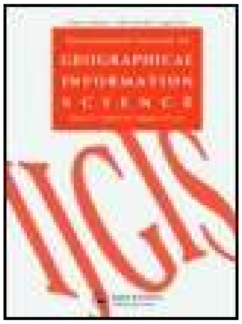

International Journal of Geographical Information Science

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tgis20

Walking through the forests of the future: using data-driven virtual reality to visualize forests under climate change

Jiawei Huang , Melissa S. Lucash , Robert M. Scheller & Alexander Klippel

INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE
https://doi.org/10.1080/13658816.2020.1830997

RESEARCH ARTICLE

Walking through the forests of the future: using data-driven virtual reality to visualize forests under climate change

Jiawei Huang [a], Melissa S. Lucash [b], Robert M. Scheller [c] and Alexander Klippel [d]

[a]Department of Geography, Center for Immersive Experiences, Pennsylvania State University, University Park, PA, United States; [b]Department of Geography, University of Oregon, Eugene, OR, United States; [c]Department of Forestry and Environmental Sciences, North Carolina State University, Raleigh, NC, United States; [d]Department of Geography, Center for Immersive Experiences, Institute for Computational and Data Sciences, Pennsylvania State University, University Park, PA, United States

ABSTRACT

Communicating and understanding climate induced environmental changes can be challenging, especially using traditional representations such as graphs, maps or photos. Immersive visualizations and experiences offer an intuitive, visceral approach to otherwise rather abstract concepts, but creating them scientifically is challenging. In this paper, we linked ecological modeling, procedural modeling, and virtual reality to provide an immersive experience of a future forest. We mapped current tree species composition in northern Wisconsin using the Forest Inventory and Analysis (FIA) data and then forecast forest change 50 years into the future under two climate scenarios using LANDIS-II, a spatially-explicit, mechanistic simulation model. We converted the model output (e.g., tree biomass) into parameters required for 3D visualizations with analytical modeling. Procedural rules allowed us to efficiently and reproducibly translate the parameters into a simulated forest. Data visualization, environment exploration, and information retrieval were realized using the Unreal Engine. A system evaluation with experts in ecology provided positive feedback and future topics for a comprehensive ecosystem visualization and analysis approach. Our approach to create visceral experiences of forests under climate change can facilitate communication among experts, policy-makers, and the general public.

ARTICLE HISTORY
Received 28 August 2018
Accepted 27 September 2020

KEYWORDS
Virtual reality; 3d visualization; geovisualization; scientific visualization; landscape visualization

1. Introduction

Climate change threatens humans and natural ecosystems and is often deemed a 'wicked' problem (Incropera 2015). Unprecedented cuts in global emissions are required to mitigate the harmful effects of climate change, but that would necessitate international energy agreements, which have proved elusive for political reasons. In part, climate change is difficult to envision and does not readily inspire action (Clayton *et al.* 2015), given that most individuals are psychologically distant

CONTACT Jiawei Huang jzh87@psu.edu
Supplemental data for this article can be accessed here.

from its effects (Liberman and Trope 1998, Singh *et al*. 2017). Additionally, 'doom and gloom' research findings can leave individuals with feelings of fear and powerlessness (Lertzman 2015). Previous research suggests that there are three principles important for engaging the public on climate change issues by: 1) using localized scenarios instead of presenting remote locations and long time periods; 2) harnessing the power of visualization on human cognition to overcome abstract change; and 3) connecting the present to the future and connecting different locations (Sheppard 2012). Virtual reality (VR) can address these principles, transforming an abstract concept like climate change into concrete and realistic experiences.

Forest ecosystems are the largest terrestrial carbon sink on earth, providing an effective and low-cost way to offset global emissions of greenhouse gases (Canadell and Schulze 2014, Bastin *et al*. 2019). Reciprocally, forests are influenced by climate change, with altered precipitation patterns and higher temperatures causing longer growing seasons, increasing summer drought, and altering tree species distributions and abundance (e.g. Joos *et al*. 2002, Zhang *et al*. 2012). In the past, scientists have relied on graphs, maps and fact sheets to convey climate change research results, but these tools are often insufficient for inspiring concrete actions and bridging the gap between research and policy. The notion of embedding alternative future landscape visualizations with structured participatory vision to experience future or past states of the environment has been discussed in the literature (Sheppard 2015), but has seldom been used in practice.

Since the pioneering work in the 1960's (Heilig 1962, Sutherland 1968), there have been numerous applications of VR in the game and film industry, architecture, training in the military and elsewhere. Researchers argue that VR and related interactive media, such as computer games, are inherently spatial by placing users in an artificial space, making them rely upon spatial metaphors whether or not they display spatial information (Maceachren and Brewer 2004). The applications of virtual environments (VEs) in geography has been discussed extensively in earlier literature (Fisher and Unwin 2001). Recently, researchers have explored opportunities for high graphics quality VEs on landscape modelling and geography in an online assessment with over 2200 responses. Results showed that a computer-generated environment could be used in a similar way as photographs to assess landscape visual quality (Swetnam and Korenko 2019). Another study used online geospatial games to simulate the influence of land management on hydrology and water quality (Ahlqvist *et al*. 2018). Google Earth VR offers both bird's eye views and close-up views in different places around the Earth, although the available locations are quite limited.

Someday, we will be able to create experiences for every place on earth and 'be there' through immersive experiences, while also being able to investigate a place spatially, temporally, and semantically. Spatially, VR can offer experiences beyond constraints of physical space by providing a contextualized and embodied experience across regions, scales or from different perspectives (Dede 2009). Temporally, we can connect immersive experiences to historical information or future projections, moving a user back or forward in time (Ch'ng 2009, Huang *et al*. 2018). We can visualize and analyze ecosystems and climate change scenarios not as distant events but in direct and/or familiar contexts (Sheppard 2012). Semantically, we can connect the experience to databases and other additional information that may be useful for understanding a place (Marriott *et al*. 2018); we are also able to quickly translate spatial field and remote sensing data such as light detection and ranging (LiDAR) and photogrammetry data into immersive experiences.

In this article, we describe a data-driven workflow that combines publicly-available datasets, an ecological model, and a widely-used game engine to create a compelling VR forest.[1] The workflow allows for modeling efficiency, large-scale creation and placement, fast prototyping, input-output functionality, controllability and reproducibility. The resulting immersive experience presented is a forest ecosystem, including topography, species composition and density, coarse woody debris, and understory conditions. The prototype described here can potentially be applied in various capacities, including education, public engagement, and forest management planning.

In this paper, we will briefly describe the state of the art of modeling forest landscapes. We then demonstrate the feasibility of modeling, visualizing, and experiencing environmental change using a forest in Wisconsin about forty-five miles northwest of Green Bay, Wisconsin, US, as an example. We also invited experts for a heuristic evaluation of the system that showed positive responses and allowed us for laying out future research avenues.

2. Background

Given the preponderance of evidence for climate change, researchers have turned to various tools to understand the impacts of rising temperatures and altered precipitation and disturbance regimes on ecological systems. After theoretical or conceptual tools which are most suited for hypothesis testing, the simplest tool used by researchers is analytical modeling or a regression-based approach (Bolliger *et al*. 2005, Perry and Enright 2006). This assumes, however, that past relationships between variables can be used to predict the future (see Gustafson 2013 for a discussion about the fallacy of this argument). Since we know that ecological systems can show abrupt changes (Alley *et al*. 2003), species can shift and reorganize into novel, no-analog plant communities (Williams and Jackson 2007), and it is difficult to extrapolate to large scales with analytical modeling, many scientists have turned to using computer models for projecting how climate change will affect ecosystems (e.g. (Mladenoff 2004). Over the last 20 years, there has been a rapid development of landscape models fueled by increased computing capacity, spatial data and improvements in spatial analysis, which has shifted the emphasis from purely gap models at the plot scale to a whole range of simulation models at large (landscape) scales. These simulation models differ in their treatment of spatial processes, resolution, and their utility (i.e., theoretical, tactical, or strategic planning), which has been described elsewhere (Scheller and Mladenoff 2007, He 2008). The most recent simulation models incorporate multiple stochastic processes, for example, dispersal and disturbances, such as fire and insects, and mediate spatial interactions across a heterogeneous landscape, and the most sophisticated spatial models simulate feedbacks among ecological processes. We used the LANDIS-II model (Scheller *et al.* 2007) because it is widely-used, captures a large suite of ecological processes and has previously been used to inform landscape management.

The field of computer graphics has developed methods to model natural environments from individual plants to ecosystems. Sketch-based methods allow for modeling plants through artistic drawing (Wither *et al.* 2009), while bio-inspired approaches can model plants and ecosystems based on biological processes (Makowski *et al.* 2019, Kohek *et al.* 2019). Plant models can also be created from images (Tan *et al.* 2007, Neubert *et al.* 2007), videos (Li *et al.* 2011) and laser scanning (Zhang *et al.* 2014). Geometry reduction methods have also been proposed given the increasingly complex scenes (Decaudin and Neyret 2009, Neubert *et al.* 2011, Gumbau *et al.* 2011, Zhang *et al.* 2017, Kohek and Strnad 2018). After the generation of 3D models, real-time rendering is required to display the models on screen with realistic lighting, shading, and colors. Real-time forest rendering methods include point-/line-based rendering; image-based rendering, volume-based rendering, polygon-based rendering, and progressive transmission (Bao *et al.* 2012, Bruneton and Neyret 2012).

New software tools have emerged in recent years. They can be broadly divided into *vegetation modeling* and *ecosystem modeling* tools. Vegetation modeling tools focus on individual plants, such as xFrog, SpeedTree, Onyx, Marlin Studios, PlantFactory, Laubwerk, and others. Ecosystem modeling tools include Visual Nature Studio (VNS), Terrasolid, Bionatics, Terragen, GRASS, Object Raku Technology (Favorskaya and Jain 2017), VUE and CityEngine. These tools vary in their levels of functionality and flexibility.

Data-driven 3D landscape visualization has dramatically advanced in the last two decades. We conducted a literature review of data-driven, geographical information science (GIS)-based landscape visualizations which utilize spatial datasets, instead of computer graphics methods which usually generate landscapes according to mathematical laws and algorithms that mimic the geometries, or simulate processes and patterns in natural environments (Table 1). Our review identifies several gaps: (1) There have been very few VR visualizations, with generally low graphics and/or performance, (2) Much cutting-edge technological advancement in landscape visualization has occurred well outside of geography, ecology and environmental science (Swetnam and Korenko 2019). (3) In the visualization fields, data-driven approaches which utilize GIS data have been lacking. (4) There has been very little research on visualizing forests under climate change. To address these gaps, we integrated spatially-explicit ecological modeling with efficient 3D procedural modeling to create reproducible and scientific visualizations of a forest's future under climate change. Additionally, we created high quality visualization and rendering in state-of-the-art VR.

Table 1. A reversed chronological review of recent literature on data-driven, GIS-based 3D landscape visualization.

Authors and years	Purpose	Data	Functions and visualization formats	Software and tools
(Makowski et al. 2019)	Create a multi-scale approach for plant ecosystem	Hybrid approach: combining data (temperature, precipitation, terrain map) and preset parameters (seeding frequency, seeding radius, shade tolerance, temperature adaptation, precipitation adaptation)	Allow users to set parameters to generate forests in different biomes	C++ and DirectX
(Kohek et al. 2019)	Visualize forest succession simulation	Output from ForestMAS (position, species, age, height)	Visualize model output	Self-developed tool/ extension
(Fabrika et al. 2018)	VR forest thinning training tool	Terrain, aerial images, tree parameters (species (visualized by applying different textures), position, crown height, crown diameter, stem height, stem diameter, tree number, tree status)	Move, view information, cut down trees in the forest	Self-developed software developed using Virtual Reality Modeling Language (VRML) 97 language
(Schroth et al. 2015)	Evaluate a local climate change planning process in a rural town in British Columbia	DEM, topographical data, aerial photographs, etc.	Three presentation formats: a slideshow presentation, posters; and a 3D city model	Developed an application to generate Google Earth 4.x (GE) dedicated files for the 3D model
(Zamuda and Brest 2013)	Simulate and visualize woody plant forest ecosystems following a spontaneous afforestation process considering species interactions such as clustering, clumping, under-dispersion, and competition	DEM, sea level, moisture, sun, wind, forest species	Produce rendered images, animations, and graphs showing simulation results	Self-developed software
((Pettit et al. 2012)	Establish a multi-scale visualization framework for use in climate change response	GIS dataset, digital global	Produce visualizations under different scales: eg., from worldwide of sea-surface temperature to climate change on a farm level	Google Earth
(Chou et al. 2012)	Visualize different forest restoration scenarios	GIS dataset (number of trees per acre, percentage of different species, diameter classes, average height, disturbance occurrence date and size), DEM, remote sensing images,	Produce rendered images and animations	OnyxTree for generating 3D models with tree photos and VNS for distributing models
(Griffon et al. 2011)	Visualize landscape changes	DEM, land use, satellite images, vegetation model library	Visualize houses, trees, ground covers, etc.	Self-developed plug-in on QGIS

(*Continued*)

Table 1. A reversed chronological review of recent literature on data-driven, GIS-based 3D landscape visualization. (Continued).

Authors and years	Purpose	Data	Functions and visualization formats	Software and tools
(Xie et al. 2011)	Visualize forest from database	DEM, satellite images, GIS database (tree species, age, diameter at breast height (DBH), height, understory)	Walkthrough or fly over of forest, perform buffer analysis, information query, etc.	Self-developed forest stand virtual system using VRML
(Fiore et al. 2009)	Study decision making by presenting participants with two different forest fire scenarios under different policies	GIS dataset	Present participants either: a video game-like experience of fire renderings in VR where they can move in space and time; or 2 picture static renderings; or a 52 pictures static renderings	SpeedTree for creating forest and Fire AreaSimulator (FARSITE) for importing GIS dataset and simulate fire
(Shaw et al. 2009)	Synthesize global climate change scenarios, downscale to regional and local level, and do a participatory comparison of 4 local policy scenarios, and 4 regional policy scenarios	GIS database, LiDAR data	Visualize sea level change and impact to landscape	Photoshop, ArcScene, google Earth, sketchUp, VNS
(Fujisaki et al. 2008)	Study how the immersive virtual environment technologies are potentially useful in natural resources management by estimating forest stand information with VR visualization and traditional video	Tree locations, species group (pine or hardwood), height, mean crown radius, DBH, etc., derived from LiDAR	A visualizationapplication in a Cave automatic virtual environment (CAVE) system	
(Saito et al. 2007)	Develop the historical forest landscape reconstruction to demonstrate forest landscape changes	GIS data (2D subcompartment polygon, 2D contour line, species, stand age, tree height, stand density, mixture rate), DEM, map and documents	Rendered forestlandscape simulation images in different years	
(Wang et al. 2006)	Visualize forest landscape with public data sources	Species, basal area, DBH, estimated stand density and estimated tree height of forest stand from Forest Inventory and Analysis (FIA) database, Landsat Thematic Mapper (TM) imagery		Visual Nature Studio (VNS)
(Dockerty et al. 2005)	Visualize potential impact of climate change on rural landscapes	DEM; GIS database of land use from CLUAM (a climate and land use allocation model)	Produce static before and after realistic rendered images of specific point	VNS

3. Methodology

The general workflow is as follows: (1) forecast forest change using the LANDIS-II modeling framework, (2) convert LANDIS-II output into variables and formatting necessary for 3D modeling, (3) model the forest procedurally in Esri CityEngine, (4) import the forest into the Unreal Engine and add necessary environmental elements (sky, understory vegetation, snags, deadfall, and ground cover), (5) optimize the VR experience, (6) add interactions. We applied this workflow to two climate scenarios to highlight potential differences between them (see Figure 1). The data and codes for steps (1)-(3) are available at Figshare,[2] [3].

3.1 Forecast forest change

Forest landscape simulation model

To forecast future changes in the forests of Wisconsin, we used LANDIS-II, a spatially-dynamic landscape model that simulates plant establishment, growth, and mortality as a function of climate and multiple interacting disturbances (Scheller *et al*. 2007). LANDIS-II was chosen because of its robust representation of ecological processes, but also because it simulates individual species (e.g., bur oak instead of all oak species). It was designed for forest planning, forest management, habitat conservation, and ecological restoration; it therefore estimates many different outcomes of interest including the amount of wildlife habitat, total carbon storage, etc. Finally, LANDIS-II is one of the most widely-used landscape models in the U.S. and

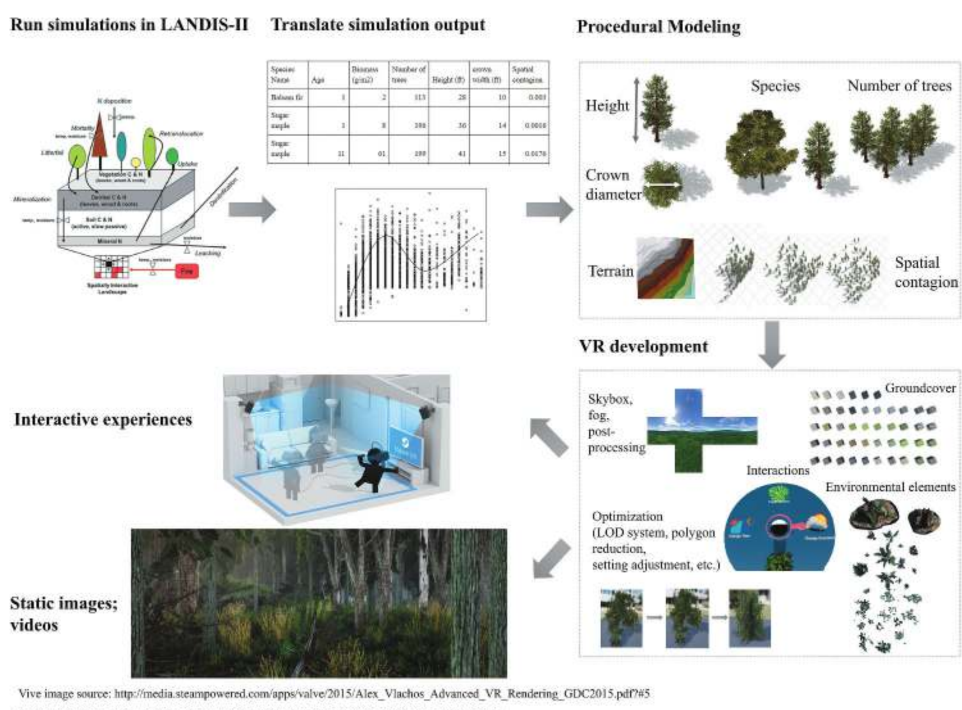

Figure 1. The general workflow was to forecast forest change using the LANDIS-II modeling framework, convert LANDIS-II output into the variables needed for 3D modeling, model the forest procedurally in Esri CityEngine, import the forest into the Unreal Engine and add necessary environmental elements (sky, understory vegetation, snags, deadfall, and ground cover), optimize the VR experience and add interactions.

has been used in over 56 landscapes, including the midwestern U.S. (Scheller and Mladenoff 2005, Gustafson and Sturtevant 2013, Lucash *et al*. 2017). In LANDIS-II, the landscape is comprised of interconnecting grid cells, which in our study were one hectare in size. Each raster cell contains species-age cohorts of trees and these cells are dynamic over time (Mladenoff 2004). To populate our landscape with species-age cohorts, we combined imputed maps of Forest Inventory and Analysis (FIA[4]) plot data with FIA maps of species distribution (Wilson *et al*. 2012). We used the Net Ecosystem Carbon and Nitrogen (NECN) extension of LANDIS-II v6.1 (Scheller *et al*. 2011), to forecast future changes and parameterized NECN using life history attributes (e.g., shade tolerance[5]) and biogeochemistry (e.g., leaf carbon to nitrogen ratios) of each tree species. We also used soil data from the Soil Survey Geographic Database (SSURGO[6]), vegetation data from the literature (e.g. maximum growth rates) and data from past studies (Lucash *et al*. 2017, 2018). Once NECN was parameterized, we divided our landscape into 38 climate ecoregions (regions with homogenous climate) using isocluster analysis of temperature and precipitation using the methods outlined in (Lucash *et al*. 2017).

Our historical climate data were derived from the University of Idaho meteorological data[7] over the period 1979–2010 using area-weighted averages. Our climate change projection was a hot and dry scenario using HadGEM2-ES365-r1i1p1_ rcp 8.5, which was derived from the Bias Corrected Constructed Analogs V2 Daily Climate Projections from Coupled Model Intercomparison Project Phase 5 (CMIP5) from the United States Geological Survey (USGS) data portal.[8] Typical model runs of LANDIS-II produce maps of biomass (g/m2) for each species over time. While species biomass is well-suited for traditional information visualization approaches, such as choropleth maps, it is not sufficient for creating realistic, scientifically informed 3D visualizations as the basis for immersive experiences. To address this issue, we created a new extension of LANDIS-II called Output Biomass Community, which creates maps detailing the species, age and biomass of each cohort in each raster cell of the landscape at each specified time period. The NECN and Output Biomass Community extensions of LANDIS-II were run for 50 years; changes in species composition over time reflect the integration of model algorithms of cohort growth, competition, establishment and mortality under the two different climate scenarios (Scheller *et al*. 2011, Lucash *et al*. 2017).

To automate the creation of a 3D forest, biomass was not sufficient and a more concrete representation of trees was needed, such as height, crown size, and number of trees. To convert LANDIS-II output to these metrics, we used the largest forest plot inventory dataset available in the FIA database.[9] We utilized all 34,495 plots in WI and Michigan (MI), which contained 804,815 trees. After aggregating the data from the tree-level to the 1 ha resolution of our landscape, we regressed age against each parameter (e.g., age vs height, age vs. number of trees) for each species present in our landscape (a sample image of balsam fir is shown in Figure 8 in the supplementary material) using a second order polynomial (Table 3 in the supplementary material). Then we used those polynomial equations to take the age and species output from LANDIS-II and convert them into height, number of trees and crown size.

Spatial contagion was also critical for 3D modeling. It quantifies of how evenly spaced or clumped a species grows on the landscape. This parameter was not available in any database, so we used expert opinion to derive this index (0–1) for each species (Table 3). The value ranges from 0 to 1, with high values indicating that the species grows in a few large, clumped patches, and lower values indicating that the species occurs in many small patches (O'Neill *et al*. 1988, Li and Reynolds 1993).

3.2 3D visualization of tree data

The forest was procedurally generated with Computer Generated Architecture (CGA) rules in CityEngine[10] which has the advantages of large-scale modeling (~30,000 trees in this case) and automation over traditional 3D modeling software. Procedural modeling/grammar-based modeling uses a set of predefined CGA rules to iteratively refine a model by creating more details. It is specialized in global control, individual model positioning, level-of-detail (LOD) control, and large model data handling (Müller *et al.* 2006). Procedural modeling is suitable when large numbers of iterations of design, architectures, or blocks which obey certain standardized rules have to be created (Esri 2019). It is suitable for both built and natural environments (Huang *et al.* 2018). However, to achieve the same LOD as hand-modeling, procedural rules would have to be rather complex. In this project, we used procedural modeling as a distribution tool to control the attributes and spatial relationships of 3D models created by hand-modeling.

Our 3D modeling work started with creating the terrain using the DEM with a resolution of 1/3 arc-second (~8.80 m with WGS 1984/UTM zone 16 N projection).[11] LANDIS-II modeling results were read by Python to CityEngine, and then the 3D modeling work was completed in CityEngine. We wrote the procedural rules to be able to generate trees according to different parameters from LANDIS-II. Each row in the csv output of LANDIS-II was considered to be a cohort of trees with a given set of derived characteristics (height, crown size, age, species, and spatial contagion). At the meantime, the same tree species was usually constituted of several cohorts. 3D modeling was done iteratively with each cohort, where we scattered and generated all trees in the same cohort in one loop, and then continued on to the next record, until all cohorts of trees were generated to form the entire forest. Different cohorts of trees mix together during the process. The procedural modeling process is shown in the pseudocode in the supplementary material. The following parameters were controlled:

(1) height and crown size: Each tree model was scaled according to its height and crown diameter.

(2) spatial contagion: we used the Gaussian function to distribute tree cohorts. The standard deviation (σ) in the Gaussian distribution was used to quantify different spatial contagions (smaller σ signifies larger species contagion). In our visualization, σ to spatial contagion was not a one to one mapping as we did not have precise knowledge of how aggregated one specific value of spatial contagion is.

(3) species: because we had access to a wide suite of online tree libraries, we did not model our own tree models from scratch. Instead, we used two plant libraries, 3D Vegetation with LumenRT package,[12] and XfrogPlants. Because the two libraries did not cover all types of trees in our dataset, certain approximations were made. For example, trees of the same genus were sometimes visualized by one model (approximation details are in Table 4 of the supplementary material).

We conducted our model simulations and VR development in the forests of Wisconsin about forty-five miles northwest of Green Bay, Wisconsin, US, along the shores of Lake Michigan. Our study area contains ~2 million hectares of land in central WI, including the Menominee Reservation. This study area region is an ideal location to test the integration of landscape modeling and VR under different climate change scenarios for several reasons: 1) it is located in a region which has already experienced reductions in forest health due to climate change, (2) projections indicate temperatures will continue to rise sharply over the next 50–100 years, and (3) this landscape is located at the nexus between northern hardwoods and boreal forest and therefore has a high potential for changes in tree species and declines in diversity. The area that have been visualized is 300 m by 300 m with 28,939 trees.

3.3 VR development

We had three design considerations in mind from the beginning: graphics, usability and system performance. In terms of graphics, we used the Unreal Engine for its AAA graphics and large dataset handling capability. In Unreal, we remade two-sided translucent foliage materials with wind effects to create realistically-behaving leaves, adapted and used a heterogeneous landscape material[13] (Figure 2); and created the understories which included a diverse understory of 44 difference species (ferns, grass, wild flowers, trunks, bush, clover, root, nettle, etc.) with Unreal procedural foliage spawner diverse understories based on the natural environment of Wisconsin (Figure 2). After content creation, we used post-processing to bring scenes to life. In terms of usability, we followed an iterative design approach (Nielsen 1993). We gathered desired functions from ecologists

Figure 2. The heterogeneous understories. The bottom image shows a partial list of the understories species used.

before the initial design and conducted several rounds of evaluations with VR experts after having the initial prototype to refine. Finally, to ensure the system performance, we optimized the experience to deliver adequate frames per second (around 70) by using the native level-of-detail (LOD) system in the Unreal Engine, reducing polygon count, minimizing dynamic lighting, decreasing global settings while maintaining graphics quality.

4. Results

4.1 Results from LANDIS-II

In the LANDIS-II simulations, we found that climate change increased the biomass of some species but not others in our 9 ha landscape. Red oak, sugar maple, and white cedar all had higher biomass, while red maple, white pine, and balsam fir all had lower biomass under climate change (Figure 3). Figure 7 shows some of the differences reflected in our visualizations.

While this information is well-suited for traditional data transfer to other researchers and for traditional visualization approaches, such as choropleth maps, it is not sufficient for creating realistic, scientifically informed 3D visualizations as the basis for immersive experiences. Using our new Output Biomass Community extension of LANDIS-II and the regression equations developed with FIA, we were able to estimate the number of trees, height and crown width under climate change for each 1-ha plot (Figure 4). Because we regressed density, height, and crown-height against age (and because biomass is generally correlated with age), the visualized parameters generally mimicked biomass with declines in balsam fir, red maple, and white pine and increases in red oak and sugar maple.

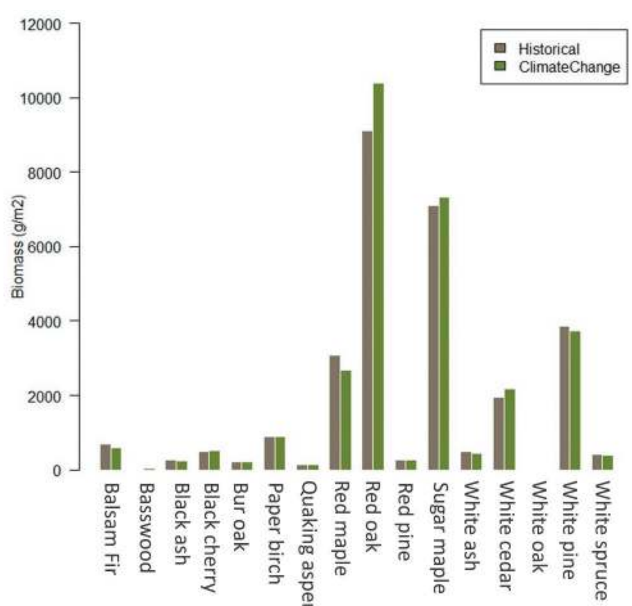

Figure 3. Average species biomass under no climate change (historical) and climate change scenarios (HadGEM2 rcp 8.5).

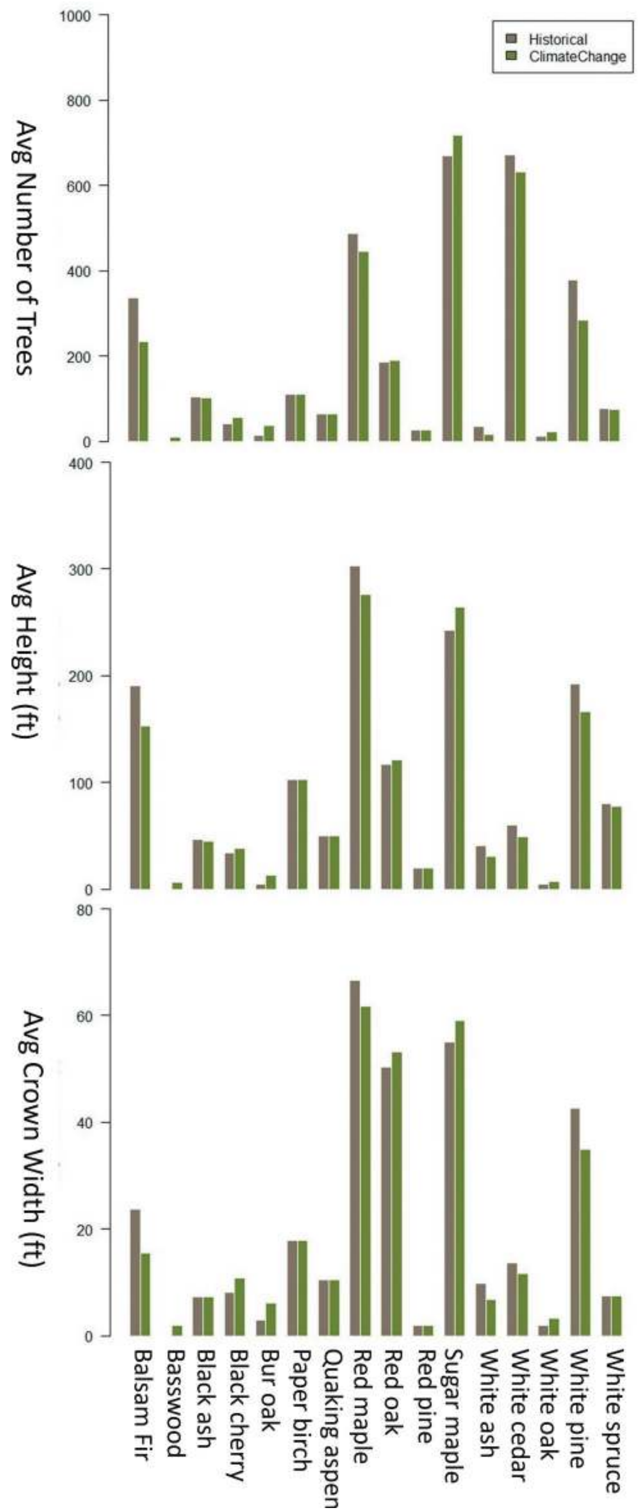

Figure 4. Average number of trees, tree height (ft) and crown width (ft) under no climate change (historical) and climate change scenarios (HadGEM2 rcp 8.5).

4.2 Results from 3D modeling and VR

The virtual forest system provides an embodied experience in which the users can freely explore and interact with the forest intuitively with either Oculus Rift or HTC Vive. Figure 5 shows a user querying how specific species responds to climate change. The rendered forest and the demo video[14] can be found online and in the supplementary material. Upon entering the virtual forest, users can teleport with either hand. Slightly different from the common teleportation methods, the hand emits a waving laser. Users can also change the direction that they will be facing after teleportation by gently swiping to different directions on the touchpad. We implemented a 3D user interface (3DUI) using the Unreal Blueprint and an online asset called VR Integrator Radial and Dockable Menus.[15] There are different functionalities which are suggested by ecologists that can be accessed from the main menu (Huang *et al*. 2019a): (1) select climate change scenarios. Users can explore historical and dry/hot scenarios. (2) retrieve information from the database (e.g., species name, height, diagram of biomass). (3) learn species identification by selecting in the species browser (Figure 6). Users can view species vulnerability and climate change adaptivity (4) change viewing height. Previous research has found that the exocentric and the egocentric perspectives evoke different types of learning: egocentric perspectives enables participants' actional immersion and motivation through embodied, concrete learning, whereas exocentric perspectives foster abstract, symbolic intelligence gained from distancing oneself from the context (Dede 2009). The above functions can be used simultaneously.

The Unreal profiling tool showed the GPU memory usage was around 2000 MB; object count was 107,416 for the entire forest; in the test area, the scene polygon count averaged 25 million; frame per second (fps) averaged at 70. The VR application was tested on HTC Vive and Oculus Rift with a gaming PC (3.60 GHz Intel i7-6950 processor, 64 GB RAM, and two NVidia GTX 1080 Ti graphics cards).

Figure 5. A user exploring how specific species (such as red pine) responds to climate change.

Figure 6. The user selects basswood to view how this species reacts to climate change.

Figure 7. Visualization of white ash and black ash from the same location under historic climate (1979–2010, top) and climate change (HadGEM2 rcp 8.5, lower). In our simulations, the number of white ash trees decreased 57.28%, while black ash decreased only 1.8%, which are visible in visualizations.

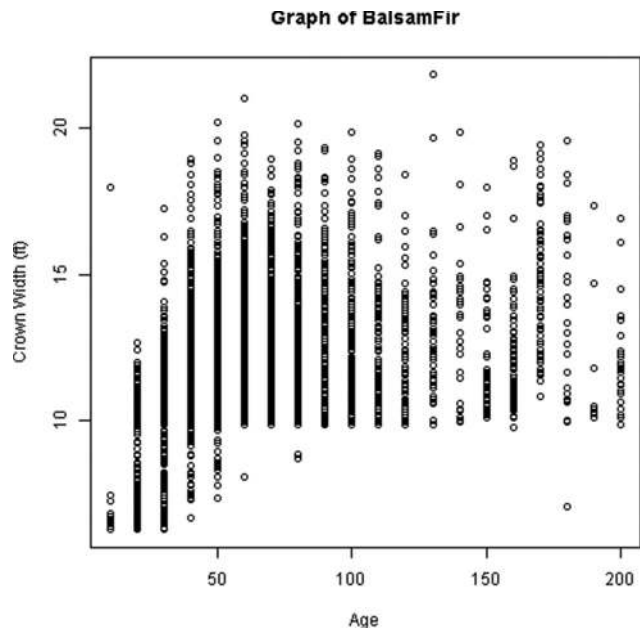

Figure 8. Crown width of balsam fir as a function of cohort age.

5. Evaluation

5.1 Modified heuristics evaluation

To evaluate the VR experience, we adapted the *VR heuristics evaluation* method (Sutcliffe and Gault 2004). Heuristics evaluation is tailored to situations of small numbers of expert evaluators. The original heuristics evaluation method was not delivered through questionnaires but required VR experts to identify issues present in the system and categorize them according to 12 heuristics. We designed questions that reflect the meaning of the 12 heuristics, such that the domain experts, who may lack extensive VR knowledge, are able to evaluate the VR system. In addition, it provides a common evaluation standard for all evaluators. For the presence heuristics, we adopted the Spatial Presence Experience Scale (SPES) (Hartmann *et al.* 2016) as part of our questionnaire since it is already an established measure. Five expert evaluators, unrelated to the project, with an ecology background from the Department of Geography at Pennsylvania State University were invited to complete the heuristics evaluation.

5.2 Evaluation results

Table 2 shows the questionnaires we designed grouped by 12 heuristics, and the mean score for each of the heuristics. The overall score is 6.25 on a 7-level likert scale, indicating a highly positive rating of the system in terms of usability and graphics.

Table 2. Questionnaire adapted from heuristic evaluation method

Heuristics	Questionnaire item	Mean	Median
Natural engagement	● The overall graphics look good (for example, aesthetics, color schemes, lightings, 3D models details, textures, no serious lag or flickering). ● I think the interactions with the menus were intuitive. ● I think the interactions with the environment and objects were intuitive.	5.87	6
Compatibility with the user's task and domain	● The virtual environment is close to my expectation of real world environment. There was no unexpected objects/ events that contradict my knowledge and/or physics laws (for example, floating objects, etc.). ● I feel the interactions were compatible with the tasks needed to be performed.	5.8	6
Natural expression of action	● My body representation allowed me to act and explore in a natural manner. ● I had no issue with the hardware (e.g., headset, earphones, straps, controllers)	5.8	7
Close coordination of action and representation	● The system responded to my actions smoothly and without delay.	5.9	7
Realistic feedback	● The effects of my actions were immediately visible and conform to the laws of physics and my perceptual expectations.	6.8	7
Faithful viewpoints	● The visual representation of the virtual world mapped to my normal perception. ● The viewpoint change by head movement was rendered without delays that could impact my overall experience.	6.8	7
Navigation and orientation support	● I was able to know where I was in the virtual environment and was able to navigate from place to place.	6.4	7
Support for learning	● I feel the system provided support for learning of the virtual environment.	6.6	7
Clear turn-taking	● N/A		
Sense of presence	● I felt like I was actually there in the environment of the presentation. ● It seemed as though I actually took part in the action of the presentation. ● It was as though my true location had shifted into the environment in the presentation. ● I felt as though I was physically present in the environment of the presentation. ● The objects in the presentation gave me the feeling that I could do things with them. ● I had the impression that I could be active in the environment of the presentation. ● I felt like I could move around among the objects in the presentation. ● It seemed to me that I could do whatever I wanted in the environment of the presentation.	3.9 (five-level likert scale)	4
Score except for presence		6.35	
Overall score with all factors		6.25	

In addition to the questionnaire, we also gathered open-ended responses. In terms of system design, evaluators generally commented on the graphics having high visual fidelity, and the interactions being smooth and intuitive: 'I like the variability in the forest, everything was not the same. I never felt lost, I always had control of when and where I moved.', 'I like the menu options and found them easy to interact with. I liked being able to toggle between species and have the text on the screen telling me which climate scenario I was looking at.' "I think the trees looked decently close to what they look like in reality, 'Graphics are detailed and realistically represent a deciduous forest as a whole.' 'Texture and lighting were good.' Although some evaluators mentioned that 'though the details necessary to identify trees to the species level are lacking'.

Comparing this kind of VR visualization with 2D visualizations, the evaluators commented on the benefits of having interactivity, embodiment, agency, multiple reference frames, and immediate feedback in VR: 'This visualization goes a step further by immersing the user in a 3D environment that allows the user to feel like they are really exploring the environment rather than just looking at it from a static viewpoint or just scrolling around a screen.', and (the advantages over 2D maps are) 'interactive experiences and being able to see the consequences of our actions immediately are two advantages of this method'. However, evaluators also acknowledged that 2D maps might have higher precision, information density, and simplicity: 'In some ways [virtual reality] might be less concise as say a heatmap of tree densities, so slight changes might be lost, but in more extreme cases I think it provides a compelling view.' These problems could be mitigated by integrating 2D maps into the VR experience.

In regards to questions about tool applicability to user groups, evaluators mentioned the following: 1. land managers and property owners for landscape change communication; 2. forest managers and conservation planners for visualizing climate change impacts on biodiversity, species composition and abundance; 3. researchers who are interested in different environmental scenarios, and 4. decision makers.

5.3 Demos and informal evaluations

In addition to the formal evaluation, we also gathered feedback from an international audience of VR experts as well as ecology experts. We held a demo session at the IEEE Conference on Virtual Reality and 3D User Interfaces in 2019 (IEEE VR 2019), and demoed a simplified, less interactive Oculus Go version at the 2019 annual meeting of the International Associate for Landscape Ecology. Both demos received positive feedback.

Summarizing the feedback from formal and informal evaluations, the following functions were identified for future developments: 1. increase tree bark and leaf resolution to enable close-up observation and tree identification; 2. add seasonal changes to the forests; 3. create experiences after wildfire or an insect outbreak forest fire impacts; 4. add additional scenarios such as insect/pathogen outbreak, etc.; 5. add additional climate scenarios, to see how they would affect the forest; 6. add an analysis tool such as a larger scale measuring tool to try to catch the changes in height for the entire set or subset of trees.

6. Discussion and conclusions

Given that climate change is projected to have a large effect on forest species composition and structure, visualizing these shifts is important for communicating climate change to a wider audience. We created data-driven 3D modeling and immersive experiences by visualizing output from a forest change model. The designed workflow allows for modeling efficiency, large-scale creation and placement, fast prototyping, input-output functionality, controllability and reproducibility. Our approach can also be adapted to other ecological systems.

We demonstrated 3D modeling efficiency, large-scale creation and placement with the hybrid approach of combining hand-modeling and procedural modeling. With procedural modeling, it took less than 20 seconds to generate ~30,000 trees. In contrast, hand-modeling is not only time-consuming, but also repetitive, cost-intensive, and subjective. As the size of the scene and the number of objects increase, the advantages of procedural modeling increase dramatically compared to hand-modeling (Esri 2019). However, hand-modeling allows for more details than procedural modeling. Using a hybrid approach, we applied procedural rules to realistic trees created by hand-modeling, and it took only seconds to minutes to generate medium to large scenes with rich details, combining the strength of both procedural modelling and hand-modeling.

3D modeling and immersive visualizations of output from ecological models using fast prototyping is important as it provides a feedback loop for scientists that benefits from the constraints of real-world environments and corresponding 3D models. For example, during the first iterations of our 3D modeling and prototyping, the 3D visualizations revealed some potential problems- trees were too dense and tree crown widths were too small. These kinds of problems are much harder to notice with graphs and maps than with immersive visualizations as humans have evolved to be more observant of discrepancies inside 3D environments than 2D illustrations. We were able to trace the problem back to the algorithms in the FIA crosswalk between LANDIS-II and Unreal, correct the problem in the equations, and update the visualization.

Data input-output functionality, controllability and reproducibility presented in our workflow are also crucial for scientific visualization (i.e., scene extension or modification with the addition or adjustment of parameters). There have been many successful commercial examples of 3D landscape visualizations, but most software has been designed for 3D artists and has focused on ease of creating visually appealing scenes rather than for scientific visualization. The workflow provided here is both efficient and has the potential of being automated further, and it allows for detailing exactly and explicitly which assumptions were made to design the immersive, visceral forest experiences.

There also remain challenges with the developed prototype. First, our predefined 3D models are unable to dynamically change according to growth, disease and interactions with neighboring trees once the visualization is created. The visualizations are a 'snapshot' of the simulations, and reflect the tree growth, competition, and disturbance interactions at a given point in time. Although not included here, disturbances like wind, disease, wildland fire, and insects, could be included in the simulation model (www.landis.org) and then visualized using this workflow. Second, in the evaluation, we have focused on the system graphics and usability. Although the experts mentioned that the forest was realistic based on their knowledge of the forest in the area, and suggested ways this could be useful for stakeholders, we did not validate the visualization against reality. Currently, we are conducting another round of validation which compares our visualizations directly with the plot photographs.

In summary, we created a high-quality experience of 'walking' through the forests of the future under climate change by combining a state-of-the-art ecological model with VR, which can potentially help experts, decision-makers, and lay-people to develop a better picture of how climate change might affect forests. By using an efficient, procedurally-driven method, we can provide people with access to the effects of climate change in their own backyards through an embodied, visceral experience. With immersive technologies becoming a medium of mass communication, there are additional opportunities to further our understanding of what communicating environmental change in a more visceral way means from a perceptual and cognitive perspective. While beyond the scope of this article, we consider it essential to advance empirical evaluations of how uncertainty can be included in rather explicit 3D models (Huang *et al*. 2019b) to understand what embodied experiences mean in terms of creating a connection to nature and a more empathetic response to those affected by climate change, and whether visceral experiences allow for creating ripple effects that facilitate system thinking and potential long-term changes in human behavior.

Notes

1. The demo video of the visualization can be found at https://vimeo.com/320844373 and in the supplementary material.
2. 10.6084/m9.figshare.11873883
3. 10.6084/m9.figshare.11873967
4. https://www.fia.fs.fed.us/
5. https://www.feis-crs.org/feis/
6. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_053627
7. http://www.climatologylab.org/gridmet.html
8. http://cida.usgs.gov/gdp/
9. https://apps.fs.usda.gov/fia/datamart/datamart.html
10. http://www.esri.com/software/cityengine
11. https://viewer.nationalmap.gov/basic/?basemap=b1&category=ned,nedsrc&title=3DEP%20View
12. https://www.arcgis.com/home/item.html?id=0fd3bbe496c14844968011332f9f39b7
13. https://www.unrealengine.com/marketplace/en-US/product/environment-set
14. https://vimeo.com/320844373
15. https://www.unrealengine.com/marketplace/en-US/product/vr-integrator-radial-and-dockable-menus

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the National Science Foundation [1617396].

Notes on contributors

Jiawei Huang is a fifth year Ph.D. student (major: GIS; minor: computational science). Before Ph.D., she completed her master at University of Michigan – Ann Arbor in 2016. Her research interest lies in VR, 3D and HCI. Development-wise, she has been developing VR and 3D applications for geovisualization, digital humanities, and environmental visualization. Research-wise, her dissertation is on the effects of fidelities on spatial memory. Her portfolio can be found here: https://sites.psu.edu/jade/. Contact her at jzh87@psu.edu.

Dr. Melissa Lucash is a research assistant professor at University of Oregon with a Ph.D. in Forest Ecology (SUNY College of Environmental Science and Forestry, 2005) and a M.D. degree in Environmental Science (Oregon State University, 1996). Dr. Lucash has acquired over $7 million in federal grants and published 24 peer-reviewed papers. Her research interests are in forest ecology, disturbances (especially wildfire) and visualization. Her website can be found here: https://melissalucash.com/. Contact her at mslucash@gmail.com.

Dr. Robert M. Scheller. Education: B.S., Biology, University of Minnesota-Duluth, 1991; M.S. Forestry, University of Wisconsin-Madison, May 2000; Ph.D., Forest Ecology, University of Wisconsin-Madison, May 2004. Employment: University of Wisconsin-Madison, Research Associate, 2004 – 2005; University of Wisconsin-Madison, Assistant Scientist, 2005 – 2007; Conservation Biology Institute, Senior Ecologist, 2007 – 2009; Portland State University, Assistant Professor, 2009 – 2014; Portland State University, Associate Professor, 2014– 2017; North Carolina State University, Professor, 2017 – present. Achievements: Member Chancellor's Faculty Excellence Program and the Emerging Plant Diseases and Global Food Security Cluster; President of the International Association for Landscape Ecology; Director of the Dynamic Ecosystems and Landscape Lab with 5/3 PhD/MS students graduated and 4 current PhD students; Founder and Treasurer of The LANDIS-II Foundation; Faculty Fellow of the Center for Geospatial Analytics and Faculty Affiliate of the Southeast Climate Science Center; Associate Editor of Landscape Ecology and Frontiers in Forests and Global Change; Published more than 80 manuscripts and book chapters (h-index = 32); Received funding from NSF, DOD, USDA, USFS, USGS, BLM, EPA, TNC, and others. Over $7.2M funded in the past 10 years; Member of the American Geophysical Union, Ecological Society of America, Int'l Assoc. for Landscape Ecology, Society of American Foresters. Scheller's research focuses on how landscapes have changed, how they will change, and why it matters. Specifically, his research examines landscape change, specifically in regards to climate change and human activities, management, and values. He forecasts landscape change to inform policy choices, regionally and globally.

Dr. Alexander Klippel received his masters in Geography in 1997 and his Ph.D. in Informatics and Mathematics in 2003. He is Professor of Geographic Information Science and Affiliate Professor of Information Science and Technology at The Pennsylvania State University, Department of Geography since 2007, held a post-doctoral fellowship at the University of Melbourne (School of Engineering, 2004-06) as well as UC Santa Barbara (Geography, 2003-04). He is on the editorial board of Spatial Cognition and Computation, Geo-Spatial Information Science, and Journal of Spatial Information Science. He was the General Chair of the 2008 Spatial Cognition Conference and is Technical Co-Chair of the Immersive Learning Research Network Conference 2020. Alexander is the current Gosnell Senior Faculty Scholar in the College of Earth and Mineral Sciences, was the first Stuckeman Center for Design Computing Faculty Fellow as well as a Teaching and Learning with Technology Fellow. Alexander has received four best paper awards of which he was lead-author on three. He is and was PI or Co-PI on more than a dozen funded research grants and has published over 100 peer-reviewd papers, including 34 journal papers. He has been named the inaugural Director of Penn State's Center for Immersive Experiences (https://immersive.psu.edu/).

ORCID

Jiawei Huang http://orcid.org/0000-0002-8606-1204
Melissa S. Lucash http://orcid.org/0000-0003-1509-3273
Robert M. Scheller http://orcid.org/0000-0002-7507-4499
Alexander Klippel http://orcid.org/0000-0002-7171-492X

Data and codes availability statement

The data and codes that support the findings of this study are available with a DOI at http://doi.org/10.6084/m9.figshare.11873883 and http://doi.org/10.6084/m9.figshare.11873967

References

Ahlqvist, O., Khodke, N., and Ramnath, R., 2018. GeoGame analytics – A cyber-enabled petri dish for geographic modeling and simulation. *Computers, Environment and Urban Systems*, 67, 1–8. doi:10.1016/j.compenvurbsys.2017.08.013

Alley, R.B., *et al*., 2003. Abrupt climate change. *Science*, 299 (5615), 2005–2010. doi:10.1126/science.1081056

Bao, G., *et al*., 2012. Large-scale forest rendering. Real-time, realistic, and progressive. *Computers & Graphics*, 36 (3), 140–151. doi:10.1016/j.cag.2012.01.005

Bastin, J.-F., *et al*., 2019. The global tree restoration potential. *Science (New York, N.Y.)*, 365 (6448), 76–79. doi:10.1126/science.aax0848

Bolliger, J., Lischke, H., and Green, D.G., 2005. Simulating the spatial and temporal dynamics of landscapes using generic and complex models. *Ecological Complexity*, 2 (2), 107–116. doi:10.1016/j.ecocom.2004.11.005

Bruneton, E. and Neyret, F., 2012. Real-time Realistic Rendering and Lighting of Forests. *Computer Graphics Forum*, 31 (2pt1), 373–382. doi:10.1111/j.1467-8659.2012.03016.x

Canadell, J.G. and Schulze, E.D., 2014. Global potential of biospheric carbon management for climate mitigation. *Nature Communications*, 5 (1), 5282. doi:10.1038/ncomms6282

Ch'ng, E., 2009. Experiential archaeology. Is virtual time travel possible? *Journal of Cultural Heritage*, 10 (4). [Accessed 27 August 2017, pp. 458–470. doi:10.1016/j.culher.2009.02.001

Chou, C.-Y., *et al*., 2012. Three-dimensional landscape visualizations of forest restoration scenarios for southern pine beetle-infected forests. *Tree and Forestry Science and Biotechnology*, 6 (1), 40–50. [Accessed 31 May 2018].

Clayton, S., *et al*., 2015. Psychological research and global climate change. *Nature Climate Change*, 5 (7), 640–646. doi:10.1038/nclimate2622

Decaudin, P. and Neyret, F., 2009. Volumetric Billboards. *Computer Graphics Forum*, 26 (3), 553.

Dede, C., 2009. Immersive interfaces for engagement and learning. *Science*, 323 (5910), 66–69. Available from: http://www.jstor.org/stable/20177121 [Accessed: [25 october 2017].

Dockerty, T., *et al*., 2005. Visualising the potential impacts of climate change on rural landscapes. *Computers, Environment and Urban Systems*, 29 (3), 297–320. doi:10.1016/j.compenvurbsys.2004.05.004

Esri, 2019. *About CityEngine* [online]. Available from: https://doc.arcgis.com/en/cityengine/latest/get-started/get-started-about-cityengine.htm [Accessed 4 February 2020].

Fabrika, M., Valent, P., and Scheer, Ľ., 2018. Thinning trainer based on forest-growth model, virtual reality and computer-aided virtual environment. *Environmental Modelling and Software*, 100, 11–23. doi:10.1016/j.envsoft.2017.11.015

Favorskaya, M.N. and Jain, L.C., 2017. *Handbook on Advances in Remote Sensing and Geographic Information Systems*, Paradigms and Applications in Forest Landscape Modeling. Berlin: Springer.

Fiore, S.M., *et al*., 2009. Virtual experiments and environmental policy. *Journal of Environmental Economics and Management*, 57 (1), 65–86. doi:10.1016/j.jeem.2008.08.002

Fisher, P. and Unwin, D., eds.. 2001. *Virtual reality in geography*. Boca Raton: CRC Press.

Fujisaki, I., *et al*., 2008. Stand assessment through Lidar-based forest visualization using immersive virtual environment technology. *Forest Science*, 54 (1), 1–7.

Griffon, S., *et al*., 2011. Virtual reality for cultural landscape visualization. *Virtual Reality*, 154, 279–294. [Accessed 13 January 2017 doi:10.1007/s10055-010-0160-z

Gumbau, J., *et al*., 2011. View-dependent pruning for real-time rendering of trees. *Computers & Graphics*, 35 (2), 364–374. doi:10.1016/j.cag.2010.11.014

Gustafson, E.J., 2013. When relationships estimated in the past cannot be used to predict the future. Using mechanistic models to predict landscape ecological dynamics in a changing world. *Landscape Ecology*, 28 (8), 1429–1437. [Accessed 21 July 2018. doi:10.1007/s10980-013-9927-4

Gustafson, E.J. and Sturtevant, B.R., 2013. Modeling forest mortality caused by drought stress. Implications for climate change. *Ecosystems*, 16 (1), 60–74. doi:10.1007/s10021-012-9596-1

Hartmann, T., *et al*., 2016. The spatial presence experience scale (SPES). *Journal of Media Psychology*, 28 (1), 1–15. doi:10.1027/1864-1105/a000137

He, H.S., 2008. Forest landscape models. Definitions, characterization, and classification. *Forest Ecology and Management*, 254 (3), 484–498. doi:10.1016/j.foreco.2007.08.022

Heilig, M.L., 1962. *Sensorama Patent*. United States patent application 3050870. 28 August.

Huang, J., *et al*., 2018. From archive, to access, to experience – historical documents as a basis for immersive virtual reality. *Journal of Map & Geography Libraries*, 14 (1), 40–63. Available from: https://www.tandfonline.com/doi/full/10.1080/15420353.2018.1498427.

Huang, J., *et al*., 2019a. Visualizing ecological data in virtual reality. *In:. 2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, 23–27 March 2019 Osaka. Piscataway, NJ: IEEE, 1311–1312.

Huang, J., *et al*., 2019b. Visualizing natural environments from data in virtual reality: combining realism and uncertainty. *In:. 2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR),* 23–27 March 2019 Osaka. Piscataway, NJ: IEEE, 1485–1488.

Incropera, F.P., 2015. *Climate Change: A Wicked Problem:. Complexity and Uncertainty at the Intersection of Science, Economics, Politics*. and Human Behavior. New York: Cambridge University Press.

Joos, F., Prentice, I.C., and House, J.I., 2002. Growth enhancement due to global atmospheric change as predicted by terrestrial ecosystem models: consistent with US forest inventory data. *Global Change Biology*, 8 (4), 299–303. doi:10.1046/j.1354-1013.2002.00505.x

Kohek, Š., *et al*., 2019. Interactive synthesis and visualization of self-organizing trees for large-scale forest succession simulation. *Multimedia Systems*, 25 (3), 213–227. doi:10.1007/s00530-018-0597-6

Kohek, Š. and Strnad, D., 2018. Interactive large-scale procedural forest construction and visualization based on particle flow simulation. *Computer Graphics Forum*, 37 (1), 389–402. doi:10.1111/cgf.13304

Lertzman, R., 2015. *Environmental melancholia:*. Psychoanalytic dimensions of engagement. London: Routledge.

Li, C., *et al*., 2011. Modeling and generating moving trees from video. *ACM Trans. Graph*, 30 (6), 1–12. doi:10.1145/2070781.2024161

Li, H. and Reynolds, J.F., 1993. A new contagion index to quantify spatial patterns of landscapes. *Landscape Ecology*, 8 (3), 155–162. doi:10.1007/BF00125347

Liberman, N. and Trope, Y., 1998. The role of feasibility and desirability considerations in near and distant future decisions: A test of temporal construal theory. *Journal of Personality and Social Psychology*, 75 (1), 5–18. doi:10.1037/0022-3514.75.1.5

Lucash, M.S., *et al*., 2017. Spatial resilience of forested landscapes under climate change and management. *Landscape Ecology*, 32 (5), 953–969.

Lucash, M.S., *et al*., 2018. More than the sum of its parts. How disturbance interactions shape forest dynamics under climate change. *Ecosphere*, 9 (6), e02293. doi:10.1002/ecs2.2293

Maceachren, A.M. and Brewer, I., 2004. Developing a conceptual framework for visually-enabled geocollaboration. *International Journal of Geographical Information Science*, 18 (1), 1–34. doi:10.1080/13658810310001596094

Makowski, M., *et al*., 2019. Synthetic silviculture. multi-scale modeling of plant ecosystems. *ACM Transactions on Graphics*, 38 (4), 1–14. doi:10.1145/3306346.3323039

Marriott, K., *et al*., *eds*., 2018. *Immersive Analytics*. Cham: Springer International Publishing.

Mladenoff, D.J., 2004. LANDIS and forest landscape models. *Ecological Modelling*, 180 (1), 7–19. doi:10.1016/j.ecolmodel.2004.03.016

Müller, P., *et al*., 2006. Procedural modeling of buildings. *ACM Transactions on Graphics*, 25 (3), 614. doi:10.1145/1141911.1141931

Neubert, B., *et al*., 2011. Improved model- and view-dependent pruning of large botanical scenes. *Computer Graphics Forum*, 30 (6), 1708–1718. doi:10.1111/j.1467-8659.2011.01897.x

Neubert, B., Franken, T., and Deussen, O., 2007. Approximate image-based tree-modeling using particle flows. *ACM Transactions on Graphics*, 26 (99), 88. doi:10.1145/1276377.1276487

Nielsen, J., 1993. Iterative user-interface design. *Computer*, 26 (11), 32–41.

O'Neill, R.V., *et al*., 1988. Indices of landscape pattern. *Landscape Ecology*, 1 (3), 153–162. doi:10.1007/BF00162741

Perry, G.L.W. and Enright, N.J., 2006. Spatial modelling of vegetation change in dynamic landscapes: a review of methods and applications. *Progress in Physical Geography*, 30 (1), 47–72. doi:10.1191/0309133306pp469ra

Pettit, C., *et al*., 2012. Developing a multi-scale visualisation framework for use in climate change response. *Landscape Ecology*, 27 (4), 487–508.

Saito, K., *et al*., 2007. Historical forest landscape reconstruction using continuous forest management data from 1931 to 2001 at Tokyo university forest in Chichibu, central Japan. *Journal of Forest Research*, 12 (3), 193–200. doi:10.1007/s10310-007-0010-3

Scheller, R.M., *et al*., 2007. Design, development, and application of LANDIS-II, a spatial landscape simulation model with flexible temporal and spatial resolution. *Ecological Modelling*, 201 (3–4), 409–419. doi:10.1016/j.ecolmodel.2006.10.009

Scheller, R.M., *et al*., 2011. The effects of forest harvest intensity in combination with wind disturbance on carbon dynamics in lake states Mesic forests. *Ecological Modelling*, 222 (1), 144–153. doi:10.1016/j.ecolmodel.2010.09.009

Scheller, R.M. and Mladenoff, D.J., 2005. A spatially interactive simulation of climate change, harvesting, wind, and tree species migration and projected changes to forest composition and biomass in northern Wisconsin, USA. *Global Change Biology*, 11 (2), 307–321. doi:10.1111/j.1365-2486.2005.00906.x

Scheller, R.M. and Mladenoff, D.J., 2007. An ecological classification of forest landscape simulation models. Tools and strategies for understanding broad-scale forested ecosystems. *Landscape Ecology*, 22 (4), 491–505. doi:10.1007/s10980-006-9048-4

Schroth, O., Pond, E., and Sheppard, S.R.J., 2015. Evaluating presentation formats of local climate change in community planning with regard to process and outcomes. *Landscape and Urban Planning*, 142, 147–158. doi:10.1016/j.landurbplan.2015.03.011

1962. *Sensorama Patent*.

Shaw, A., *et al*., 2009. Making local futures tangible—synthesizing, downscaling, and visualizing climate change scenarios for participatory capacity building. *Global Environmental Change*, 19 (4), 447–463. doi:10.1016/j.gloenvcha.2009.04.002

Sheppard, S., 2012. *Visualizing Climate Change. A guide to visual communication of climate change and developing local solutions*. London: Earthscan.

Sheppard, S.R.J., 2015. Making climate change visible. A critical role for landscape professionals. *Landscape and Urban Planning*, 142, 95–105. [Accessed 11 January 2017 doi:10.1016/j.landurbplan.2015.07.006

Singh, A.S., *et al*., 2017. The perceived psychological distance of climate change impacts and its influence on support for adaptation policy. *Environmental Science & Policy*, 73, 93–99. doi:10.1016/j.envsci.2017.04.011

Sutcliffe, A. and Gault, B., 2004. Heuristic evaluation of virtual reality applications. *Interacting with Computers*, 16 (4), 831–849. doi:10.1016/j.intcom.2004.05.001

Sutherland, I.E., 1968. A head-mounted three dimensional display. *In*: 1968.

Swetnam, R.D. and Korenko, J., 2019. Can computer game landscapes target new audiences for landscape quality assessment? *Applied Geography*, 113, 102102. doi:10.1016/j.apgeog.2019.102102

Tan, P., *et al*., 2007. Image-based tree modeling. *ACM Transactions on Graphics*, 26 (99), 87. doi:10.1145/1276377.1276486

Wang, X., *et al*., 2006. Visualizing forest landscapes using public data sources. *Landscape and Urban Planning*, 75 (1–2), 111–124. doi:10.1016/j.landurbplan.2004.12.010

Williams, J.W. and Jackson, S.T., 2007. Novel climates, no-analog communities, and ecological surprises. *Paleoecology*, 5 (9), 475–482.

Wilson, B.T., Lister, A.J., and Riemann, R.I., 2012. A nearest-neighbor imputation approach to mapping tree species over large areas using forest inventory plots and moderate resolution raster data. *Forest Ecology and Management*, 271, 182–198. doi:10.1016/j.foreco.2012.02.002

Wither, J., *et al*., 2009. *Structure from silhouettes: a new paradigm for fast sketch-based design of trees*. EUROGRAPHICS, 30 March–3 April 2009 Munich. Oxford: Blackwell Publishing, 541–550.

Xie, X., *et al*., 2011. Application of China's national forest continuous inventory database. *Environmental Management*, 48 (6), 1095–1106. doi:10.1007/s00267-011-9716-2

Zamuda, A. and Brest, J., 2013. Environmental framework to visualize emergent artificial forest ecosystems. *Information Sciences*, 220, 522–540. doi:10.1016/j.ins.2012.07.031

Zhang, F., *et al*., 2012. Attributing carbon changes in conterminous U.S. forests to disturbance and non-disturbance factors from 1901 to 2010. *Journal of Geophysical Research: Biogeosciences*, 117 (G2), n/a-n/a.

Zhang, X., *et al*., 2014. Data-driven synthetic modeling of trees. *IEEE Transactions on Visualization and Computer Graphics*, 20 (9), 1214–1226. doi:10.1109/TVCG.2014.2316001

Zhang, X., *et al*., 2017. Tree branch level of detail models for forest navigation. *Computer Graphics Forum*, 36 (8), 402–417. doi:10.1111/cgf.13088