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Multi-Agent Systems and Distributed Constraint Satisfaction for Decision Support in Marine Ecosystem Management

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Abstract

Real-world problems can be formulated as distributed constraint satisfaction problems. Marine resources are subject to certain constraints relating to their physical design, their interactions and legal requirements. Decision making is a major problem since the resource management is distributed and threatened by socio economic activities and environmental factors. A target species with high consumption demand (rabbitfish) is modelled using a system dynamic model builder as a prey agent of the system and predators as the predator agents, other agents including primary production and fishing and aggregation gears are also used. Primary productivity and Predators through aggregation, exploitation and predation affects the population dynamics of the prey agent. Modelling and simulation helps increase the understanding of the behaviour of the prey fish and help explore the potential effect of different management scenario on the exposure of the prey fish to such constraint violation. This study proposes a multi-agent system (MAS) model simulated to explore the impact of different management decision strategies on a marine ecosystems management problem involving several environmental agents. Focussing on the multiple agents within a dynamic environment facing several distributed environmental constraints. A population growth curve is used to identify the initial state (problem) of the marine ecosystem based on available data and how different decision strategies affect the state as they are implemented (problem solving using constraints). A simulation toolkit (Netlogo V5) is used to model different environmental dynamics, interactions and constraints satisfaction to realise an increase in population for the target species. The proposed model examines distributed data among different government agencies databases and publications. The proposed model is analysed and produce results confirming improved decision support through the use of multi agent systems and distributed constraint satisfaction.

Keywords: Multi-agent systems; Distributed constraint satisfaction; Marine ecosystem

Introduction

Background of the study

Computer systems have evolved into essential tools for modelling, assessment and support in any domain requiring decision making. As management try to adapt in a world of rapid change, decision making has become increasingly dynamic and complex. Distributed decision making should be based on evidence gained from the source of problem. Such evidence can only be gathered while researching and developing an outcome, one being from technological modelling.

Decision making complexity: In recent years, there has been considerable growth of interest in the design of distributed, intelligent agents capable of dealing with complex distributed problems and vast amounts of information collaboratively. There has been a rapid growth in application of agent-based systems to deal with real-world problems by taking advantage of the intelligent, autonomous, and active nature of this technology. Benefits of an agent-based approach come from its flexibility, adaptability, and decentralization.

In relation to nature, natural resources are a set of critical domains where incorrect management decisions may have disastrous social, economic and ecological consequences. The complexity of environmental problems requires the development and application of new models capable of processing not only numerical aspects, but also experience from experts together with wide public participation, which are all needed in decision-making processes [1]. Most environmental system problems cannot be only tackled with the traditional tools of mathematical modelling [2]. To avert such complexity, a new paradigm is needed, and it requires new intellectual challenges. According to literature the reason for using multi-agent system (MAS) for modelling ecosystems and addressing environmental problems is multifaceted [3].

Multi agent systems for distributed problem solving: MAS approaches may provide a valuable framework for new kinds of decision making models in marine ecosystems management using the techniques of distributed problem solving especially self-interested agents. MAS are widely adopted across disciplines as different as biology, economics and sociology. They are especially capable of modelling distributed complex systems which is a valuable characteristic in the context of marine ecosystem management to realise a global solution to a problem. Additionally, their ability to represent individuals explicitly in the models is promising for applications related to marine ecosystem management.

MAS has the ability to model distributed decision-making process at the environment agent level and ecosystems can be naturally modelled as MAS, where each real-world actor is represented one-to-one by an agent, defined as a computer system situated in some environment and capable of autonomous actions to meet its design objectives [4]. MAS

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approaches have been explored in environmental systems from the late 1990s [5] and, recently, they have been exploited in several research contexts e.g., [6,7]. Despite the wide application, the use of MAS for marine ecosystems management has not been fully explored.

This study examines application of artificial intelligence through the use of multi-agent system and distributed constraint satisfaction in distributed problem solving to guide decision making process in a specific domain. It demonstrates how agents are able to manage the complexity of real world domains and capable of supporting the decision making process Agents have individual behaviour, are driven by a set of goals and can communicate with each other based on certain rules which can be modified to assist in learning and evolution among them. Key focus will be to model the different agents (cognitive and reactive) according to variables, and constraints. The marine ecosystems management problem is therefore formulated as a distributed constrained problem, which can be effectively managed [8] which to guarantee a global solution efficiently. The model is focused on using DCSP since the data needed to solve the problem is distributed. The model is simulated while controlling the constraints to monitor changes in the population growth. The more the target agents are observed, the better the population growth curve.

Problem statement

Currently problem solving in marine ecosystem management requires intervention of human users at all stages in a distributed approach. When making decisions under conditions where available information is incomplete or overly complex, subjects rely on a number of simplifying heuristics, or efficient rules of thumb, rather than extensive algorithmic processing [9]. The difficulty with such scientific technical presentations is that it is hard for managers and readers to determine precisely the implications of the ideas being put forward; there are inconsistencies between the various concepts, their relationships and what inferences can be made. There is even more emphasis on ecosystem based management systems for marine waters through the frame work for decision making [10]. Traditional quantitative systems lacked intelligence, hence have to put up with a lot of risk controls. There is need for an integrated approach to natural resource management; many governmental and other agencies still rely on sectorial approaches with limited cross-sectorial planning and coordination [11].

Managers of the marine parks and proposed community conserved areas are faced with the challenge of developing integrated management plans that protects and conserves the marine biodiversity of our region, while at the same time ensuring the economic viability of regional tourism relying heavily on coral garden snorkelling, ornamental fisheries and endangered species sightings including dolphins, turtle activities. Tourism and fisheries are major drivers of the local economies of several small coastal communities. Park and MPA managers must, therefore, manage human activities in the region so as to meet the multiple objectives of the local tourist economy, commercial shipping and conservation of ecosystem health and resilience.

In informal consultations with various stakeholders, there is a growing requirement to justify management decisions based on sound scientific arguments, which is where modelling plays an increasingly important role.

The complexity of problem in marine ecosystems management decision making include but not limited to:

Inherent complexity of the systems in place: The decision making processes involve a huge amount of knowledge containing complex interactions between physical–chemical, biological, ecological, social and, economical processes.

Huge quantity of data/information: These domains tend to produce a great volume of data and information.

Many of the facts and principles underlying: The domain cannot be characterized precisely solely in terms of a mathematical theory or a deterministic model.

The urgency of environmental problems and complexity involved in solving them require new advances to computational approaches to these problems. More powerful approaches are needed to explore more and larger networks of increased complexity that reflect more of the variability, interactions, and environmental problems found in nature. The main gap is how to reach a solution if all knowledge about the problem can be gathered based on evidence of real situation.

The entire decision making process for effective management of marine ecosystems has proved difficult and it requires a lot of human group thinking to reach at a single decision which may not be certain but a trial and error due to many assumptions. It is therefore necessary to come up with a model that puts up evidence or real situation that triggers sound decision by different stakeholders. A lot of survey data is been collected through natural resource management agencies along the Kenyan coast with key focus on marine ecosystems but little on interactions within this ecosystems. Data is necessary to be able to know the interferences within the ecosystems. This is a problem in the setting since there is a lot of decision overlaps leading to ill-structured biased decisions. Even with the most advanced techniques, solving such problems is both space and time costly [12]. Hence a model will reduce these overlaps.

Justification

There is need for technological model that can help understand the real situation of such ecosystems. There is need to link the distributed datasets using a smart approach i.e., come up with a model that can assist in making quick decisions about a specific ecosystem situation assuming decisions cannot be made centrally.

This study aims to apply the use of a multi-agent system model in distributed problem solving. Key focus will be given to distributed constraint satisfaction to model the individual behaviour according to variables, domains and constraints. Also by having different coherent distributed agents assigned to different levels of the ecosystems while collaborating and modelling different states of each ecosystem. The solution model is expected to guide the decision makers on what conditions and regulations they need to put in place to safeguard marine resources given the model flexibility.

Possible outcomes based on the nature of the problems considering global constraints can be suggested for implementation in a coherent manner and a subsequent monitoring to test the passing or failure of a solution against the environment.

Research questions

I. Can multi-agent systems assist in decision making of marine ecosystem management?

II. Which distributed problem solving model can be simulated to show the interactions of different parameters in an environment?

III. How a distributed constraint satisfaction model will be used to solve distributed decision problems in marine ecosystem management?

Objectives

General objective: To model a multi-agent system that investigates the interactions between different environmental parameters on the marine resource.

Specific objectives:

I. To investigate how multi-agent systems techniques, assist in making strategic decisions.

II. To simulate the biophysical parameters, the cognitive and reactive agents and their interaction based on behaviour rules and constraints

III. To test the model outcome based on the factorial index.

Scope of study

This study is going to focus on data based on Kenyan coast marine ecosystem surveys. This data will then be simulated based on the proposed model to realize the population change. The proposed site has been selected since it is a key resource for the local community, tourist attraction and also subjected to human induced and natural constraints. The area is rich in corals and seagrass and forms a good habitat for fisheries.

Literature Review

Artificial intelligence is used for solving dynamic complex problems or as a decision support tool. There is an extraordinary explosion of multi-agent based applications in a diversity of fields: e-commerce, supply chain management, resource allocation, intelligent production, industrial control, decision support, simulations, production planning and control. Intelligent multi-agents as an artificial intelligence technique can inhabit a complex, constantly changing environment. It can sense what is going on, and act independently to accomplish a specified set of tasks or achieve certain goals [13]. It plays multiple roles in real world problem solving applications including taking over repetitive tasks, customizing interaction information, user notification when important events occur, user behaviour learning, context-based user assistance, remote task execution etc. Today, successful cases like computational studies of species loss can now quantitatively predict the varied effects on the abundance of other species in field experiments [14] and suggest which additional species that it may be necessary to eliminate in order to prevent extinction cascades resulting from the initial loss [15]. The theoretical and mathematical framework for these studies has been successfully extended to seasonal dynamics of species groups within a large natural ecosystem [16]. These promising results suggest that application of artificial intelligence techniques to computational models of specific habitats (e.g., coral reefs, lakes, forests, etc.) may form a firm foundation for integrating human exploitation of these ecosystems.

Artificial intelligence techniques have also been incorporated into decision support application design frameworks in order to include intelligent problem solving mechanism. Today strategic management of resources involves cooperation between several actors in order to propose a global plan of coherent actions.

Decision making processes in strategic management of resources are usually very complex and are frequently partitioned into sub problems then solutions proposed into those sub problems. There is always a multiple complex interaction between actors and processes and the participation of diverse decision centers in the process of defining a plan of action.

One of the main problems in decision making is to find a way to automate the process as much as possible so as to obtain automatically coherence and coordination among decisions made by different actors.

Most solutions that exist are in levels and the objective of problem solving is not to find an optimal solution but rather to be able to formulate alternatives which there may exist a satisfactory solution.

Review indicates that most decision support frameworks should focus more into structuring and modelling than problem definitions [17]. The study further states that many model focus on qualitative information, intelligent behaviour but do not consider constraints involved in those models.

Multi-Agent systems approach to strategic decision support

Considering the above scenario, the combination of decision support and multi-agent systems offers great promise in modelling strategic management applications. MAS models were derived from work in a sub-area of artificial intelligence called distributed artificial intelligence (DAI). DAI aims at solve problems by dividing them amongst a number of programs or agents, each with its own particular type of knowledge or expertise.

In the last decade there has been increasing interest in software designs based on multi-agent systems (MAS), i.e., a range of techniques that share a common bond in that they describe systems in terms of aggregations of goal-oriented, interacting and autonomous entities, placed in a shared environment. Although agents and MAS have become important metaphors in model construction there has been no consensus regarding what an agent is and what distinguishes agency from related concepts such as objects. An agent is a computer system that is capable of independent action on behalf of its user or owner and a multi-agent system consists of a number of agents which interact with each other, typically by exchanging messages [4]. In the case of MAS, several agents interact in a goal or task oriented coordination that can be both cooperative and competitive. The interaction between the various agents in the system provides an interesting way for solving problems.

A more concrete approach to defining agents is by means of a set of properties, all or some of which an agent must possess:

Autonomy: An agent is able to execute tasks with little or no intervention from other entities.

I. Adaptively: An agent can adapt to future behaviour based on past experiences, i.e., can learn.

II. Goal-orientation: An agent does not solely react to environmental stimuli, but may act proactively according to a set of persistent goals. To meet these goals, an agent is able to execute plans over time.

III. Mobility: An agent is able to change its location within a physical or virtual environment (e.g., a computer simulation model)

IV. **Reactivity:** An agent is able to respond to changes in its environment in a timely fashion.

In combination, the collection of agents would be better at finding solutions than any one agent working on its own.

Multi-agent systems application

Multi-agent based models have been developed and applied with success in a wide array of areas including natural resource management. Successful works on companion modelling and multi-agent systems for integrated natural resource management in Asia have been undertaken so far [18]. Complimentary activities were developed including artificial societies that help to understand generic properties of interacting processes, models applied to concrete and local problems to understand the dynamics of natural and renewable resources and their management. Applications were developed in irrigation, wildlife management and pasture management. MAS simulation tools were selected. Agents acted and transformed their common environment, which were modified for other agents. By doing this, they generate "externalities" while this environment also has its own ecological dynamics of change. Field investigations and a literature search supplied information and helped to generate hypotheses for modelling by raising a set of initial key questions to be examined by using the model. The companion modelling cycle was composed of role-playing games, multi-agent systems, simulations and the observed world.

A MAS model [19] using the COR-MAS (common-pool resources for multi-agent systems) platform was developed to simulate scenarios of resource management processes of land-use and hydrological dynamics of a catchment in northern Thailand. They used stakeholder elicitation techniques in digesting key perceptions of farmers toward agricultural practices related to water use to be used in model design and development. The model emphasized farmers' individual decision-making based on different viewpoints regarding house- hold resources and land and water management without interventions from local and government institutions.

Other successful cases include land use and land cover change [20]; wildlife management [21]; watershed management [22] and the results have proved its viability to many real time problems. But the use of Multi-agent systems in support of marine ecosystems management is rare especially in decision making environment.

The advantages of using distributed intelligent agents include but are not limited to reducing the information overload and the amount of work by use of agents instead of humans, cutting down operational costs, reduced human errors, fast analytical processing, off-line work mode that is vital for distance working agents, restricted by technical limitations.

Distributed problem solving

Multi agent-based modelling is most appropriate for domains characterized by a high degree of localization and distribution and dominated by discrete decision, thus given the characteristics of marine ecosystems, it is a promising approach. Based on the examples given above it is noticeable that there is application of system dynamics with focus on feedback mechanism, conflict resolution to allow for agent cooperation but so far nothing touches on constraint satisfaction considering different goals and agent types so as to arrive to a concrete solution that will advise policymaking or support decision.

Related work

Focussing on coastal and marine ecosystems, [23] a study on a modular autonomous multi-agent system had been developed to accommodate a variety of research activities. The study demonstrates the complementary capabilities of agents by simultaneously surveying a time-varying coastal environment and using that information to obtain a sparse but representative set of water samples. The autonomous system enables the elimination of redundant resources, thereby reducing the overall cost of at-sea sampling and improving sample quality. This study only focussed on the biophysical parameters only and lacked the feedback mechanism and constraints were not considered.

Another [24] study presented a spatial integrated bio-economic model for fisheries. In the model fishers' behaviour were simulated based on optimal effort allocation. The added value of this model compared to other existing spatial management tools lay in the presence of short and long term fishers' behaviour, spatial explicit stock and fleet dynamics and relatively low data requirements. The model was applied to estimate the impact of area closures in the North Sea. Overall area closures had a negative impact on the profitability of the fleets. This would be worsened with higher fuel prices and decreased stock productivity. The model was applied in a case study to analyse how area closures in the North Sea impact shrimp and flatfish fisheries. This model focussed on fish stocks control based on closure as a management intervention. Biophysical characteristics and inputs from other could also have had an input to stock productivity. Constraint satisfaction is seen as a gap in this model.

A study [3] was undertaken to develop a multi-agent system (MAS) to investigate the interactions between the maritime traffic and the marine mammals in the Saguenay St. Lawrence estuary, in Quebec. The study proposed a MAS model where the focus was on the whale-watching boats. It discusses the conceptual model with its principal components: the physical environment and the boat agents and whale entities, Simulations were run to assess different decision strategies of the boat agents and their impacts on the whales. Results indicated that cooperative behaviour that involves a combination of innovator and imitator strategies yields a higher average happiness factor over non-cooperative, purely innovators, behaviour. The limitation with his approach is that as long as the boats still innovate or imitate they still put a risk to the whales. This study entirely focussed on the interactions within the environment. There was no focus on after incidents of coalition, i.e., rate of mortality and how to regain the population of whales considering the reproduction rate of whales. This is a gap in setting. Another issue of concern is the behaviour between the whales including their feeding habits. This can be managed by introducing constraints including speed, minimum allowable distance to the area of interest while still considering the environment dynamics.

Findings

The studies indicated above have truly shown the viability of applying MAS approach to marine resources. The limitations are clear. Major issues in multi-agent systems for decision support including control of environment (behaviour and population dynamics), interactions among population of agents and coordination need to be considered. Decisions are supported by a wide range of factors. It is worth noting that multiple decisions are undertaken to control a state of environment either a decision at a time or several decision as an effort to either maintain or improve the state of the environment. Such a step of strategic planning should involve the generation and evaluation of different strategic options in order to select an overall strategy that satisfies close to all factors. This study covers the gap by introducing the aspect of distributed constraint satisfaction within multi agent systems in support of decision. The model is expected to solve such problems by creation of an envelope which allows modelling of different actors, their behaviour and simulation of their interaction and application of controls until a global solution is arrived at. Any constraint violation will lead to an ill informed decision. The evidence is expected to support management decision from different management agencies by defining rules and policies based on tested controls.

Methodology

The study focused on agent interactions with the environment while trying to control constraints. The constraints determined the different management strategies employed to put the ecosystem to a sustainable state.

The schematic diagram presented in Figure 1 shows how different agents in populations interact with each other and to the environment. Agents of the same type cooperate or coordinate their daily activities while facing different constraints distributed across the environment.

Experimental design

In this study a scenario is experimented, the experiment involves a number of interrelated activities. A classical system dynamics methodology [25] was used. The system dynamics process follows three steps as follows:

I. Understanding of situation/problem definition: For this case the focus was on constraints, interactions and interference within the environment. Modelling the initial state of the ecosystem helped to determine the problem area and the decision strategy required. The process involved putting different agents' populations with their environmental constraints and observing the outcome based on their individual behaviour.

II. Model conceptualisation/model building: The model formulation was done using one of many computer software developed to assist SD modelling logic (NetLogo v5). A system dynamic model builder was used to set and understanding the influences between the agent variables including speed, flow, and stock. These define the dynamic behaviour.

III. Running the simulation model/using the results: Once the model was built, different scenarios were analysed and used to test different policies/decisions. Explore different situations. The model was used as an ontological description of the situation perceived and it successfully accepted both the structural changes and recommendations for policy making that were introduced. Data based on the desired attributes was collected so as to gather key agent attributes. The focus will be on gears-fish, fish-nutrients, fish-predator interaction within an ecosystem. An output is then defined by obtaining the time which high fish population is observed at different given constraints. The above listed constraint variables define the general population output. Hence changes in different levels of variables constraints will affect the overall population of the target species.

Agent architecture

The model is composed of n agents $A_1, A_2, \dots, A_k$. Each agent Ai contains constrained variables $X_{i1}, X_{i2}, \dots, X_{ini}$. For a set of constrained variables $X_{ik}, X_{jl}, \dots, X_{mn}$, with domains of values for each variable D_{ik}, $D_{jl}, \dots, D_{mn}$, the constraint defined as R $D_{ik} \times D_{jl} \times \dots \times D_{mn}$. In this proposed distributed constraint satisfaction problem, the agents are connected by constraints between variables that belong to different agents. Different types of agents' populations are incorporated here including the fish aggregating devices (FADs), primary production, predators' agents and the fish.

Fish (Prey) agent: A population of a target species of fish (prey) is used as stock to represent equal agents cooperating and coordinating. Fish move in school's form during feeding or spawning (behavioural). They work in a reactive mode as triggered by predators' agents or constraints and are capable of communicating among themselves.

Predator agent: This population of agents' coordinates as they move around the environment in search of food. They also face threats including fishing. Their survival is heavily dependent on the prey agent. They have a cognitive agent characteristic which is to sight and attack the prey.

Other agents: Agents like primary production, fishing which also exhibit complex interactions were also used to bring the out the focus of distributed constraints.

The variables in Table 1 were selected based on their importance at different levels (i.e., the Rabbit fish is of high socio economic value listed in the top 15 most abundant species landed (Hicks et al.) and the grouper is highly ranked as a predator to certain age/size of Rabbit fish. The general population of the target species is highly determined by the above listed variables.

Data source

The data has been derived from previous field surveys/ publications undertaken by different institutions along the Kenyan coast including but not limited to Kenya marine and fisheries research institute and Kenya wildlife service. The study focusses on coral ecosystem in a marine reserve which is a habitat to rich reef fish species.

Input data

The input data is as listed in Table 2 detailing the agents and the constraint variables.

Model analysis

The goal here was to derive the initial state of the ecosystem, and then apply the different decision strategies as listed below to derive a

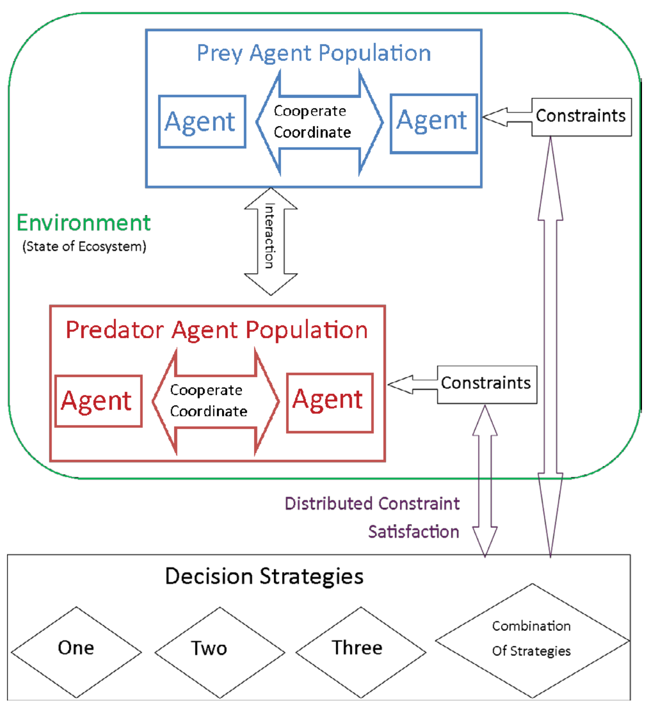

Figure 1: Schematic diagram showing agent interactions with environmental constraints while implementing different decision strategies.

The DCSP model	Ecosystem
Agents	Fish (Rabbit fish), Vessels, Predators (Groupers)
Constraints	Recruitment rate, carrying capacity, reproduction rate, predation rate, fish aggregation device rate, death, rate *k*, number of fish

Table 1: Formulation of the DCSP model components.

Data Item	Item Type	Variable	Unit	Value	Source
Rabbit Fish	Agent	Prey	Counts	Varied	Hicks et al.
Grouper	Agent	predator	Counts	Varied	Hicks et al.
Rabbit Fish	Constraint	Reproduction rate	Cm/day	0.06 (random float)	Arara et al.
Rabbit Fish	Constraint	Mortality Rate	day	0.005 (random float)	Arara et al., Hicks et al.
Grouper	Constraint	Mortality Rate	day	0.008 (random float)	Arara et al., Hicks et al.
Grouper	Constraint	Reproduction rate	Cm/day	0.003 (random float)	Arara et al., Robinson et al.
Rabbit Fish	Constraint	Ecosystem Carrying Capacity	Counts	1000	Robinson et al.
FADs	Constraint	Aggregation rate	day	0.5 (random float)	Aura (Unpublished)
Fishing	Constraint	Exploitation rate	day	0.001 (random float)	Arara et al., Hicks et al.
Primary Productivity	Constraint	Food	day	0.05 (random float)	Kimireri et al.

Table 2: List of agents and variables used.

solution that satisfies all constraints within the ecosystem including:

I. Introduction of more fish aggregating devices (strategy one)

II. Control of fishing by use of closure mechanism (strategy two)

III. Restoration of habitat that provides food for the target species (strategy three)

IV. Combination of strategy one and two

V. Combination of strategy one and three

VI. Combination of strategy one, two and three.

The constraints were fed to the model while tracking the changes in abundance over time (bad constraints led to depletion of fish stock over time). The solution to this problem was a compound label that includes all variables of all agents, that satisfies all the constraints as annotated in Figure 1.

The process of solving the problem involves simulating the different decision strategies while focusing on constraints to discover changes in the population of the target species. The DCSP model is applied in exploring and understanding individual behaviour and interaction among agents and the environment.

Output

This was obtained from the maximum time of observing target species abundance considering all constraints are controlled. A graph monitor was used to display the results as shown in Figure 2 below.

Research Results and Discussion

Multi-Agent Systems (MAS) have increasingly been used as simulation tools to explore and solve complex relationships between environmental change, human actions, and policy interventions. This study has demonstrated the use several different population of agents with their own different behaviours on a single environment (ecosystems). The constraint satisfaction approach has been used to study the status of the ecosystem and its impact to different species. All the data that was used was obtained from researchers and published papers according to the area of interest. The model was designed using the systems dynamics life cycle. This model was preferred since it allows for modelling of individual agent behaviours. All the data was obtained and broken down into days to represent the daily scenario of the ecosystem.

Simulating multiple agents and their interaction and constraints distribution

The model was simulated using NetLogo V5 simulation tool kit. Agents were built using stocks which represent population of agents. This allows for control of agent counts. Stock flows were used to show how population increases or decreases as a result of constraint changes. Links were used to show the interactions between different agents and also the impact of distributed constraints. The changes in population of the target fish was observed.

Modelling the initial state of ecosystem (Population growth curve)

The growth of population of the target species measured as increase in its size over a period of time and populations show characteristic patterns of growth with time as defined in the J-shaped population growth curve as shown in Figure 3 below. The population grows exponentially and after attaining the peak value, the population crashes abruptly.

From running the model, a J-shaped population growth curve was observed. The population density of the target agent (rabbitfish) increases rapidly in a logarithmic approach as shown in Figure 4, but then stops abruptly as environmental resistance (e.g., predation interference, overexploitation) or some other constraints (e.g., mortality) suddenly becomes effective. The other cause of such a decrease could be as a result of poor management decisions i.e., solving part of a problem instead of the whole global problem. The actual rate of population change also depends on the distributed constraint. Given $dN/dt=rN$ (with a definite limit on N) where N is the number of individuals in the population, t is time, and r is a constant representing the intrinsic rate of increase (constraints potential) of the species concerned, population numbers typically show great fluctuation. This is clearly a density-independent population growth as the regulation of growth rate is not tied to the population density until the final crash.

The growth phase: (exponential phase) has rapid increase in population growth, Low mortality rate, abundant resources available

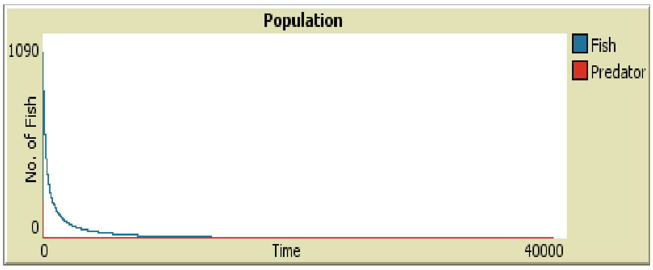

Figure 2: Graph to be used to display the model results.

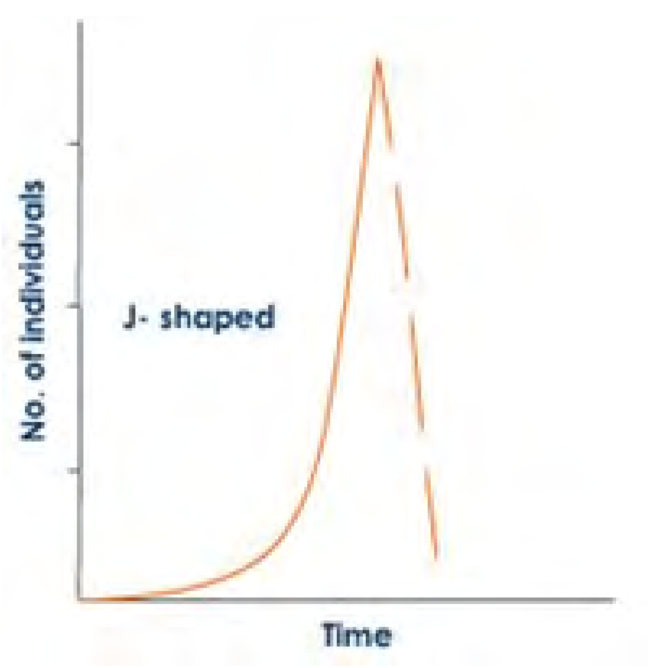

Figure 3: The J-shaped and Sigmoid curve for population.

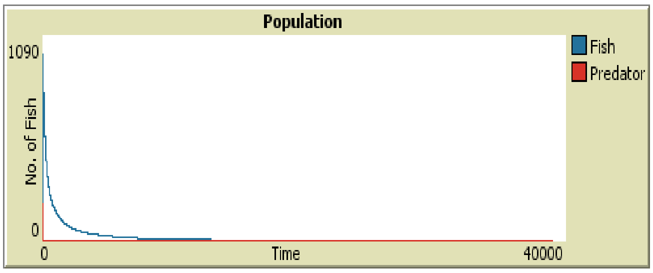

Figure 4: Output from the model showing current state of the population.

(Food), predators are rare.

Peak phase: mortality rate starting to rise, decrease in the number of resources, an increase in the number of predators and diseases, population still increasing but at a slower rate.

Crushing phase: The ecosystem has reached the carrying capacity for the target species and the number of predators has risen, with other constraints factored in.

Decision making strategy implementation based on the model

Three decision making approaches were tested including, introduction of more fish aggregating devices that are used to attract more fish into the plot (strategy one), control of fishing by use of closure mechanism (strategy two), and restoration habitat that provides food for the target species (strategy three).

Introduction of more fish aggregating devices (strategy one): The current rate of fish aggregation using FADs is a random float of ≤ 0.5. Considering all constraint remain constant and we increase the aggregation rate to ≤ 2.0. We notice a drastic change in the population of the target species as seen in Figure 5 below.

Control of fishing by use of closure mechanism (strategy two): When an ecosystem is at a level of crashing down, a closure decision may be reached so as to salvage and restore the ecosystem. This means the exploitation rate is reduced to almost nil (≤ 0.001) from the model to allow for recovery as seen in Figure 6.

Observations after imposing a closure (reducing the constraint to ≤ 0.0001) raised the stock level by almost 10% of the initial stock level. This is an improvement but also the level is still low as. The FADs rate is then introduced while still maintaining closure to test if there is any notable change.

Restoration of habitat that provides food for the target species (strategy three): The constraint current primary production rate is ≤ 0.01. This is attributed by natural disturbances and also use of illegal gears. Through the Kenya coastal development project, participatory habitats restoration exercise has been introduced and this is expected to increase the yield and hence enough food for the target species as seen in Figure 7.

The constraint was changed to ≤ 0.05 and an increase in population was observed. This has a direct effect in the ecosystem carrying capacity. When the primary productivity level increase, the ecosystem carrying capacity also increase hence more stocks can be sustained.

Combination of strategy one and two: After altering the FADs rate by ≤ 2.0, the stock level gains to above 80% of the initial stock level as shown in Figure 8. This is a confirmation that by imposing just closure as a constraint is not as effective as imposing both the closure and putting up additional mechanisms of attracting stock in including more or improved techniques of fish aggregation.

Combination of strategy one and three: An area that has been used by fishermen for years can be difficult to enforce a closure but a combination of several strategies can be used to enhance the stock levels. A combination of both the strategies one and three was tested and the results showed an amazing increase in stock level by almost hundred percent. An aggregation rate of ≤ 0.5 and primary productivity rate of ≤ 0.05 was used to do the test as demonstrated by output in Figure 9.

Combination of strategy one, two and three: It is difficult to enforce an ecosystem closure just to improve the stocks but it is possible to sustain the ecosystem by ensuring all constraints are satisfied.

This output based on different strategies as indicated in Figure 10 clearly indicate different agents and their behaviour have different impact to other agent populations. With constraint impacting on individual agents' behaviour, the constraints dynamically also affect the behaviour of other.

This output has demonstrated how multi-agent systems and

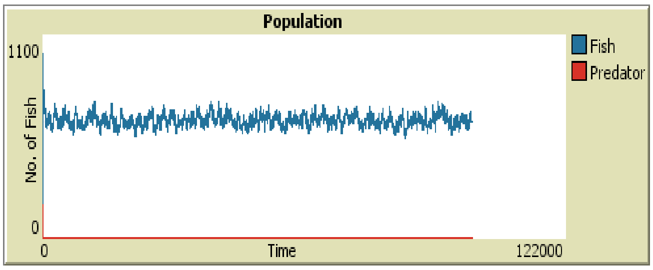

Figure 5: Showing effects of introducing more fish aggregating devices (strategy one).

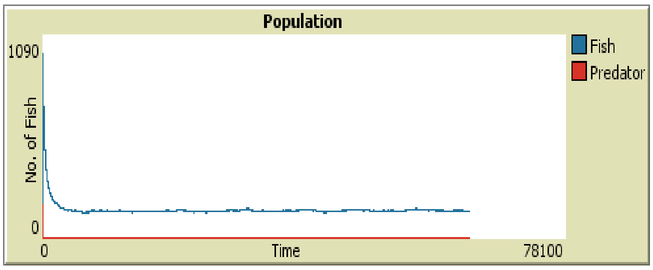

Figure 6: Showing effects of a decision strategy to enforce a closure (strategy two).

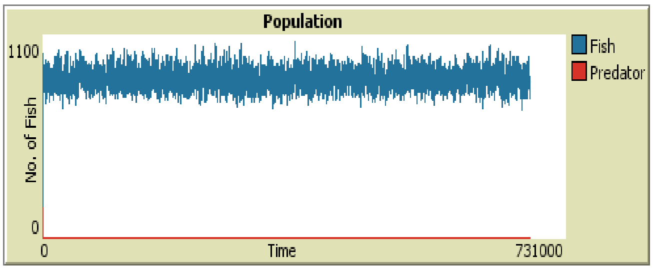

Figure 7: Showing effects of Restoration of habitat that provides food for the target.

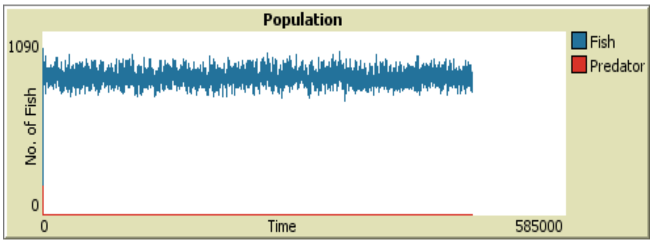

Figure 8: Showing a combination of strategy one and two.

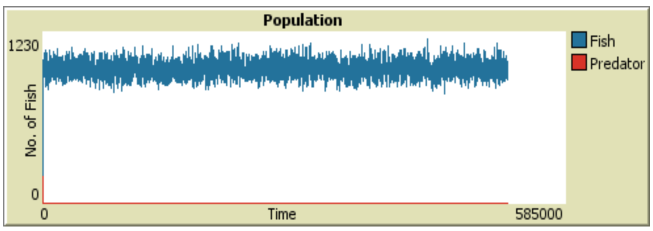

Figure 9: Showing a combination of strategy one and three.

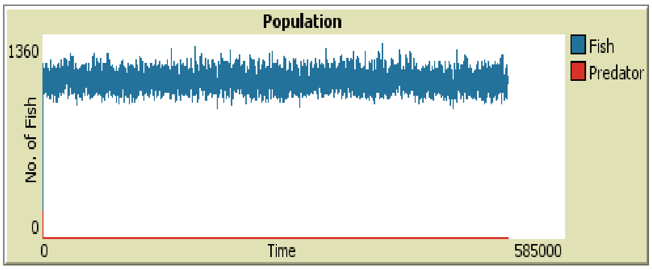

Figure 10: Showing Combination of strategy one, two and three.

distributed constraint satisfaction assist in making strategic decisions by allowing for strategic inclusion of different components of the ecosystems through the use of multiple agents while considering constraints and behaviour.

Multi-agent systems have proven flexible in their representation of different decision strategies concerning natural resources. The behaviour of individual actors can be modelled one-to-one with computational agents which allows for direct observation and interpretation of simulation results. A combination with distributed constraint satisfaction has shown how the decisions/policies affects marine ecosystem management.

This paper has demonstrated on the use of multi-agent models for the ex-ante assessment of multiple decision/policy interventions on ecosystem population dynamics.

Conclusion

The results have demonstrated an increase in the population index based on different strategies. This forms guide for the managers in setting up regulations concerning management of marine ecosystems through the use of this model just by adding data from the field surveys reports and predicting the outcome before implementing or formalizing any actual management intervention. The findings are expected to improve decision making process through fast reliable marine ecosystem problem identification and solution through the use of multi-agent systems model hence better management. Any decision support system that focuses on marine environment can incorporate and modify this proposed model and be able to address most ecological questions including ecosystems effects of fishing, evaluation of management policy options, evaluating impact and placement of different management interventions and general effects of environmental changes so as to maximize ecosystem health, mandated rebuilding of species hence maximizing social benefit.

It also builds on the productivity of decision makers and other stakeholders by better understanding the complexity of interactions in co- management of the resource.

Recommendations

This model is scalable since it allows for additional agents and constraints to be added to for complex problem solving. The model can be adapted by any form of ecosystem including corals and mangroves to assist in management effectiveness.

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