12-2015

Growth and Migration of Benthic Habitats: A Spatial Microsimulation Approach

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Research-in-Progress

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Abstract

Spatiotemporal visualization of the impact of geomorphological changes in coastlines benthic habitats can generate insight needful in understanding the spatial ecology of seafloors and in anticipating the location, growth and migration of marine sanctuary and marine protected areas (MPAs). Such understanding has implication for effective development and conservation of these MPAs. To date, there are limited studies that have applied complex adaptive systems (CAS) to investigate the impact of geomorphological changes on the location, growth and migration of benthic habitats. Also, there is a gap in our knowledge of the marine geographical information system (marine GIS).

To fill these gaps in the literature, we propose the use of the CAS theory as a lens to study the growth and migration of underwater (benthic) habitats in the Hawaii coastline using bathymetric SoNAR Multibeam data. We investigate the research question that concerns whether spatial approach helps in understanding the impact of projected geomorphological changes on patterns of growth and migration of benthic habitats of Hawaii coastlines. We develop a spatiotemporal IT antifact that engages a prediction machine to project individual data units (micro-data) to future states based on geomorphological changes using dynamic spatial microsimulation based method. The results of our study provide evidence of the contributions of spatial approach to understanding benthic habitat. The results also present research and practical implications for marine exploration and resource managers, and governments.

Keywords: spatiotemporal IT antifact, geographic information system, marine protection area, geomorphological change, complex adaptive system, marine reserve conservation.

Introduction

Studies have shown that many micro invertebrates and exploited fish in the coastal habitats have declined drastically; and the causes of these declines are unknown (Worm et al. 2006). These coastal habitats are no longer adequate to fulfil reproductive functions (McClanahan et al. 2011). Hence, we conduct our study using CAS to provide insight and understanding to top managements and government officials on how to improve the coastal (benthic) habitats for reproductive functions of micro invertebrates and exploited fish. Specifically we investigate whether spatial approach can aid our understanding of the impact of projected geomorphological changes on patterns of growth or migration of benthic habitats of Hawaii coastlines.

GIS-based mapping applications can serve as useful tools for communicating the status of marine ecosystems to policymakers and the society in general. Benthic habitat mapping helps to enhance stakeholder awareness and knowledge of the marine spatial landscape, facilitate public engagement with marine ecosystems, and provide a stepping board for marine conservation and management initiatives.

Stakeholders and policymakers in marine conservation, fishery development, oil and gas exploration and production, and governments require dependable information on marine reserves, benthic habitats and marine protected areas. Benthic habitat mapping and acoustic techniques have been recommended as useful techniques for exploring and understanding the spatial ecology of the seafloor (Brown et al. 2011). Interactive spatial mapping and visualization of the impact of geomorphic changes on coastlines benthic habitats can help in anticipating migration and location of marine sanctuary or marine protected areas (MPAs). Guest et al. (2014) argue for the emergency response application of similar visualization and analytic techniques in the evacuation of large urban structures, campus buildings, arenas, or stadiums, is of prime interest to emergency responders and planners. The taking and analysis of bathymetric measurements is one of the core areas of modern hydrography, and a fundamental component in ensuring the safe transport of goods worldwide

The size and composition of benthic habitats are ever changing spatiotemporally. These changes, driven by marine geomorphological, deformational, and water column processes (Halpern et al. 2008) need to be properly measured and analzed to provide actionable information for cost-effective developmental, risk management, and conservation initiatives. However, the paucity of marine data constitutes an impediment in getting such spatiotemporal information (Birkin and Malleson 2010). This study conceptualizes benthic habitats as complex adaptive systems and uses the dynamic spatial microsimulation method for generating useful benthic habitat data to overcome the data paucity problem.

Background and Motivation

Geomorphological processes are extensively studied in disciplines such as geology, geophysics, and geography. While geomorphologic processes do not fully account for the entire factors of change in benthic habitats, they can, however, serve as a proxy for defining or identifying such habitats (Halpern et al. 2008; Halpin et al. 2007).

Geomorphology explains the frictional effects of individual rock fragments, mineral particles, or sand grains robbing against the coastline rock material but may be ineffective in explaining or revealing the aggregate change effect of the combined natural agents. The geologic time required for enactment of appreciable geologic change makes empiric observation impractical. In order to address the time problem and the problem of capturing and visualizing overall change, a spatial microsimulation analysis is proposed.

Friedlandera and Parrisha (1998) present an identification process based on the habitat characteristics affecting fish assemblages while Iampietro and Kvitek (2002) present a habitat classification method, but they did not explain the aggregate growth and migration of marine sanctuaries. They did not perform any sensitivity (what if) analysis.

The entire process of a marine habitat's spatiotemporal change is viewed as a complex system because the abrasion of one surficial (near surface earth deposit) unit cannot determine the macro-level nature, growth and migration of the habitat. Rather, these macro level emergent behaviors, as is typical of complex, lack any single point of control. The emergent behaviors of complex systems can be unpredictable (Cooke-Davies et al. 2008; Rouse 2000).

CAS allows the analysis of complex systems without having to disaggregate them down into parts, before studying the disaggregated parts and then aggregating the results. We employ CAS to identify the agent components of benthic habitat change, study how these components interact to emerge patterns of coastline habitats, and develop a set of criteria for evaluating the effectiveness of change factors in determining the growth and migration of marine habitats.

We aim to present a dynamic spatial microsimulation model that can be used in generating and projecting microdata about the Hawaiian benthic habitat. Because the Hawaiian coastline does not have a continental shelf, its benthic ecosystems have not been adequately mapped. The paper is structured as follows. Literature review section briefly reviews the literature on complex adaptive systems and the use of dynamic spatial microsimulation method in modelling emergent system behaviors. Methodology section presents a novel method of updating the survey microdata and also describes a Markov model for the projection of the microdata. Results section shows the original bathymetry map of Haiwan islands and conclusion section offers some concluding comments.

Literature Review

There are multiple processes responsible for changes in benthic habits (Wright and Heyman 2008). These processes include geomorphology, deformation and chemical processes including water column (Samuel-Ojo ; Samuel-Ojo 2014). However, there is a growing body of work suggesting that the underlying geology and geomorphology are determining factors for the location and size of critical life habitat for variety of marine species. For example, the spawning aggregate of many species of commercially important reef fishes are found at the windward edge of reef promontories that jut into deep water(Heyman et al. 2007; Heyman et al. 2005) Pelagic fishes are attracted by seamounts (de Forges 2000). These findings imply that marine geomorphology can serve as a proxy for identifying critical life habitat for marine species (Lubchenco et al. 2007).

Geomorphology is the physical processes and products of gravitational or molecular shear stresses acting upon elastic, plastic or fluid earth material to produce abrasion effect of strain or failure that constitute weathering, erosion, transportation, and deposition (Strahler 1952). Marine geomorphology is the abrasion of the seafloor by these processes. With only 5-10% of the world's seafloor mapped, marine geomorphology and GIS remains a persistent gap in our knowledge (Sandwell et al. 2003; Wright 2003; Wright and Heyman 2008). Thus, study attempts to address this marine GIS gap of being able to predict growth and migration of habits.

Marine Geomorphology Processes

Recent advances in technology have enabled us to map the physical aspects of the geomorphic products of marine and coastal areas. These technologies include active remote sensing by airborne Light Detection and Ranging (LiDAR), and by ship-based multibeam echo sounder (MBES) Sound Navigation and Ranging (SoNAR). With these tools, we able to gain the geomorphology and habitat information through hydrographic surveys (Wright and Heyman 2008). We are also able to capture the water column properties (e.g. salinity, temperature, current speed and direction, chlorophyll content, turbidity, nutrients).

With the current technology and research, we are able to locate and classify habitats. However there exit little research on how interactive spatial visualization can be used to reveal the link properties of coastline data and geomorphology processes to the growth and migration of benthic habitats. This research proposes the use of complex adaptive systems as a lens to explore the growth and migration phenomena.

Complex Adaptive System

Complexity theories, in contrast to mechanistic theories, posit that complex systems exhibit macroscopic properties that emerge from interactions among system components rather than from a central governing structure (Beeson and Davis 2000). Those properties are irreducible, the underlying multiple causality invalidating any attempt at linear solution. Where studies based on mechanistic theories would seek to explain migratory and locational benthic events through deterministic rules, those adopting complexity science would recognize the recursive causal interplay of geomorphological and ecological processes. Complexity theories originated from the modeling of natural phenomena in natural sciences where they address the emergence of higher level order in dynamic non-linear systems. Non-linear systems are systems where the law of cause and effect does not apply directly (Beeson and Davis 2000; Gleick 1997)

There are three main branches of complexity theories: chaos, dissipative structure, and complex adaptive system (Bechtold 1997; Goodwin 1994; Prigogine et al. 1985). The complex adaptive system is more appropriate because it is the only one that does not create rules a priori for the whole system (macro approach), rather, it allows us to define rules for interactions between components (micro approach) of the benthic habitat. Thus, it is appropriate for exploring the link properties between the coastline data and geomorphic task characteristics to the growth and migration of benthic habitat.

Complex adaptive system is defined as a system consisting of agents interacting in self-organizing ways with each other and their environment (Holland 1992; Nan 2011). Complex adaptive system is poised between order and chaos, that self organizes and directs its activity towards its own optimization (Benbya and McKelvey 2006). It is a system that exhibits self-organization and emergence under tension (Vessey and Ward 2013). CAS is a complex system that consist of interacting agent, that undergo constant changes both autonomously and in interaction with their environment, through feedback and self-organizing by simple rules to produce complex and adaptive behaviors and pattern (Holland 1995). The patterns (habitat structure) are aggregated behavior and structure that are not predictable from the analysis of the parts of the system.

CAS provides the theory underlying the agent-based modeling simulation method allowing researchers to capture the interaction and relationship between entities and their environment. Agent-based modeling is a simulation method for modeling dynamic processes, autonomous agents and adaptive systems (Macal and North 2014; Marshall et al. 2015).

The uniqueness of agent-based modeling stimulation is in allowing for the development of individual level rules of behavior; it captures demographic and geographic heterogeneity; it enables agent interactions; it facilitates the modeling of grinding and wearing progression; it generates results that are natural representation of the special target, that can be synthesized and aggregated to define and understand outcomes (Gilbert 2008b; Macal and North 2010; Rahmandad and Sterman 2008; Siebers et al. 2010).

One of the agent-based modeling simulation methods is microsimulation. Microsimulation starts with a large database describing samples of individual members of a collection such as household, organization, or geomorphic and depositional system, then uses rules to update the sample members as though time is advancing. The seed data relates to the specific time period when the survey was carried out but microsimulation allows us to ask what the sample would look like in the future (Gilbert 2008a). Microsimulation has been used to access the distributional implications of changes in social security, in personal tax, in macroeconomic variables such as inflation, in different demographics and also in understanding spatiotemporal dimension of changes (Gupta and Kapur 2000; Harding 1996). Geographers have applied microsimulation to geospatial problems and introduced the spatial dimension (Tanton and Edwards 2014). With spatial microsimulation, we able to address the spatial effect of aging change processes.

Spatial Microsimulation

Spatiotemporal visualization of the impact of geomorphic changes on coastlines benthic habitats can help in anticipating migration and location of marine sanctuary or marine protected areas (MPAs) for effective development and conservation.

Spatial microsimulation has been successfully studied in other disciplines and used for analyzing small area income deprivation in economies, for understanding inequality in education, for reward and penalty processing games and for understanding demographic planning in public administration but it has not been studied widely in coastline spatial geographic information system.

The basic premise of microsimulation is that a more realistic picture of aggregate behavior can be derived from looking at individual behavior and modeling the interaction between individual unit in the system under consideration (Tanton and Edwards 2014; Zaidi et al. 2009). It was first used in social science by the pioneering work of Guy Orcutt and his colleagues (Orcutt et al. 1961). There are two main spatial microsimulation approaches: static and dynamic. Static spatial microsimulation concerns adding spatial dimension to target dataset and using aging technique by either updating or reweighting sample data to future generation but the process of aging is not modelled. Dynamic spatial microsimulation ages sample data and models the ageing process. We employ dynamic spatial microsimulation so that we are able to visualize the growth and migration of benthic habitats.

Spatial microsimulation is the process of creating synthetic spatial microdata to investigate real-world behaviors (Vidyattama and Tanton 2010). The number of the applications of spatial microsimulation is steadily growing worldwide; and there is a sizable literature on how spatial microsimulations have been applied to social policy, health care, spatial economics, and population forecasting (Birkin and Clarke 2012). Microsimulation can be used to maximize scarce survey data to investigate real world problems (Ramilan et al. 2012). Cullinan (2011) argues that spatial microsimulation approach can be used to simultaneously estimate the total number and economic value of sites in travel cost modelling. Microsimulation models are typically large-scale datasets of the attributes of micro-units (individuals, households or firms). Spatial microsimulation models can provide insights and understanding on 'real-world' counterparts (Ballas et al. 2006). One of the goals of spatial microsimulation is to 'construct' small area population microdata .Travel Microsimulation models are useful for short-term prediction relating to real-time setting or short-term policy measure (Flötteröd et al. 2012). Spatial microsimulation can provide insights and understanding to estimate expenditure flows from households to retail stores (Nakaya et al. 2007). Microsimulation models can be used to estimate farm income from farm accountancy data network database (Hlouskova and Slížka 2014).

Spatial microsimulation and in particular dynamic spatial microsimulation is attracting a growing interest in various domains. The following section describes the process of dynamic spatial microsimulation method in order to investigate the temporal and spatial impact of geomorphological changes on patterns of growth or migration of benthic habitats.

Methodology

We address the research question that concerns whether spatial approach helps in understanding the impact of projected geomorphological changes on patterns of growth and migration of benthic habitats of Hawaii coastlines. With the complex adaptive systems (CAS) theory as the study lens, we develop a spatiotemporal IT antifact that engages a prediction machine to project individual data units to future states based on geomorphological changes using dynamic spatial microsimulation. We employ bathymetric ship-based multibeam (MBES) Sound Navigation and Ranging (SoNAR) datasets. The multibeam datasets capture the seafloor, backscatters and water column data using SoNAR sensors and are both structured and unstructured, with tendency to grow in volume, velocity, variety, and variability, in hundreds of Terabyte size, a description that warrants a big data treatment (Bizer et al. 2011; Han et al. 2011; Junwei et al. 2011). These datasets are georeferenced and thus provide the spatial reference as well as the attribute dataset.

This spatial dynamic microsimulation approach will provide rich insights into the growth and migration of benthic habitats.

Dynamic spatial microsimulation

Dynamic spatial simulation method projects each individual units of data (micro-units) to a future state while altering its attributes based on predefined rules. The rules relate to the unit's properties and change factors. The method can be used to model series of geomorphic and deformation transitions much like it has been used to model series of demographic and socio-economic transitions. Rules are used to update the transition states of the micro-units. Updating process could be based on deterministic rules (unit ageing or change in depositional or weathering state) or probabilistic change of state (i.e. probability of depositional sequence changes due to the prevalence of weathering, transportation and deformation situation) (Birkin and Clarke 1995).

The dataset requisite datasets include at least two datasets: geospatial and attribute datasets. The attribute dataset is used to create a microdataset and should contain detailed sample of the population. Transition probabilities are derived from the proportion of units engaged in a transition from one state to another. They can also be assigned by stochastic methods such as Hidden Markov Model (HMM). With the transition probabilities, the dynamic spatial microsimulation model predicts the future states of the original dataset.

Formulation of the antifact prediction machine

This section discusses the formulation of the prediction machine that constitutes the core of the artifact. The prediction machine consists of the observed micro-units inputs (geomorphological units), hidden states (unobserved geomorphological states), and generated states (mapped habitat showing spatiotemporal pattern).

Geomorphological units

We define the structural features of the benthic environment (geomorphologic units) as the micro-units. These geomorphologic units form the building block of the proposed spatiotemporal IT antifact. The geomorphological units constitute the individual rock units that interact with the benthic environment. The inhabiting organisms (for example fishes, planktons, sea reptiles and mammals) are modelled as the interacting environment. The interaction between the geomorphologic units and organic environment evolves the habitat and is mediated by three core geomorphological processes: physical, biological and chemical.

We define benthic transition states based on habitat classification of the European Union habitat classification called EUNIS (EUNIS 2015). The classification recognizes the following types of benthic habitat.

Sandbanks. They are sands that are slightly covered by seawater. Examples include living and engineered shorelines, beaches with abrasive substrate which are dominated by burrowing organisms.

Estuaries. They are locations where rivers meet the sea. An example includes a delta area.

Sandflats. They are areas not covered by seawater at high tide condition.

Salt marsh. They are areas used by organisms for resting.

Mussel bed. They are locations used by organisms for feeding.

Mudflats. They are areas not covered by seawater at low tide condition.

Intertidal flats. They rival rainforests on land for biomass production per square meter. Examples include rocky tide-pool habitats, seaweed and kelp forests.

Subtidal regions. These regions contain channels and gullies.

Coral reefs. These habitats are hard surfaces and are created by corals. Corals are colonies of animals and individual polyps. They create the reefs and host zooxanthellae which are photosynthesizers.

Open seafloor. This area consists of hard surfaces with burrow for breeding and is inhabited by organisms that utilize chemosynthesis (use of chemical energy for carbohydrate production) other than photosynthesis (use of sunlight energy for carbohydrate production). It may exhibits seamounts, canyons, mud volcanoes and spreading ridges.

Since the multibeam field data does not discriminate these geomorphological units, a bathymetric map is produced from the multibeam (as shown in figure 1) and then supplied as input to an unsupervised classifier. These classifier provides the micro-units that will be used as an intermediate input to the first order hidden Markov model.

First order hidden Markov model

The Hidden Markov Model (HMM) as an analysis tool has been employed for: investigating handwriting and speech recognition (Liu et al. 2003; Rabiner 1989), computer vision (Bunke and Caelli 2001), evaluating the creditworthiness and likelihood of defaults of corporations, sovereigns and borrowers

(Jarrow and Turnbull 1995), Bioinformatics (Koski 2001), estimating transition probabilities and discrete value time (MacDonald and Zucchini 1997). HMM consists of two types of states: the observable states and the hidden states. In our method, we formulate the hidden states by combining the types of habitats and their possible migration from one state to another.

We propose a Hidden Markov Model to assign the transition probability. Let a Markov chain consist of 10 geomorphological states namely Sandbanks, Estuaries, Sandflats, Salt marsh, Mussel bed, Mudflats, Intertidal flats, Subtidal regions, Coral reefs, Open seafloor, represented by S^1, S^2, S^3, S^4, S^5,S^6, S^7, S^8, S^9, S^{10} respectively.

1. A set of n individual states S^n,

   $S = \{ S^1, S^2, \ldots, S^n\}$, and the state at the length t is q_t.

2. A set of m distinct observed sequence symbols V^m (or states) which correspond to the physical geomorphological units of benthic habitat being modeled.
   $V = \{ V^1, V^2, \ldots, V^m\}$
3. Let a_{ij} be the probability of transition from ith geomorphological state (i = 1, 2, 3, … 10) to jth geomorphological state (j = 1, 2, 3, … 10) in which the ith state precedes the jth state. Then the probability of transition, parameter A, is given the expression:

$$A = \begin{array}{cc} & S^1 \ldots S^{10} \\ \begin{array}{c} S^1 \\ \vdots \\ S^{10} \end{array} & \begin{bmatrix} a_{1,1} & \cdots & a_{1,10} \\ \vdots & \ddots & \vdots \\ a_{10,1} & \cdots & a_{10,10} \end{bmatrix} \end{array}$$

   where

   $a_{ij} = P(q_{t+1} = S_j | q_t = S_i), \quad 1 \leq i,j \leq n$

4. The observation likelihood distribution in state j, $B = \{b_j(k)\}$, where

   $b_j(k) = P(O_t = v_k | q_t = S_j), \quad 1 \leq j \leq n; 1 \leq k \leq m$

5. The initial state or start state distribution of the model is $\pi = \pi_i$ where

   $\pi_i = P(q_1 = S_i), \quad 1 \leq i \leq n$

   Given the values of n, m, A, B, and π, the HMM can generate a projected observation sequence

   $O = O_1 O_2 O_3 \ldots . O_T$

   where each observation Ot is one of the symbols from V, and T is the number of observations in the sequence.

   Then the parameter of the proposed HMM model compact notation is

   $\Lambda = (A,B, \pi)$

The second parameter in the Markov chain, B, is a sequence of observation likelihoods (also called emission probability) which expresses the probability of an observation Ot being generated from a state i. This parameter may be estimated from the proportion of observations generated from a state using the local geologic information and water column data.

Hidden spatiotemporal states

We propose 10 hidden geomorphological states namely sandbanks, estuaries, sandflats, salt marsh, mussel bed, mudflats, intertidal flats, subtidal regions, coral reefs, and open seafloor. Based on the above model specification, we employ Markov chain of first order. A Markov chain is said to be of first order if each state has one-step backward memory, i.e. each future state in the chain is dependent on the immediate present state only. We formulate plausible assumptions about the depositional probabilities of different individual observable geomorphological units and incorporate them in the model. For example, the interaction between physical and biological processes lead to the development of tidal flats with pioneer plant that may eventually form salt marsh (Harris and Baker 2011)

Generated spatiotemporal states

The dynamic spatial microsimulation model is based on geomorphological rules used for transiting from one state to another. These rules help in the determination of the observed likelihood probabilities for generated geomorphological unit. The solution of the above HMM specification requires three tasks: evaluation of the likelihood probability, decoding the best hidden state, and training. The evaluation task is performed by the forward-backward procedure. The decoding task is the process of determining which sequence of variables is the underlying source of some sequence of observations. Decoding can be solved by the Viterbi algorithm. The training task is performed by Baun-Welch algorithm. Further details of these procedures are presented in (El-Yacoubi et al. 1999; Rabiner 1989).

It is important to note that the proposed dynamic model of Hawaii benthic habitat in this paper is a basic form and is at an experimental stage. As a subject of further research, a robust validation of the generated data output will be performed. Despite this stage, this paper provides useful information concerning using spatial approach (via spatial dynamic microsimulation) to simulate future benthic habitats, thereby improving our understanding of the impact of projected geomorphological changes on patterns of benthic habitats.

Results

The study utilizes the dynamic spatial microsimulation method to project Hawaii habitat ecosystems data into the future and visualize possible MPA growth and migration. The bathymetry map in figure 1 shows a synthesis of SoNAR multibeams into a bathymetry map. This map serves as the input map to an autoclassifier. The autoclassifier detects various geomorphological units as discussed in the methodology section. These units are fed into the prediction machine of the spatiotemporal IT antifact that produces a projected spatial pattern of growth or migration of the benthic habitats.

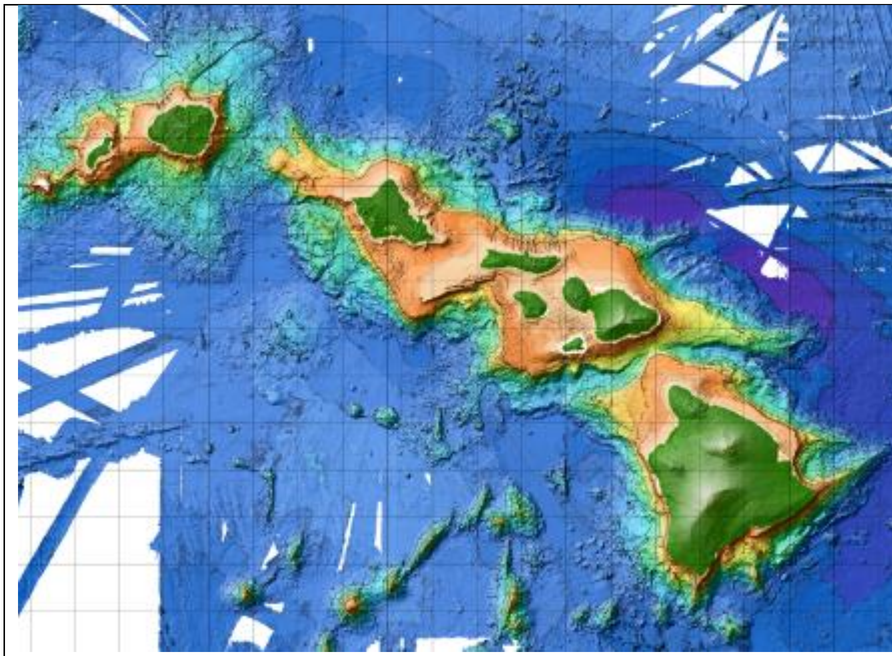

Figure 1. A bathymetry map of main Hawaiian islands derived from multibeam data synthesis on scale of 1:200,000.

The geodetic parameters of the map in figure 1 include horizontal datum and ellipsoid are WGS-84 on Mercator projection and central Meridian of 0. The grid cell size is 50 meters with a 200 meter contour interval. The illumination is from the Northwest. Elevations for the islands are derived from USGS digital elevation model. Courtesy of Hawaii Mapping Research Group, University of Hawaii School of Ocean and Earth Science & Technology.

We hope to show that spatial approach helps in understanding the impact of projected geomorphological changes on patterns of growth or migration of benthic habitats of the Hawaii coastlines. In addition we hope to provide evidence in support of CAS theory and insights for theory and practice of benthic habitat conservation.

Conclusion

The location and size of benthic habits influences marine reserves such as fish assemblage, marine protected areas (MPAs) and historical sanctuaries. In this study we propose the use of complex adaptive systems (CAS) as a lens to explore the growth and migration of marine sanctuary or MPAs by a spatiotemporal visualization of the impact of geomorphic changes on patterns of coastlines benthic habitats using dynamic spatial microsimulation method. Spatiotemporal visualization can help in anticipating location, growth or migration (if any) of marine sanctuary or marine MPAs for effective development and conservation.

We review spatial microsimulation studies and how spatial microsimulation based method has been used in other domains: for analyzing small area income deprivation in economies, for understand inequality in education, for reward and penalty processing games and for understanding demographic planning in public administration but it has not been studied widely as a spatial approach to understanding coastline spatial geographic information system (spatial GIS). We address this gap in literature by proposing the use of CAS theory as the lens to study the growth and migration of underwater (benthic) habitats in the Hawaii coastline using bathymetric SoNAR Multibeam data.

We investigate the research question that concerns whether spatial approach helps in understanding the impact of projected geomorphological changes on patterns of growth and migration of benthic habitats of Hawaii coastlines. We develop a spatiotemporal IT antifact that engages a prediction machine to project individual data units (micro-data) to future states based on geomorphological changes using dynamic spatial microsimulation based method.

We conclude by discussing the method of dynamic spatial microsimulation for projecting the benthic habitat data to expose possible MPA growth and migration. The results of this simulation will provide spatiotemporal visualization that can generate insight needful in understanding the spatial ecology of seafloors, an understanding that has implication for effective development and conservation of marine sanctuary and marine protected areas. It will provide evidence of the contribution of spatial approach in understanding the impact of projected geomorphological changes on patterns of growth or migration of benthic habitats. Finally, it will present research and practical implications for marine exploration and resource managers, and governments.

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