, 374.21)	-	-	-	-	0.0654	-
growth-coef	0.075 (0.06375, 0.08625)	-	-	-	-	0.0279	-
age-when-size-0	-3.342 (-2.8407, -3.8433)	-	-	-	-	0.0113	-
female-len-offset	10 (8.5, 11.5)	-	-	-	-	0.0029	-
coop-not-share-sharks	30 (25.5, 34.5)	-	-	0.2838	0.1212	-	-

4.4.1 Overall sensitivity

The sensitivity scores $\bar{S}$ of the parameters under different strategies are reported in table 3. Some parameters, including *asymp-size* and *coop-not-share-sharks*, are only relevant to specific strategies such as LEN and COMM, and are not expected to interfere with other strategies.

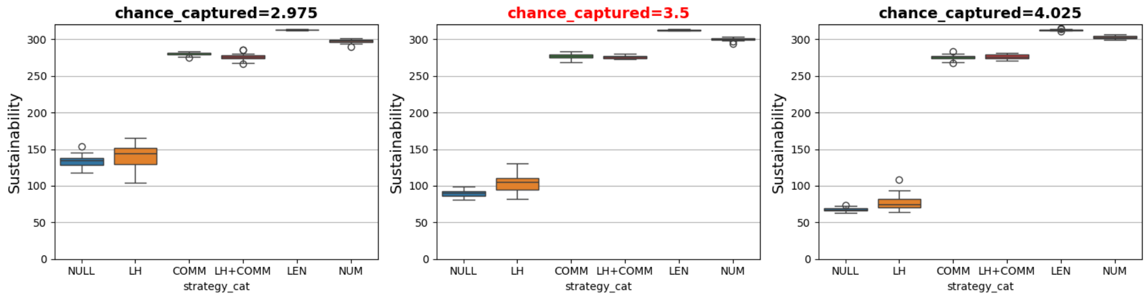


Figure 8: Robust relative sustainability across strategies at different chance-captured rates.

Overall, ***fishers-num***, ***chance-captured*** and ***mature-age-in-months*** show higher sensitivity, especially in scenarios with minimal intervention like NULL and LH. This emphasizes the need for effective strategies to stabilize fishing pressure as harvester preferences and fishing techniques evolve.

The NUM strategy is also sensitive to ***fishers-num***, ***life-expectancy-in-months*** and ***mature-age-in-months***, with high sensitivities observed only when changes in the parameters negatively impact sustainability. Specifically: (1) increasing ***fishers-num*** ($|S^+| = 1.3806$) raises shark consumption, as NUM imposes a harvest limit per fisher where the total harvest limit grows linearly with ***fishers-num***; (2) decreasing ***life-expectancy-in-months*** ($|S^-| = 2.3853$) leads to a shorter shark lifespan which reduces shark population; and (3) increasing ***mature-age-in-months*** ($|S^+| = 1.5889$), the duration to reach maturity, leads to lower reproduction rates and thus overall population. These variations cause notably lower sustainability for NUM, making it underperform compared to COMM and LH+COMM, and only better than LH in terms of sustainability.

In contrast, COMM strategy is less sensitive as their harvest limits adjust dynamically based on shark population and number of fishers to ensure a minimal shark population. This indicates that the NUM strategy would benefit from frequent readjustments, rather than relying on a constant harvest limit at all times. Similarly, the LEN strategy demonstrates low sensitivity to most parameters, due to the strict enforcement (***min-harvest-len*** $= 170$) which enhances its robustness.

Despite parameter sensitivities, the relative effectiveness of strategies mostly remained consistent, except for NUM. For example, Figure 8 illustrates the impact of changes in ***chance-captured***.

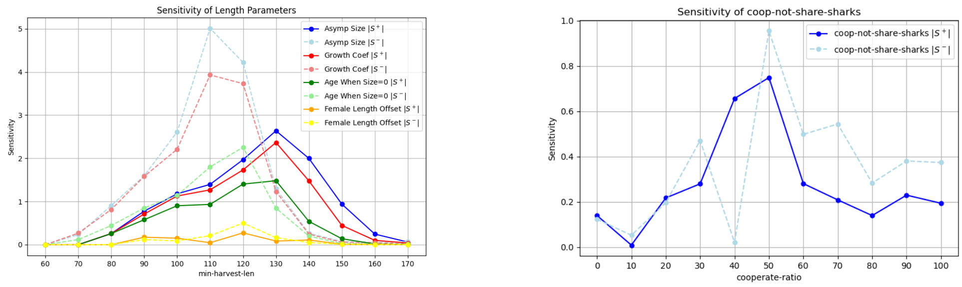
The model shows very low sensitivity to ***patch-max-shark***, suggesting it could likely be excluded without significantly impacting model behaviour. This parameter prevents unrealistic shark population growth under minimal fishing pressure and ensures the computational feasibility of simulations. A potential improvement could involve incorporating predator-induced mortality to enhance the realism of population dynamics. However, calibrating the population under natural conditions without human interference and over-exploitation is challenging due to limited data and patterns.

4.4.2 LEN: Shark Length

Further experiments assess the LEN strategy's sensitivity to shark length at varying enforcement levels. $|S^+|$ typically correspond to increased shark length, necessitating a higher *min-harvest-len* to account for more harvestable sharks. Figure 9a reveals significant changes in $|S^+|$ around a *min-harvest-len* of 130, where performance was initially high under the original parameters but decreases significantly as shark length increases. Conversely, lower sensitivity values reflect a decrease in shark length, with substantial sustainability improvements seen around a *min-harvest-len* of 110. At the extremes (60 and 170), small length changes do not lead to significant effects. This highlights the need to consider species size and select a sufficiently high enforcement level to address uncertainties. Additionally, the *female-length-offset* shows minimal sensitivity, suggesting that small differences in the probability of harvesting sharks by sex due to length difference have a negligible impact on overall sustainability, and this pattern may be relevant for species with greater sexual dimorphism in length instead.

4.4.3 COMM: Minimum shark population to maintain

We also further examine the sensitivity of COMM to the minimum shark populations to maintain (***coop-not-share-sharks***) under different intervention strengths. From Figure 9b, the sensitivities across varying proportions of cooperating fishers are small (consistently below 1) overall, with a



(a) Four length parameters for LEN.

(b) *coop-not-share-sharks* for COMM.

Figure 9: $|S^{+}|$ and $|S^{-}|$ of different parameters on sustainability under LEN and COMM.

symmetric pattern centred at 50 cooperating ratio.

When the proportions of cooperate and defect fishers are very similar, the occurrence of either exhaustion or a sustainable outcome is highly uncertain, as shown in Figure 3c. A higher ***coop-not-share-sharks*** can effectively increase the likelihood of a sustainable outcome, and vice versa. On the other hand, with a majority of fishers not cooperating, the effect of ***coop-not-share-sharks*** fades out as it only applies to cooperating fishers. With cooperate fishers being the majority, the sustainability of COMM is also not sensitive to it as it is more certain that sharks will not be exhausted over time, allowing all fishers to gain rewards consistently. However, it is worth noting that the lower sensitivity tends to be higher than the upper because maintaining a lower shark population will reduce the rate of population growth and thus, it is more likely that no patches contain extra sharks for fishers to harvest, i.e., the populations of all patches are under the minimum shark population to maintain. Hence, fishers are more likely to gain no rewards over the simulation, reducing the sustainability.

5 Conclusion and Reflection

In conclusion, the Minimum Length Limit (LEN) strategy, which forbids the fishing of small sharks, is recognized to be the most effective for sustainable consumption of Whitetip Sharks. Protecting young fish, which possess relatively higher reproductive values, can maintain the consistent growth of the population and prevent population collapse. This reveals that ensuring the catalysts for population growth is crucial in achieving a sustainable population for CPR. For some types of resources, one can leverage the appearance of the resource, such as length and colour, to evaluate the reproduction value.

The second best-performing strategy is the Consumption Constraint (NUM), which sets a harvest cap on fishers to reduce shark consumption. With optimal enforcement strength, both LEN and NUM not only avert shark extinction but also boost the shark population to healthy levels over the next 50 years. In contrast, Local Harvesting (LH) and Communication to Maintain Minimum Shark Population (COMM) can stabilize the population at lower levels, merely avoiding extinction. Extensive sensitivity analysis confirms the robustness of most results in terms of the relative sustainability across strategies, though a dynamic limit for NUM may further enhance its robustness.

This work evaluates diverse and common conservation strategies, using a pattern-oriented design, and is informed by existing literature on the Whitetip Shark biological system to reach meaningful conclusions. However, the model proposes some unrealistic assumptions, such as perfect sensing of shark population for fishers in COMM and estimating shark length from age using the Von Bertalanffy growth function [10]. Additionally, the model assumes perfect compliance from fishers with policies, including cooperating fishers never cheat in COMM. Moreover, we attribute the underperformance of LH to the uneven distribution of fishers across different rows, where allocating fishers evenly during model initialization may better balance fishing pressure and align with the original objective of this strategy. Finally, we acknowledge that the large number of parameters in the model has hindered the model evaluation and sensitivity analysis; it is challenging to balance between model complexity and realism in implementing strategies to address our question.

In future studies, we may introduce uncertainty in the sensing of shark population for fishers in COMM to improve its practicality. We can also investigate the synergy of multiple strategies beyond combining LH and COMM. For example, deploying LEN and NUM together and applying Sobel sampling to discover the best set of parameters in terms of sustainability. Shifting multiple parameters simultaneously, global sensitivity analysis can be applied to examine the potential interaction among them, despite the difficulty in carrying out it for all parameters given the amount of them.

Throughout the project, we applied the skills and knowledge from this subject to drive the model design and research focus. We realized that it would be more impactful to focus the research on a concrete topic with a specific real system. Also, model complexity is our enemy: while we aim to implement interesting strategies such as cooperation among fishers, we must also consider the complexity added by new processes and parameters. Lastly, conducting sensitivity analysis is crucial for evaluating result robustness, providing us with deeper insights into the model's nuanced behaviours.

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