Iterative Design and Development of the 'World of Balance' Game: From Ecosystem Education to Scientific Discovery

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Abstract-Advances in computer science are continuing to help expand a new subfield of ecology based on computational analyses of complex ecological networks where the nonlinear dynamics of many interacting species can be more realistically modeled and understood. Research has recently elucidated how the network structure of feeding relationships both generally stabilize complex ecosystems and also specifically predict effects of experimentally removing species. Still, further research is inhibited by the exponential increase of parameter space with the number of nonlinearly interacting species. Such increases prevent more thorough exploration and understanding of complex ecosystems. Here, we describe how intelligent interfaces for multiplayer games help researchers surpass these limitations. Our applications including a multiplayer online game, "World of Balance," educates players about interdependence and non-linear population dynamics among species within ecosystems while helping to explore critically important parameter space in a scientifically productive manner. Our evaluation tests found that benefits of playing World of Balance on knowledge gain and learning significantly surpassed the benefits of reading scientific articles among undergraduates. Such work efficiently leverages multiple resources to expand education and research potential within critically important areas of ecology and sustainability science.

Keywords— Ecology game, Science Discovery Game, Education game, Food Webs, Ecological Networks

I. INTRODUCTION

Computer games lie at the core of human computer interaction both in terms of technical advances and sheer volume of such interaction. Such games go beyond entertainment to include education, training, human computing and even science discovery. These games serve as intellectual interface in human computer interaction to make use of the individual and collective problem solving skills of non-experts using a game-like mechanism [1,2,3,4,5,6,7]. For example, Google helps produce high quality WWW image search results by employing an image labeling game that synergizes human image-recognition and computational abilities [1,2]. Anonymous people are paired over the Internet to match labels for the same image within a given time as they are entertained while labeling images. Several other approaches also achieve successful results [6,7,8]. Another example is the multiplayer game, "Foldit," which helped launch a new 'science discovery' gaming genre. Foldit has

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enabled interested game players to collaboratively use their learned and intuitive skills to quickly solve a protein folding problem for an important AIDS-related enzyme that stymied the scientific community for a decade [3,4].

The central challenge in developing scientific discovery games is transforming scientific exploration activities with an application that synergizes human problem solving skills and compelling human-computer interaction design. This process benefits from iterative game design that incorporates feedback from players and content experts [9] where a team of developers including game developers, content experts, and players effectively explore the connection between science and meaningful game play. We used this iterative process to develop the 'World of Balance' game ('WoB' hereafter) as an educational multiplayer online game that emphasizes ecological community assembly and management via species establishment using a simulation engine based on recent advances in ecological network dynamics. This basis also enables WoB to facilitate scientific discovery in ecological research on the effects of critical ecosystem threats from biodiversity loss and species invasions to climate change and pollution. WoB game play explores how these threats impact nature's dynamic balance of many different species interacting within complex ecosystems. The many parameters governing the high dimensional and nonlinear dynamics of tens to hundreds of interacting populations within these networks form huge parameter spaces. Scientists have explored only a small fraction of this space so far. Beyond entertainment and education, we also developed WoB as a Science Discovery Game that helps explore this space based on cutting edge software and hardware. WoB is designed to engage many players employing both the adaptive strategies at which human players excel and also collective computational power in order to surpass critical limitations of the relatively small community of scientists currently active in this area. WoB gameplay can greatly and strategically increase the parameter space explored by simulations. It can do this by adding data to WWW-accessible databases containing the time series from game simulations that could be accessed and analyzed by scientists and statisticians. Such analyses could substantially help illuminate how ecosystems may be sustained, exploited and harvested. While scientists currently pursue such research with methods such as stochastic parameter selection using limited cyber-infrastructure [10,11,12,13,14], such research is insufficient given the importance and urgency of sustaining critical human interactions with ecosystems.

II. GAME DESIGN AND DEVELOPMENT

A. Ecological Research

The destruction of biodiversity continues to degrade ecosystems' abilities to sustain human and non-human life [15]. Ecosystems are complex systems comprised by networks of diverse interacting and interdependent species. At the core of these networks is a "food web" that depicts consumer-resource interactions that are primarily feeding relationships among species. These interactions make up the interconnected food chains found within habitats such as lakes or forests [16]. Ecologists and the rest of humanity need to better understand ecosystems in order to help manage threats to them. Only recently has this understanding progressed to the point that realistically complex ecosystems can be computationally modeled [13,17]. This advance emerged from computational studies of ecosystems that uncovered how such nonlinear high dimensional systems may dynamically persist despite their well-known mathematical improbability [18]. While earlier models of such systems failed to persist, the new insights into the network structure, feeding behavior. and metabolic maintenance costs of species' persistence enabled such systems to be modeled as nonlinear, high dimensional, coupled with ordinary differential equations that characterize the bioenergetic feeding and biomass dynamics of complex networks of persistently interacting species [10]. Such advances led to a resurgence of basic research on ecological stability and initiated new and highly active computational research focused on the ecological effects of species invasion, extinction, and metabolic requirements as well as pollution [10,11,12,13,14,19].



Fig. 1. Network3D provides user friendly browser based interface and visualization and analysis tools for computational ecology models [20]

Computational studies of species loss can now quantitatively predict the effects experimental species removals on the abundance of other species [10] and suggest which additional species to eliminate in order to prevent extinction cascades resulting from the initial loss [12]. The urgency of environmental problems and complexity involved in solving them require new advances to computational approaches to these problems. More usable approaches are needed to enable ecologists and other non-computational experts to conduct computational research. More powerful approaches are needed to explore more in depth and larger networks of increased complexity that reflect more of the variability, interactions, and environmental problems found in nature.

Computational approaches are helping to continue such research by modeling specific habitats [14] (e.g., coral reefs, lakes, forests, etc.). Below, we describe an advanced and highly general approach [10] that improves the power and usability of modeling, data management, and visualization (Fig. 1). The Niche Model [13, 21] generates the initial structure of the food webs and has two input parameters: the number of species S and connectance C where $C = L/S^2$ and L is the number of trophic links. The model assigns a uniformly random "niche value" $(0 \le n_i \le 1)$ to each of S species [22]. Consumer *i* eats only species whose niche values are contained within a range r_i with a center of $c_i < n_i$. c_i is randomly chosen from a uniform distribution between r_i/r_i 2 and $min(n_i, 1 - r_i/2)$. $r_i = xn_i$, where x is a random variable defined on [0,1] with a beta-distributed probability density function $p(x) = \beta(1-x)^{\beta-1}$ with $\beta = 1/(2C) - 1$.

We use 17 network properties to describe food-web structure [13,16,21,23]: Top, Int, Bas are the proportions of species that are respectively without predators (top), with both predators and prey (intermediate), and without prey (basal); Can, Herb, Omn and Loop are the fractions of species that are cannibals, herbivores (only basal prey), omnivores (i.e. feeding on multiple trophic levels) and involved in loops (apart from cannibalism); ChLen, and ChNum, the mean length, standard deviation of length and log number of the food chains; TL, the mean short-weighted trophic level of species [13]; MaxSim, the mean of the maximum trophic similarity of each species; VulSD, GenSD and LinkSD are the normalized standard deviations of vulnerability (number of predators), generality (number of prey) and total links; Path is the mean shortest food-chain length between two species and *Clust* is the clustering coefficient.

$$\dot{B}_{i} = r_{i} \left(1 - \sum_{j \in autotrophs} \frac{B_{j}}{K}\right) B_{i} - \sum_{j \in consumers} x_{j} y_{ji} B_{j} \frac{F_{ji}}{e_{ji}}$$
(1)

$$\dot{B}_{i} = -x_{i}B_{i} + \sum_{j \in resources} x_{i}y_{ij}B_{i}F_{ij} - \sum_{j \in consumers} x_{j}y_{ji}B_{j}\frac{F_{ji}}{e_{ji}} - \sum_{k \in firms} q_{k}E_{ki}B_{i} \qquad (2)$$

$$F_{ij} = \frac{\omega_{ij} b_j}{B_0^h + c B_i B_0^h + \sum_{k \in resources} \omega_{ik} B_k^h}$$
(3)

Eq. 1 and 2 describe the changes in the biomass densities of an autotroph and a heterotroph species, respectively where r_i is intrinsic growth-rate of basal species *i*, *K* is plant carrying capacity, x_i is *i*'s metabolic rate ($x_{basal} = 0$), y_{ij} is the maximum consumption rate of *i* eating *j*, e_{ij} is *i*'s assimilation efficiency when consuming *j*. Eq. 3 is the functional response [13] with B_0 as the half-saturation density, *h* is the Hill exponent set to 1.2, *c* is predator interference and ω_{ij} is *i*'s preference towards *j*). The current implementation of these equations includes 3 node parameters and 6 link parameters which cause parameter species to very quickly increase with the number of nodes and links making vast variations of simulations possible as well as conceptually and computationally highly demanding. The high dimensional, nonlinear, and nonrandom nature of these networks largely prohibits more analytical approaches from shedding much light on their behavior. This makes the harnessing of science discovery game approaches to scientific problem solving a novel computer science challenge deserving of innovative research efforts.

B. Specific Aims and Methods

Game Mechanics of Season 1 (1st Iteration)

We iteratively designed and developed the 'World of Balance' game. The 1st iteration's objective during season 1 was to develop effective gameplay that connects the game contents with the state-of-the-art computational population dynamics simulation engine from Pacific Ecoinformatics and Computational Ecology Lab (www.foodwebs.org) based on the equations in the previous section. While such an engine could be applied to any ecosystem, we decided to apply it to the Serengeti ecosystem of Africa to minimize development time and maximize user engagement with game content. Much pre-existing artwork is available for the Serengeti organisms from Baobab trees through elephants, zebras and lions. Also, due to widespread familiarity of players with these organisms and their feeding habits, players can quickly understand ecological game dynamics. Finally, the food web of the Serengeti is well studied by ecologists [24,25] which illuminates many of the species' interactions and parameters essential to running the simulation engine.

Inside WoB, players are given money (gold) and empty land that they use to nurture their Serengeti ecosystems by buying plant, animal, and insect species (biotic components) to add one by one up to 95 real representative species in a recently described food web of the Serengeti [24,25]. The site http://smurf.sfsu.edu/~debugger/wb/ provides a downloadable client, user guide, animated tutorials, and tips to play the game. Season 1 is largely inspired by "Farmville", a farmnurturing game that is leisurely played by over 100 million players. The survival and abundance of the species are dynamically determined by the abundance of resources such as food and water as well as the abundance of consumers such as herbivores and carnivores as determined by equations 1 and 2. Players maintain an ecological balance by buying resources for species heading for extinction and buying consumers for species whose expanding populations are driving their resource species extinct. The game is designed to provide a core compelling experience of discovering ecological interdependence by drawing the player's attention to these dynamics as well as to the checks and balances of these dynamics. As players advance to higher levels by maintaining a diverse ecosystem, they gain access to new species and powers to alter their dynamics. Figure 2 and 3 shows the architecture of the game; how clients, the game server and simulation engine web services interact with each other. Figure 2 shows the view from the Network3D Research Computation Framework where WoB utilizes the computation model as other research tools do while figure 3 focuses the view from the WoB game where the game server connects to computational model.



Fig. 2. A tool called Network3D is used to simulate the complex non-linear systems that characterize these problems (i.e., Equations 1-3 and Fig. 1). A web service provides the user with an interface where the user can initiate, monitor and manage their manipulations as well for other sites and visualization clients. The Network3D visualization client (research tool for ecologists) communicates through web services and visualizes the ecological network and population dynamics results in the same way that World of Balance game communicates.



Fig. 3. The WoB game supports multiple players connected through game server that communicates with simulation engine web services.

Figure 4 shows the communication and interpretation between the simulation engine, web service, game server, and client. Biomass data of the current species at a certain time stamp called "game month" is sent to simulation engine via the game engine. The game engine receives the list of species and their biomass data for the next game month as well as other parameters from the simulation engine. The game server interprets the biomass data produced by the simulation engine as a prediction for the next game month events and sends instructions of actions (lion A eats giraffe B, giraffe C gives a birth to giraffe D, giraffe C walks to water source to drink, etc.) to clients.

Good communication and rewards are key to successful gameplay. Better gameplay is communicated by higher scores for maintaining more species and higher biomass during gameplay. This key feedback emerges from the environmental score formula:

Score = $([\log_2 (\text{Total Biomass})] * 5)^2 + (\# \text{ of Species})^2$



Fig. 4. Biomass data per species related from (1) client to server, (2) converted at server to be sent to simulation engine, (3) simulation engine back to game server, and then (4) interpreted by game server back to client.



Fig. 5a. Ecosystem with 15 species without user intervention



Fig. 5b. Corresponding Environment Score char for an ecosystem with 15 species (figure 5a), a very ideal case.

The charts above and below (Fig. 4-6) show changes of biomass of species in the game and the corresponding environment score. Purchasing more species and nurturing the growth of new and existing species' populations increases the score. The scoreboard shows the records of the highest score holders and its visibility to all players provides the highly motivating reward of social status to players achieving highest environment score. Players have the option of seeing other player's badge counts. Eagle badges are given to those who achieve the highest environment score for each time they achieve it. Elephant badges are given to those who maintain a minimum of 80% of the eagle badge threshold for 12 consecutive game months. The figures below (Fig. 7a-c) show screen shots of the game and user interfaces.



Fig. 6a. Ecosystem with same 15 species, but different starting biomass and parameters. Not a good gameplay as species are quickly dying out.



Fig. 6b. Corresponding Environment Score char for an ecosystem with 15 species (figure 6a), not so good case.

WoB encourages players to learn important aspects of ecosystem development, ecological balance and system stability while producing large amounts of useful scientific data. Players use the game interface to intuitively explore huge parameter spaces. Many parameters are determined by the network structure of feeding relationships which determine the consumers (e.g., predators) and resources (e.g., prey). Given the 95 species to choose from, players explore 95! \approx 10¹⁴⁸ different sequences of adding species each species only once to their system. Such parameter space is actually effectively infinite because there is no limit to how many times players can add species. Furthermore, the abundance of added species depends on how much currency the player wants to spend. Additionally, the abundance of other species in the system are typically different every time a new species is added. Players manipulate parameters based on the knowledge and intuition about such factors as who eats whom

and carrying capacity represented by rainfall as well as metabolism and growth rates that systematically depend on body size and whether organisms are endotherm (i.e., "warmblooded" mammals and birds) or ecotherm (i.e., "coldblooded" snakes and lizards) vertebrates [26]. Further "super powers" of advanced players allow them to alter factors such as assimilation rates (e_{ii} in eq. 1 and 2) which determine how much energy within a consumer's food item provides for maintenance and growth of the consumer. Assimilation raters are typically much less when the food item is a plant compared to when it is an animal. Users can also change the feeding preferences of consumers (ω_{ij} in eq. 3) which alters the rate of consumption in response to variations in prey density. Feeding preferences mimic how consumers such as predators divide their time among searching for, attacking, and processing prey of different species as a function of prey density. Predator interference (c in eq. 3) mimics how much consumers prevent each other from eating as consumer density increases (e.g., when consumers maintain territories free from other consumers). Simulation results for each time step or a single game day depending on player activity are fed to the game engine which maps them onto meaningful game activities depicting changes in abundance of each species that users experience and interact with further.



Fig. 7a. Screen capture from World of Balance game; Orange: Game Time simply tells you how much time has past since you started the world. Red: Shop allows you to purchase a variety of different species. The cost is different for each species. The list grows as you level higher. There are multiple categories of species and are filtered using the dropdown menu in the upper-left. Blue: Stats Bar shows your current level, experience required to level up and the total amount of gold you currently have. Yellow: Chat allows you communicate with other online players. The name and message will be shown as it is received. Green: Top Scores shows the top 3 players' score from 3 categories, which are High Score, Total Score, and Current Score. High Score represents the highest Environment Score one has ever achieved. Total Score represents the most accumulated score. Current Score represents those that currently hold the highest score. Purple: Number of active players online, which includes you and others, if any. Brown: Menu provides a few options such as being able change the volume and quitting the game. Cyan: Avatar is simply just an in-game visual representation of you as a player. Magenta: Extra Features such as Stats, which displays the changes in population, Charts, which provides you with graphs that show the change that has happened over time, Params, which is short for parameters that allows you to change metabolic, growth, and other rates that affect the different species.

Results from gameplay stored in a web accessible database are the primary resource for more scientific exploration. Scientists can query the database for various systems of interest such as the systems with extreme number of species, biomass, and population stability. Other interesting results concern systems most robust to species loss and invasion. Much current research does largely the same thing without the benefit of larger volumes of results from more intuitive parameter sweeps. Future analyses may encourage players to achieve specific objectives such as the most biomass at specific trophic levels to facilitate particular research projects.



Fig. 7b. Stats is a display option used to keep track of what species was introduced into the environment including how many were given birth and even death. By looking at the present and months before allow you to see the change in population at a more technical level. The interface is divided into two sections, top and bottom. The top section shows the exact size of each species in your current environment. The bottom section shows the history of growth and reduction as each month goes by.



Fig. 7c. The Chart System is a very helpful tool that tracks different changes in a period of up to 10 months. There are a total of 3 different types of data that can be graphed, which can be selected from the drop-down menu in the upper-right. "# of Organisms" shows the abundance of each species in terms of the number of organisms in each group. Each species is represented by a different color. Biomass shows the amount of biomass for each species for each month. Environment Score shows the player's score and how it changes each month. This tells the player how well their ecosystem is now compared to before. Each chart can be manipulated by hiding each line of data by clicking on their names to the right. In doing so, the graphs may be recalculated and redrawn to only represent data that the player wants to see.

WoB uses same game engine to support both collaboratively nurturing worlds (inspired by Farmville in "Player vs. Environment" mode) and competitively battling worlds (inspired by StarCraft, or "Player vs. Player" mode). Modes are switch primarily by altering the game day scale. Players can build and nurture complex balanced ecosystems by collaborating with each other or battle out to unbalance and destroy the ecosystems created by other players. Players achieve both collaboration and competition by causing animals in their ecosystem to migrate another player's ecosystem. In both modes, players experience the process of ecosystem functioning and energy flow from producers (plants) to herbivores and carnivores. Players also experience the complex prey-predator relationships that exist among species along with the interdependence responsible for ecological balance and imbalance. The game also facilitates players to share their progress in the game with their friends by posting it on their Facebook wall.

These approaches use social interaction, cooperation, and competition to motivate and enable players to enjoyably conduct important science. Also this approach takes advantage of human's adaptive strategy development in narrowing down and directing parameter searches. To improve the environment score or earn more badges, players can decide based on heuristics and intuitive strategies that cannot be made into fixed algorithm. Human's adaptive intuition grows quickly over trial and error. Game playing also provides a safe environment where players can fail and try again.

III. RESULTS

We have completed the first iteration of user engagement evaluations and efficacy testing of the WoB season 1 game. Over the course of 2 months, 10 San Francisco State University (SFSU) undergraduates participated in user engagement evaluation where participants played and interacted with WoB consistently as the game was being further developed and updated. We applied the Agile Approach of dynamic and rapid iterative development approach by collecting user engagement data at the end of each development iteration. This allowed us to review development progress being made through the eyes of the users and help evaluate whether our goals of aligning WoB's objectives and user's experience and needs were being met.

After 2 months of user engagement evaluations, we have also conducted pilot efficacy testing of WoB. During this pilot study, we recruited twenty-five participants from SFSU undergraduate classes. Eleven participants were randomly assigned to the Experimental Group where they were asked to play WoB for 8 hours over a period of 4 days. The rest of the participants were assigned to the Control Group where they were asked to read online e-reading materials that covered Serengeti ecosystem and food network for 8 hours over the period of 4 days (i.e., academic articles, book chapters and graphic and written descriptions of Serengeti food network). Prior to participants' exposure to WoB or e-reading materials, all participants were given a pre-test that examined their general knowledge about Serengeti ecosystem in order to establish the baseline for their initial understanding. A11

questions were forced multiple-choice questions. One-sample t-tests confirmed that participants from both Experimental and Control groups performed at chance level (chance level = 25%). Further, independent samples *t*-test also revealed that Experimental and Control groups' baseline performance was the same, t(23) = 0.75, confirming both groups had little or no prior knowledge about the Serengeti ecosystem. Once the pretest was completed, participants began playing WoB or began reading e-learning materials. The experimenters kept a log of each participant's hours, ensuring that all participants were being exposed to the learning tools for similar duration of time. Furthermore, only those who have successfully completed at least 8 hours of participation were given the post-test. The Post-test was identical to the pre-test and participants' improved scores from pre- and post-test across two groups were compared. Figure 8 shows participants' mean percent correct on the pre- and post-tests.



Fig. 8. Participants' Mean Percentage Scores on Pre- and Post-tests

Repeated Measures of ANOVA was conducted with testing phase (pre- and post-test) as within-subjects factor and group (experimental and control) as between-subjects factors. ANOVA revealed that over all, participants' performance improved significantly from pre-test to post-test, F(1,23) =46.45, p < 0.001, $\eta^2 = 0.67$. Follow-up *t*-tests revealed that both Experimental and Control groups' scores improved significantly (both p's < 0.01). Thus, participants gained knowledge about Serengeti ecosystem regardless whether they played the WoB or read e-reading materials for at least 8 However, did one group's performance improve hours. significantly more than the other group's performance? Our results show that this is the case-ANOVA revealed a significant interaction between testing phase and group, F(1,25) = 4.12, p = 0.05, $\eta^2 = 0.15$. Post-hoc analysis confirmed that this significant interaction was due to our findings that participants' performance improved significantly more from pre- to post-test when they played the WoB rather than when they read e-learning materials (Experimental group: M increased score = 32.16; SD = 20.01; Control group: M increased score = 18.41; SD = 17.19), t(23) = 2.03, p = 0.05. The fact that playing the game provided knowledge gain almost 2 times more than reading scientific articles is very promising for both educators and researchers. Especially with such a short exposure to the game and small sample size, this is a powerful support for the potential effects of science discovery games for learning and for ecological research.

In addition to the general knowledge test, all participants were given a short survey that investigated their perspectives on the learning tools and experience they were exposed to in the study. Our survey results indicated positive learning experience of WoB. For example, all (100%) of the participants in the Experimental group (i.e., playing WoB) agreed or strongly agreed that they felt they have learned interesting and useful information about the Serengeti ecosystem while only 57% of participants in the control group (i.e., online reading materials) reported the similar experience. While 82% of the participants in the Experimental group reported that they would highly recommend using this type of learning methods to others, only 21% of the participants from the Control group felt the same. Lastly, 63% of the participants in the Experimental group felt that while they were playing the game, they were completely concentrated on the task while only 21.43% of the participants in the Control group felt the same. All in all, our findings from survey data strongly support the entertaining and educating potential of the WoB game.

IV. CONCLUSION

WoB opens a mutually educational communication channel between scientists and players. Players learn important aspects of ecosystem development, interdependence and food-web stability. Scientists can learn from players' strategic searches of parameter space. Parameters that maximize or minimize biomass, and/or biodiversity will be sent to interested scientists for further analyses. Scientists currently vary such parameters less strategically which limits the search for optima in high dimensional systems. The game models an ecosystem consisting of interacting biotic (living) components (organisms) and abiotic (non-living) components (e.g. air, soil, water, sunlight). Players manage these components within a game while creating new food webs. Adding novel species mimics species invasions. Adding species similar to those already there mimics sympatric speciation processes of evolution. Decreasing species' abundance mimics exploitation (e.g., hunting, removing species) and, when extreme, extirpation. These are all important problems both scientifically and socially. WoB can help understand and manage these problems.

WoB is the first of a series of ecosystem management games to be developed that will more realistically depict exploitation of forests, lakes, grasslands and oceans. Open databases containing the time series from game simulations is ready to be accessed and analyzed by scientists and statisticians to illuminate how ecosystems can be sustained, exploited and harvested in the game. This game aims to evolve after every iteration and contribute to ecology and conservation biology, some of what Foldit has contributed to molecular biology.

Considering the significance of biodiversity and sustainability education and awareness to broad audience, the series of World of Balance (ocean life and fishery for next season, for example) games can effectively disseminate the state-of-art research to general game playing audiences with a strong educational and scientific impact.

ACKNOWLEDGMENT

This project is being funded by National Science Foundation NSF DBI- 0543614 and NSF TUES- 1140939. CSc 631/831 Multiplayer Game Design and Development course students at fall 2011 contributed to majority of game concept, art work, DB, game contents, client and server implementation and SFSU Center for Computing for Life Science (CCLS) supported this project with two consecutive mini grants to enable the user studies.

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