Cognitively Grasping Topography with Tangible Landscape

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Tangible interfaces for spatial modeling combine embodied, kinaesthetic interaction with spatial computations. Theoretically this should enable users to intuitively interact with multidimensional digital models of space, offloading challenging cognitive tasks onto the body and computationally enhancing how they think about space. We have designed Tangible Landscape – a tangible interface powered by a geographic information system (GIS) that gives 3D spatial data an interactive, physical form so that users can naturally sense and shape it. Tangible Landscape couples a physical and a digital model of a landscape through real-time cycles of physical manipulation, 3D scanning, spatial computation, and projected feedback. Through a series of 3D modeling experiments assessed using both quantitative and qualitative methods we determined that Tangible Landscape can improve 3D spatial performance. Participants produced more accurate models that better represented morphological features with tangible modeling than they did with either digital or analog, hand modeling.

CCS Concepts: •**Human-centered computing** → **Human computer interaction (HCI); Laboratory experiments;**

Additional Key Words and Phrases: Human-computer interaction, tangible interfaces, interaction design, physical computation, embodied cognition, spatial thinking, geospatial modeling

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1. INTRODUCTION

Spatial thinking – 'the mental processes of representing, analyzing, and drawing inferences from spatial relations' [Uttal et al. 2013] – is used pervasively in everyday life for tasks such as recognizing things, manipulating things, interacting with others, and way-finding. Higher dimensional spatial thinking – thinking about form, volume, and processes unfolding in time – plays an important role in science, technology, engineering, the arts, and math. 3-dimensional (3D) spatial thinking is used in disciplines such as geology to understand the structure of the earth, ecology to understand the structure of ecosystems, civil engineering to shape landscapes, architecture to design buildings, urban planning to model cities, and the arts to shape sculpture.

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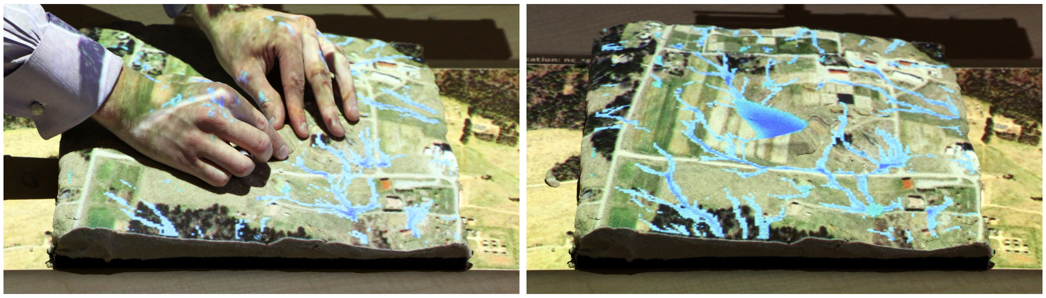


Fig. 1. Modeling the flow of water with Tangible Landscape. A user sculpts a polymeric sand model of a landscape augmented with simulated water flow and an orthophotograph. Changes to the model are scanned into in GIS and the resulting water flow simulation is projected back onto the model in real-time.

Many spatial tasks can be performed computationally enabling users to efficiently store, model, and analyze large sets of spatial data and solve complex spatiotemporal problems. In engineering, design, and the arts computer-aided design (CAD) and 3D modeling software are used to interactively, computationally model, analyze, and animate complex 3D forms. In scientific computing multidimensional spatial patterns and processes can be mathematically modeled, simulated, and optimized using geographic information systems (GIS), geospatial programming, and spatial statistics. GIS can be used to quantitatively model, analyze, simulate, and visualize complex spatial and temporal phenomena – computationally enhancing users' understanding of space. With extensive libraries for point cloud processing, 3D vector modeling, and surface and volumetric modeling and analysis GIS are powerful tools for studying 3D space.

GIS, however, can be unintuitive, challenging to use, and creatively constraining due to the complexity of the software, the complex workflows, and the limited modes of interaction and visualization [Ratti et al. 2004a]. Unintuitive interactions with GIS can frustrate users, constrain how they think about space, and add new cognitive burdens that require highly developed spatial skills and reasoning to overcome. The paradigmatic modes for interacting with GIS today – command line interfaces (CLI) and graphical user interfaces (GUI) – require physical input into devices like keyboards, mice, digitizing pens, and touch screens, but output data visually as text or graphics. Theoretically this disconnect between intention, action, and feedback makes graphical interaction unintuitive [Dourish 2001; Ishii 2008]. Since users can only think about space visually with GUIs, they need sophisticated spatial abilities like mental rotation [Shepard and Metzler 1971; Just and Carpenter 1985] to parse and understand, much less manipulate 3D space.

In order to make 3D GIS more natural and intuitive to use we have designed Tangible Landscape – a tangible interface for GIS – that physically manifests 3D data so that users can feel and manipulate it with their bodies (Fig. 1). Our goal is for users with little or no computer experience to be able to intuitively, collaboratively explore 3D spatial data and interact with scientific models so that they can rapidly test ideas while learning from computational feedback. We have begun to quantitatively analyze how Tangible Landscape mediates 3D spatial cognition. We invite other researchers to collaborate in this ongoing open source and open science project by building Tangible Landscape, contributing to its development, developing new applications, and studying how it mediates cognition.

1.1. Tangible, embodied interaction

In embodied cognition higher cognitive processes are grounded in, built upon, and mediated by bodily experiences such as kinaesthetic perception and action [Hardy-Vallée and Payette 2008]. Tangible interfaces – interfaces that couple physical and digital data [Dourish 2001] – are designed to enable embodied interaction by physically manifesting digital data so that users can cognitively grasp and absorb it, thinking with it rather than about it [Kirsh 2013]. Embodied interaction should be highly intuitive – drawing on existing motor schemas and seamlessly connecting intention, action, and feedback. It should reduce users' cognitive load by enabling them to physically simulate processes and offload tasks like spatial perception and manipulation onto the body [Kirsh 2013]. Distance and physical properties like size, shape, volume, weight, hardness, and texture can be automatically and subconsciously assessed with the body [Jeannerod 1997]. Tangible interfaces should, therefore, enable users to subconsciously, kinaesethically judge and manipulate spatial distances, relationships, patterns, 3D forms, and volumes offloading these challenging cognitive tasks onto their bodies.

1.2. Tangible interfaces for geospatial modeling

With GIS users can computationally offload complex cognitive tasks like analyzing spatial patterns and simulating spatiotemporal processes. Tangible interfaces for geospatial modeling should, therefore, enhance users' spatial performance – their ability to sense, manipulate, and interact with multidimensional space – for challenging tasks like sculpting topography and guiding the flow of water by combining these physical and computational affordances. There are already many tangible interfaces for geospatial modeling. These include actuated pin tables (Table I), augmented architectural models (Table II), augmented clay (Table III), and augmented sandboxes (Table IV).

Actuated pin tables like Relief [Leithinger et al. 2009] are a type of transformable tangible interface [Ishii et al. 2012], dynamic shape display [Poupyrev et al. 2007], or shape changing interface [Rasmussen et al. 2012] that use motor-driven pistons to actuate an array of pins that physically change the shape of a tabletop surface based on computation. These tangible interfaces have three feedback loops – users can feel the physical model for passive, kinaesthetic feedback, the model can be computationally transformed for active, kinaesthetic feedback, and users can see computationally generated, graphical feedback.

Projection-augmented tangible interfaces couple a physical and digital model through a cycle of 3D sensing or object recognition, computation, and projection. Augmented architectural models like Urp [Underkoffler and Ishii 1999] and the Collaborative Design Platform [Schubert et al. 2011b] are a type of 'discrete tabletop tangible interface' [Ishii et al. 2012] with physical models of buildings that are augmented with projected analytics. Augmented clay models like Illuminating Clay [Piper et al. 2002a] and augmented sandboxes like Sandscape [Ishii et al. 2004] are types of 'deformable, continuous tangible interfaces' [Ishii et al. 2012] that users can sculpt. These tangible interfaces have two feedback loops – there is passive, kinaesthetic feedback from grasping the physical model and active, graphical feedback from computation.

1.2.1. Actuated pin tables. Project FEELEX, an early prototype developed in 2001, used an array of 36 actuated pins to deform a 24 x 24 cm rubber sheet. This computationally deformable rubber sheet was augmented with projected graphics to create a shape changing 3D display. User studies for FEELEX included observations of user behavior and shape recognition tests. They found that 85% of their subjects used their entire hand to interact with the interface. On average subjects had 6 mm of error when perceiving shapes by touch with their system [Iwata et al. 2001].

The XenoVision Mark III Dynamic Sand Table, developed in 2004, and the Northrop Grumman Terrain Table, developed in 2006, were large actuated pin tables designed for military geospatial applications that used thousands of pins to dynamically reshape 1.32 x 1.02 m silicone surfaces representing topography.

The MIT Media Lab developed a family of actuated pin tables – Relief, Recompose, Tangible CityScape, and inFORM – to explore novel modes of interaction with dynamically changing affordances and constraints. Relief used an array to 125 actuated pins to deform a projection-augmented lycra surface representing topography [Leithinger et al. 2009]. A depth sensor was integrated into the next generation of this system, Recompose, so that users could control the surface using gestures [Leithinger et al. 2011; Blackshaw et al. 2011]. inFORM – redesigned as an array of 900 polystyrene pins forming a 381 x 381 mm 3D projection-augmented surface – affords diverse modes of interaction such as sculpting, gesture, indirectly moving passive objects with pins, and pressing user interface elements like buttons formed from pins. [Follmer et al. 2013]. The Tangible CityScape project used inFORM to physically model urban spaces and analyze urban conditions like light and shadow. Building masses formed by pins would dynamically reshape when users panned or zoomed with gestures.

While actuated pin tables afford highly intuitive, bi-directional physical interaction, they are mechanically complex, relatively low resolution, and challenging to maintain and transport. The size of the actuators limits their resolution – Project FEELEX had 40 mm spacing between pins, FEELEX 2 had 8 mm spacing, Relief had 38 mm spacing, and inFORM has 3.175 mm spacing between 9.525 mm^2 pins. These systems tend to be small and expensive to build due to their mechanical complexity.

1.2.2. Augmented architectural modeling interfaces. Urp – a projection augmented interface for urban design – used tag-based objection detection to digitize physical models of buildings on a table. Spatial analyses and simulations such as proximity, wind, shadow, and viewsheds were computed and projected onto the tabletop in real-time so that users could rapidly test different spatial configurations of buildings [Underkoffler and Ishii 1999]. As a case study Urp was used by a urban design class in the MIT School of Architecture and Planning. The researchers observed that it helped students to rapidly explore and test different configurations of space and effectively communicate their designs [Ishii et al. 2002].

The Collaborative Design Platform uses a depth camera to digitize and track physical models of buildings on a rear-projection light table. As users move polystyrene foam models of buildings, the models are 3D scanned updating a digital 3D model of a city. Analyzes like wind, light, shadow, accessibility, distance, and views are projected onto the table in realtime. Views are also rendered in 3D on a wall-mounted touch screen. Users can interact by placing and moving physical models of buldings, touching the screen, or sketching with a digitizing pen [Schubert et al. 2015].

1.2.3. Augmented clay interfaces. Illuminating Clay coupled a clay model and digital model of landscape through a cycle of laser scanning, spatial modeling, and projection. By enriching physical models of urban spaces and landscapes with spatial analyses such as elevation, aspect, slope, cast shadow, profile, curvature, viewsheds, solar irradiation, and water direction it enabled intuitive form-finding, streamlined analog and digital workflows, and enabled multiple users to simultaneously interact in a natural way [Ratti et al. 2004a]. Illuminating Clay had a very limited library of custom implemented spatial analyses. Since many of analyses were adapted from the open source GRASS GIS project [Piper et al. 2002a] there was a call for closer integration with GRASS GIS in order to draw on its extensive libraries for spatial computation [Piper et al. 2002b]. The effort to couple a physical landscape model with GRASS GIS [Mitasova et al. 2006] led to the development of the Tangible Geospatial Modeling System [Tateosian et al. 2010].

The Tangible Geospatial Modeling System coupled a physical model and GIS model of a landscape through a cycle of laser scanning, geospatial computation in GRASS GIS, and projection giving developers and users access to a sophisticated library for spatial modeling, simulation, visualization, and databasing. It enriched freeform hand modeling with geospatial simulations like diffusive water flow and erosion-deposition so that users could easily explore how changes in topographic form affect landscape processes [Tateosian et al. 2010].

1.2.4. Augmented sandbox interfaces. SandScape used infrared depth sensing to digitize a 'sandbox' of 1 mm glass beads. An infrared camera captured the intensity of infrared light passing through the beads from below in real-time. A digital elevation model computed from the light intensity and derived analyses were projected back onto the sandbox for real-time feedback. SandScape was relatively low resolution due to the quality of the infrared sensing and the size of the glass beads [Ishii et al. 2004; Ratti et al. 2004a].

Phoxel-Space adapted SandScape and Illuminating Clay for physically interacting with voxels, i.e. volumetric pixels. The system coupled a malleable physical model – built of media like clay, plasticine, cubic blocks, or glass beads – with a 3D raster dataset using either a laser scanner or an IR camera. The researchers demonstrated how Phoxel-Space could be used to explore magnetic resonance imaging data, seismic velocity, and computational fluid dynamics [Ratti et al. 2004b].

The Augmented Reality Sandbox developed by the UC Davis W.M. Keck Center for Active Visualization in the Earth Sciences couples a sandbox with a digital model of a landscape through a real-time cycle of 3D scanning with a Kinect sensor. Scans are statistically filtered to remove hands and tools, reduce noise, and fill in areas with no data. The default filtering – 30 frames – results in 1 second of lag. The digital elevation model, contours, and simulated water flow based on the shallow water equations are projected back onto the sand model of the landscape [Kreylos 2012]. It was inspired by a Czech prototype called SandyStation. The code for this open source project, released under the GNU General Public License, and blueprints for building the system are available at https://arsandbox.ucdavis.edu. 280 Augmented Reality Sandboxes have already been built around the world [Kreylos 2017].

Researchers at Eastern Carolina University built an Augmented Reality Sandbox and conducted a qualitative pilot study examining the effect of the technology on learning and engagement in geoscience education. 12 students used the Augmented Reality Sandbox to build terrain models from contours, model fluvial features and processes, and model coastal features and processes. The researchers solicited feedback with an exit survey. Students reported that the sandbox helped them learn about topography, fluvial and coastal processes, and process-form interactions more effectively. Based on the survey and their observations the researchers hypothesized that augmented sandboxes could enable embodied learning and encourage the development of scientific modeling skills [Woods et al. 2016].

Hakoniwa – a projection-augmented sandbox for making generative music and art – was inspired by sandtray therapy. The system was designed to create a playful, embodied experience that could be therapeutic. As users built landscapes in the sandbox by sculpting sand and placing wooden blocks they created music and visual patterns in real-time through a cycle of depth and color sensing, image processing, audio generation, computer graphics, and projection [Kikukawa et al. 2013]. The system evolved from PocoPoco – a tabletop tangible interface for making music [Kanai et al. 2011].

The Landscape Morphologies Lab at the University of Southern California developed the Rapid Landscape Prototyping Machine – a projection-augmented sandbox with robotic fabrication – to design and test strategies for dust control and mitigation for Lake Owens, California. The system used a 6-axis robotic arm to digitally fabricate algorithmically generated landscapes in a sandbox. The sand models were digitized with a laser scanner, the point cloud was triangulated as a terrain mesh, and spatial analyses such as viewsheds, aspect, and flooding were projected back onto the sandbox [Robinson 2014; Cantrell and Holzman 2016]

The Augmented REality Sandtable (ARES) developed by the US Army Research Laboratory is designed for military training and simulation. This system uses a depth camera to continually 3D scan a sandbox and detect gestures. The digital elevation model and contour map derived from the scans and military units created using gestures or tablet input are projected onto the sand model. Units and buildings can be visualized in 3D using tablets or augmented reality glasses. The Augmented REality Sandtable can be linked with other military software to simulate scenarios [Amburn et al. 2015]. A user study comparing users' performance with paper maps, Google Earth, and the Augmented REality Sandtable found that the sandtable was the most effective technology. Participants – especially participants who were veteran video gamers – tended to perform better with the sandtable in landmark identification, distance estimation, and situational judgment tests [Schmidt-Daly et al. 2016].

Inner Garden – a projection-augmented sandbox for contemplation and self-reflection – couples a sand model of topography with simple digital environment with water, plants, clouds, and daylight through a cycle of 3D scanning with a Kinect, biometric sensing, computation, and projection. While a user sculpts topography in the sand creating a digital elevation model, their physiological and emotional state are monitored with an electroencephalogram (EEG) and breathing sensor. Their breath controls the simulated sea level and daylight, their level of frustration controls the simulated cloud cover, and their meditativeness controls simulated plant life [Roo et al. 2016].

Tangible Landscape is a projection-augmented sandbox powered by a GIS for real-time geospatial analysis and simulation [Petrasova et al. 2015]. It evolved from Illuminating Clay [Piper et al. 2002a] and the Tangible Geospatial Modeling System [Tateosian et al. 2010]. While the Tangible Geospatial Modeling System used an expensive laser scanner for 3D sensing [Tateosian et al. 2010], Tangible Landscape – inspired by the open source Augmented Reality Sandbox [Kreylos 2012] – uses a low-cost 3D sensor for real-time depth and color sensing. The 1st generation of Tangible Landscape [Petrasova et al. 2014] used the 1st generation Kinect with structured light sensing [Smisek et al. 2011], while the 2nd [Petrasova et al. 2015] and 3rd generations of Tangible Landscape used the 2nd generation Kinect with time-of-flight sensing [Bamji et al. 2015]. Two pilot studies have quantitatively compared users' 3D spatial performance with Tangible Landscape and digital 3D modeling programs. The first pilot study found that participants tended to more accurately model landscapes using projection augmented modeling with Tangible Landscape than digital modeling with Rhinoceros [Harmon 2016]. The second pilot study found that participants tended to more accurately model topography and hydrology using Tangible Landscape with the water flow analytic than Vue's terrain editor [Harmon et al. 2016c].

1.3. Aims and objectives

Research on tangible interfaces for geospatial modeling has focused on the design of new technologies and prototypes rather than studying how they are used. A review of tangible interfaces for geospatial modeling (Tables I-IV) shows that there have been relatively few case studies [Ishii et al. 2002; Tateosian et al. 2010; Petrasova et al.

Table I. Actuated pin tables

System	Interaction	GIS	User studies	Publications
XenoVision Mark III Dynamic Sand Table	Sculpting			
Northrop Grumman Terrain Table	Sculpting			
Relief	Sculpting			[Leithinger et al. 2009]
				[Leithinger and Ishii 2010]
Recompose	Sculpting			[Leithinger et al. 2011]
	Gesture			[Blackshaw et al. 2011]
Tangible CityScape	Gesture			
inFORM	Sculpting			[Follmer et al. 2013]
	Gesture			
	Object detection			

Table II. Augmented architectural modeling interfaces

System	Interaction	GIS	User studies	Publications
Urp	Object detection		Case studies*	[Underkoffler and Ishii 1999]
				[Ishii et al. 2002]*
Collaborative Design Platform	Object detection			[Schubert et al. 2011b]
	Touch			[Schubert et al. 2011a]
	Sketching			[Schubert et al. 2012]
				[Schubert et al. 2014]
				[Schubert et al. 2015]

Table III. Augmented clay interfaces

System	Interaction	GIS	User studies	Publications
Illuminating Clay	Sculpting		Protocol analysis‡	[Piper et al. 2002a]
				[Piper et al. 2002b]
				[Piper 2002]
				[Shamonsky 2003]‡
				[Ishii et al. 2004]
				[Ratti et al. 2004a]
Tangible Geospatial Modeling System	Sculpting	✓	Case studies*	[Mitasova et al. 2006]
				[Tateosian et al. 2010]*

Table IV. Augmented sandbox interfaces

System	Interaction	GIS	User studies	Publications
SandScape	Sculpting			[Ishii et al. 2004]
				[Ratti et al. 2004a]
PhoxelSpace	Sculpting			[Ratti et al. 2004b]
SandyStation	Sculpting			
Augmented Reality Sandbox	Sculpting		Survey§	[Woods et al. 2016]§
	Gesture			
Hakoniwa	Sculpting			[Kikukawa et al. 2013]
	Object detection			
	Sound			
Rapid Landscape Prototyping Machine	Machining			[Robinson 2014]
Tangible Landscape	Sculpting	✓	Case studies*	[Petrasova et al. 2014]
	Object detection		Quantitative experiments†	[Petrasova et al. 2015]*
	Sketching			[Harmon et al. 2016c]†
				[Harmon et al. 2016a]†
The Augmented REality Sandtable (ARES)	Sculpting		Quantitative experiments†	[Amburn et al. 2015]
	Gesture			[Schmidt-Daly et al. 2016]†
Inner Garden	Sculpting			[Roo et al. 2016]
	Breathing			
	Emotion			

2015], qualitative user studies [Shamonsky 2003; Woods et al. 2016], and quantitive studies [Harmon et al. 2016c; Harmon et al. 2016a; Schmidt-Daly et al. 2016]. A review of shape-changing interfaces also found that there were relatively few user studies and called for 'more, high-quality data on user experience' in order to understand if interfaces work as designed [Rasmussen et al. 2012].

Many of the theoretical underpinnings of tangibles remain unproven and unexplored. Do current approaches to tangible, embodied interfaces really work as theorized? Can users successfully cognitively grasp digital data as an extension of their bodies, intuitively interact, and offload cognitive processes with tangibles? How does this change how users think and perform? How does it mediate spatial cognition and performance? Can tangible interfaces for geospatial modeling enhance spatial thinking through kinaesthetic interaction with spatial computations? Can users offload enough cognitive work onto their bodies to successfully parse and learn from computational feedback without suffering cognitive overload?

In order to begin to answer some of these questions we designed a tangible interface for geospatial modeling, while simultaneously conducting experiments to study how this tangible interface mediates spatial cognition. Our research objectives were to:

— Design an effective tangible interface for geospatial modeling
— Test whether coupling a physical and digital model of topography can improve 3D spatial performance
— Study how different geospatial analytics mediate users' 3D spatial performance when using a tangible interface for geospatial modeling

2. TANGIBLE LANDSCAPE

2.1. Concept

Tangible interfaces for GIS should ease the cognitive burden of visualizing, interacting with, and reasoning about space by giving spatial data an interactive, physical form that users can cognitively grasp and kinaesthetically explore. Tangible Landscape – a tangible user interface for GRASS GIS – couples a physical and digital model of a landscape through a continuous cycle of 3D scanning, geospatial modeling, and projection so that users can intuitively interact with the modeled landscape in real-time. Conceptually Tangible Landscape physically manifests 3D data so that users can hold a GIS in their hands – so that they can, for example, feel the shape of the earth, sculpt its topography, and direct the flow of water with their hands. It enables users to 3D sketch – to naturally model forms such as topography, draw points and polygons, and interact with simulated physical processes – in a rapid, iterative process of observation, hypothesis generation and testing, and inference. Tangible Landscape is meant to fluidly, seamlessly combine computational science with exploratory modes of creative thinking. Tangible Landscape is unique because it is the only real-time tangible interface for spatial modeling that (1) is powered by a GIS, (2) has extensive libraries for rasters, vectors, time-series, statistics, modeling, analysis, simulation, visualization, and databasing, (3) physically represents space with enough precision for real-world problem solving, (4) has been demonstrated for a wide range of applications, (5) and has been quantitatively tested in user experiments.

2.2. Design

Tangible Landscape was designed to let users naturally explore spatial data, models, and simulations in an engaging, playful way by 3D sketching (Fig. 5). Users can work collaboratively, simultaneously interacting with the physical model (Table V) [Tabrizian et al. 2016]. As users change the physical model the model is 3D scanned as a point cloud, georeferenced, imported into GIS, and either binned or interpolated as a digital elevation model. The digital elevation model is used to compute geospatial analyses, models, and simulations, which are then projected back onto the physical model – all in real-time (Fig. 2). Users can tangibly interact with digital models and simulations by sculpting, placing objects, or sketching (Fig. 3). They can sculpt the model with their hands to shape topography, create or move volumes like buildings or forest canopy, or explore 3D raster data. They can place objects or markers that will be identified using object and color recognition in order to draw points, polylines, polygons, or volumes. They can also use a laser pointer to draw polylines or polygons that will be detected based on light intensity. As the digital models and simulations update the results are projected back onto the model for users to see. The results can also be rendered in 3D on a screen or head-mounted display like an Oculus Rift so that users can immersively visualize the modeled landscape at a human scale (Table V) [Tabrizian et al. 2016]. Because the model is continually scanned users' hands will be digitized as they sculpt or place objects. Scanning users' hands as topography helps users understand how the system works and encourages play. Users can, for example, place their hands on the model and create simulated lakes between their fingers (Fig. 4).

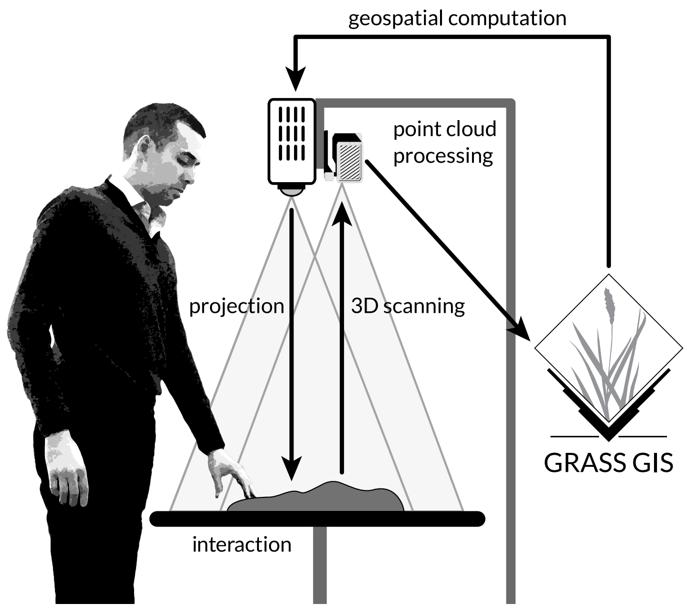


Fig. 2. How Tangible Landscape works: a real-time feedback cycle of physical interaction, 3D scanning, point cloud processing, geospatial computation, and projection.

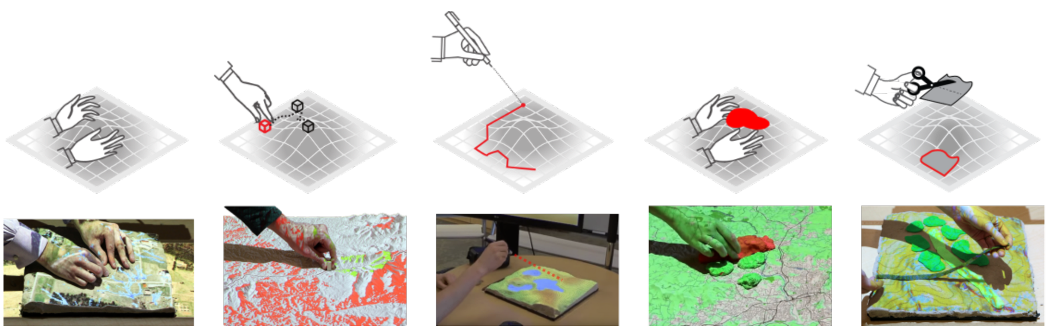


Fig. 3. Modes of interaction with Tangible Landscape: sculpting surfaces, placing points, drawing lines, building volumes, and marking areas.

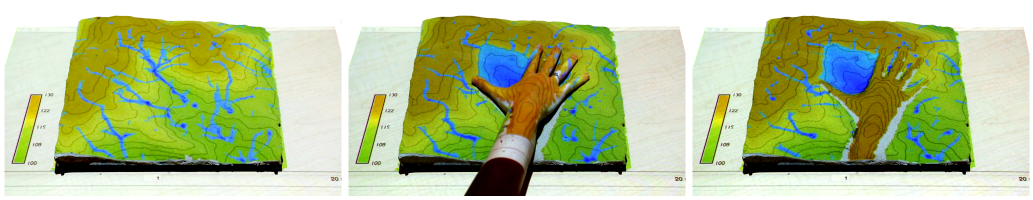


Fig. 4. With Tangible Landscape users can scan their arms and hands as topography creating lakes between their fingers.

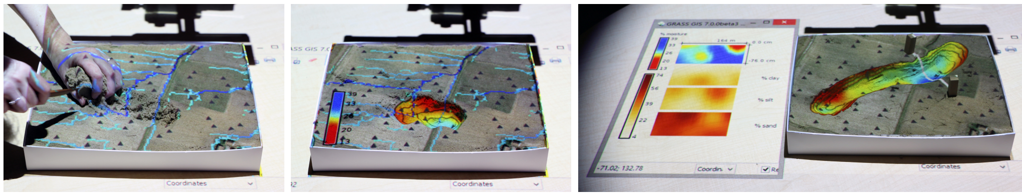
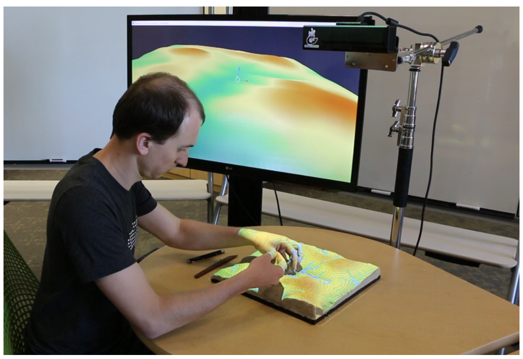
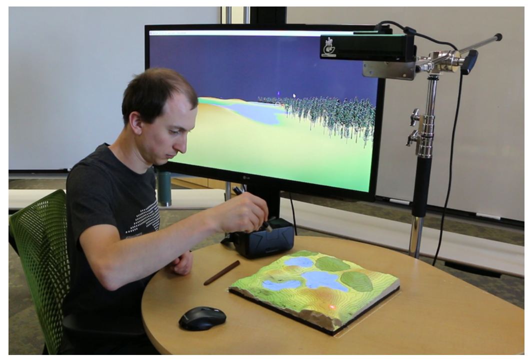
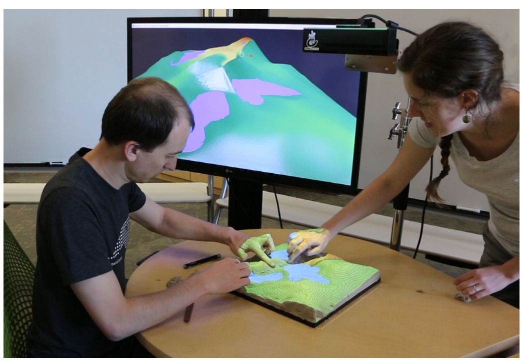
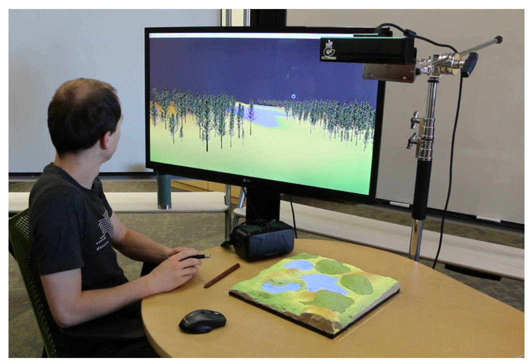
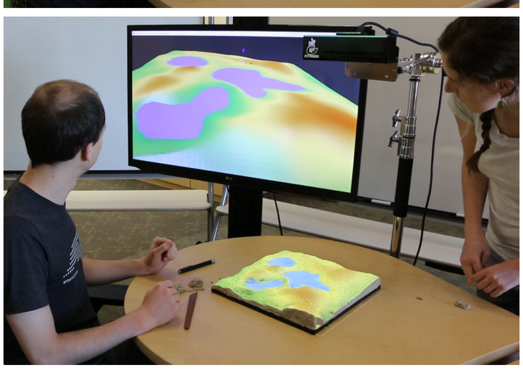
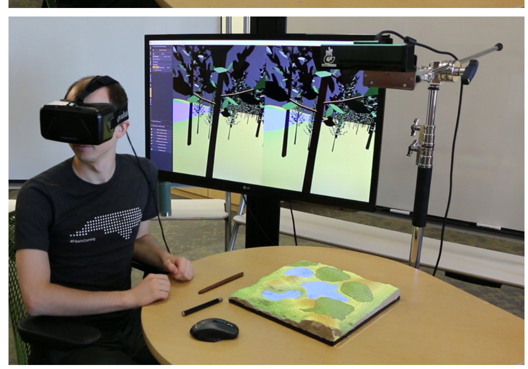


Fig. 5. Naturally exploring subsurface soil moisture and soil types with Tangible Landscape.

Table V. Collaboratively sculpting topography to create lakes, drawing trees with a laser pointer, and visualizing in VR. Source: [Tabrizian et al. 2016].

Sculpting	Drawing & Immersion
	
	
	

Multidimensional sketching. Tangible Landscape was designed to enable tangible multidimensional sketching in geographic space and time. With Tangible Landscape users can sketch in 3D by sculpting surfaces or volumes, drawing across surfaces, or placing and manipulating 3D objects. By directly manipulating 3D form users can indirectly shape other dependent dimensions of data such as simulated processes. Each scan can be stored, timestamped, and registered as a space time raster or vector dataset in GRASS GIS' temporal framework to create a time series of maps. With this time series users can animate the evolution of their model using the module *g.gui.animation*[GRASS Development Team 2016a].

Advances in virtual reality are enabling immersive 3D sketching. The illustrator Wesley Allsbrook, for example, has drawn an animated short film called Dear Angelica by sketching in 3D space using the Oculus Rift and Oculus Touch to combine the affordances of digital painting and physical sculpture [Oculus 2016; Quilez 2016]. While this sort of immersive 3D sketching is situated in a fully virtual space, tangible 3D sketching is situated in a real, but digitally augmented space. Tangible 3D sketching can be situated in a collaborative social context and may not require any new skills – for tangible interactions can be analogous to everyday actions, making use of existing motor schema. While these approaches to 3D sketching should theoretically offer very different affordances in terms of embodied and situated cognition both have the potential to revolutionize how we express ourselves in space and time.

2.3. Implementation

Tangible Landscape uses Microsoft Kinect to continuously capture the shape of the physical model as a point cloud. The point cloud is processed into a raster-based digital elevation model (DEM) in a GRASS GIS database. Since the scanner can be slightly tilted, the scan is horizontally aligned through a calibration process in which a rotation matrix is derived by scanning the horizontal surface of the table where the model will be placed. This rotation matrix is then applied to each scan. The point cloud is automatically trimmed so that it only includes points on the physical model, smoothed, and georeferenced based on the known spatial extent of the area represented by the model. Georeferencing includes translation, rotation by 180° along the z-axis, horizontal scaling, and vertical scaling to account for the vertical exaggeration, if any, of the physical model. The resulting representation of the terrain has real world dimensions and can be combined effortlessly with other GIS data, such as land cover or orthophotographs.

The DEM is reconstructed from the point cloud using either the regularized spline with tension interpolation method [Mitasova et al. 2005] or binning with cell values computed as the mean of the z-coordinates of all of the points falling into that cell. Although binning results in a noisier DEM, it is very fast, and may, therefore, be a better option for some applications. Multiple point clouds can be integrated to increase point density at the cost of increased processing time. For each new DEM a set of customizable analyses and geospatial workflows specified in a Python file is run and the display is updated. Tangible Landscape provides a library of geospatial functions built on top of GRASS GIS modules and an API for developing custom workflows. The modeled analyses and scanning parameters can be modified as the system runs.

Tangible Landscape has been implemented as a set of components – the *r.in.kinect* add-on module [Petrasova 2016b] and the *Tangible Landscape* plugin [Petrasova 2016a] – for the active development version of GRASS GIS (Fig. 6). The *r.in.kinect* add-on module continuously imports and filters point cloud data from the 2nd generation Kinect into GRASS GIS as raster or vector maps. It has been implemented as a separate component so that it can easily be used for other applications. The *Tangible Landscape* plugin provides utilities, a library of analyses, and a GUI dialog for tangible interaction in GRASS GIS. The *Tangible Landscape Immersive Extension* [Tabrizian

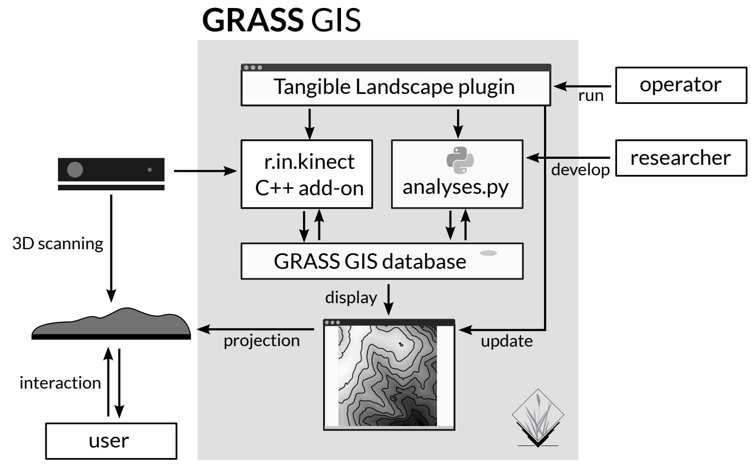


Fig. 6. Software schema for Tangible Landscape.

2016] links Tangible Landscape with Blender, an open source 3D modeling and animation program [Blender Online Community 2016] enabling 3D rendering on screens or head-mounted displays.

Users can develop new analyses for Tangible Landscape using the GRASS GIS Python Scripting Library. Since many tasks in GIS are not appropriate for tangible interaction Tangible Landscape was designed to supplement, not replace GRASS GIS's GUI, CLI, and scripting application program interface (API). Tangible Landscape currently runs on Linux and Mac OSX. Dependencies include the Point Cloud Library [Rusu and Cousins 2011; PCL Development Team 2016], OpenKinect's libfreenect2 [OpenKinect Development Team 2016], OpenCV [OpenCV Development Team 2016], watchdog [Mangalapilly 2011], and GRASS GIS [GRASS Development Team 2016f].

2.4. System resolution, accuracy, and speed

The spatial resolution of the system is determined by the depth camera's parameters and the distance from the camera to the model. Given the Kinect's 70×60 degree field of view and 512×424 pixels depth resolution, the spatial resolution of the system ranges from 1.4 to 2.7 mm when the scanner is 0.5 to 1 m above the model. In the experiments the Kinect was mounted approximately 0.6 m above a 23.5 x 23.5 cm model so we used 2 mm resolution, which translated to 6 m in the real world given the scale of the physical model. Kinect depth measurements suffer from noise as quantified by Sarbolandi et al. [Sarbolandi et al. 2015] We minimized the negative effects of noise by placing the model closer to the center of the camera and by smoothing the data using the Moving Least Squares reconstruction method [Rusu and Cousins 2011].

Fig. 7 and Table VI show the accuracy of the experimental setup. We scanned one of the CNC routed model used in this study and compared it with the original DEM. We removed the systematic error (i.e. the vertical shift) since that is corrected as part the analysis for the experiment and does not influence the results. The difference shown in Fig. 7 was computed from a single frame. Although it is possible to integrate multiple frames, we chose to construct the DEM from a single frame for faster smoothing.

Tangible Landscape's speed – typically ranging from approximately 2 fps to 0.5 fps – depends upon the size of the model, the point cloud processing methods, and the

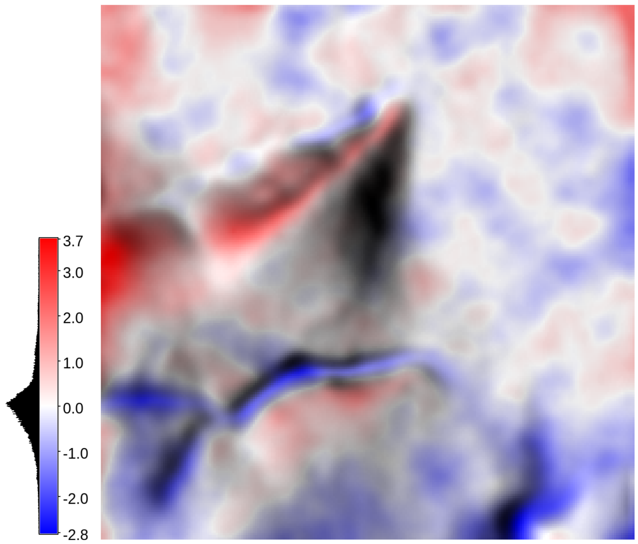


Fig. 7. Accuracy assessment: the difference between original digital elevation model and the scanned elevation of a digitally fabricated physical model of the same landscape. The scanned elevation is higher than the original digital elevation model in blue areas and lower in red areas. Legend values are in millimeters.

Table VI. Scanning accuracy (mm)

Min	Max	Mean	Stdev	1st Q	3rd Q
-2.8	3.7	-0.02	0.7	-0.4	0.3

Table VII. Scanning speed

Size, Process	Small	Medium
Physical size	23.5 cm × 23.5 cm	34 cm × 34 cm
Cells	13,456	26,235
Binning	0.51 s	0.71 s
Interpolation	0.74 s	0.97 s
Water flow	0.29 ± 0.01 s	1.05 ± 0.05 s
Contours	0.054 ± 0.004 s	0.061 ± 0.004 s
Difference	0.036 ± 0.002 s	0.042 ± 0.003 s
Landforms	0.034 ± 0.003 s	0.084 ± 0.009 s

analyses chosen. Table VII compares times for different point cloud processing methods (binning and interpolation) and analyses (e.g. simulated water flow) for small and medium sized models. We used the small model size – 23.5 cm x 23.5 cm – in this study. We recommend the medium model size – 34 cm x 34 cm – for new users getting started with Tangible Landscape. The time needed to scan and obtain a model is less than 1 s, but the subsequent analyses may take more than 1 s. It takes 1.03 s to compute water flow over the smaller model with 0.74 s for interpolation and 0.29 s for the water flow simulation. If a user interacts with Tangible Landscape immediately after a scan has been captured, then they will have to wait for that scan to be processed before their change will be processed potentially doubling the total processing time. The current system, reported here, performs approximately twice as fast as the version used in

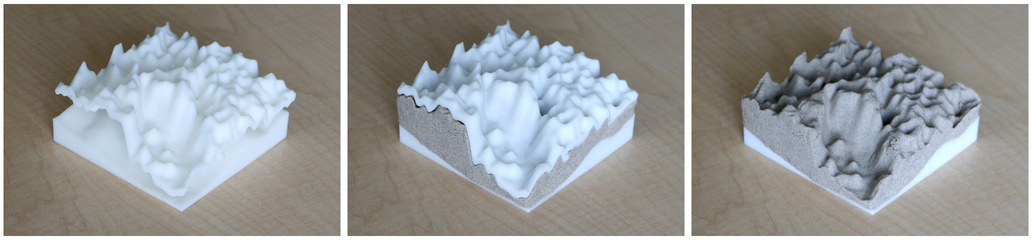


Fig. 8. Casting polymeric sand models with 3D printed molds. Source: [Petrasova et al. 2015].

this study. Benchmarks were performed using a System76 Oryx Pro with a 6th generation Intel Core processor i7-6700HQ (2.6 GHz, up to 3.5 GHz, 6 MB cache, 4 cores, 8 threads), 16 GB dual-channel DDR4 random-access memory (2 $\times$ 8 GB), M.2 SSD storage (540 MB/s sequential read, 520 MB/s write), and NVIDIA GeForce GTX 1060 running Ubuntu 16.04 LTS (64-bit), GRASS GIS 7.2, and Tangible Landscape 2c1ede9.

2.5. Fabrication

We typically use familiar, everyday materials – like sand and wooden blocks – for modeling with Tangible Landscape. Interactions – like sculpting sand and moving wooden blocks – are analogous to everyday tasks so users should subconsciously know what to do and how to do it, leveraging existing sensorimotor schemas. The materiality – the feel, look, and physics – of the media matters. The choice of material can afford different interactions and mediate meaning, emotion, and motivation. We typically use a polymer-enriched sand for the physical terrain model so that users can easily sculpt forms in a deformable medium that will hold its shape, has good plasticity, and has a familiar feel and aesthetic. Digital fabrication technologies like computer numeric control (CNC) manufacturing and 3D printing can be used to create molds for casting polymer-enriched sand into precise yet deformable models (Fig. 8). Cast sand models can precisely represent complex shapes and volumes that are challenging to model by hand and can easily be re-cast after use.

Tangible Landscape can be also be used as a modeling aid for sculpting. Static projections or dynamic analytics like differencing or water flow can be used as guides for hand sculpting terrain models. Users can project their target digital elevation model and contours over their polymeric sand model as a static guide for sculpting. Tangible Landscape can also dynamically compute the difference – i.e. cut and fill – between the target digital elevation model and the scanned model that has been sculpted. The difference can provide a real-time guide where to add or remove sand in order to match the target digital elevation model (Fig. 9).

2.6. Applications

Using GRASS GIS's extensive libraries for geospatial modeling, analysis, and simulation we have developed a wide range of applications for Tangible Landscape [Petrasova et al. 2015]. Design and planning applications include grading, cut and fill analysis, stormwater management, erosion control, trail planning (Fig. 10), viewshed analysis, and the assessment of solar potential. Scientific applications include subsurface visualization (Fig. 5), urban growth modeling, disease management, and invasive species management (Fig. 12). Disaster management applications include flood control, wildfire management, and coastal change and adaptation (Fig. 11). Educational applications include spatial training and serious gaming. See Appendix D for videos of

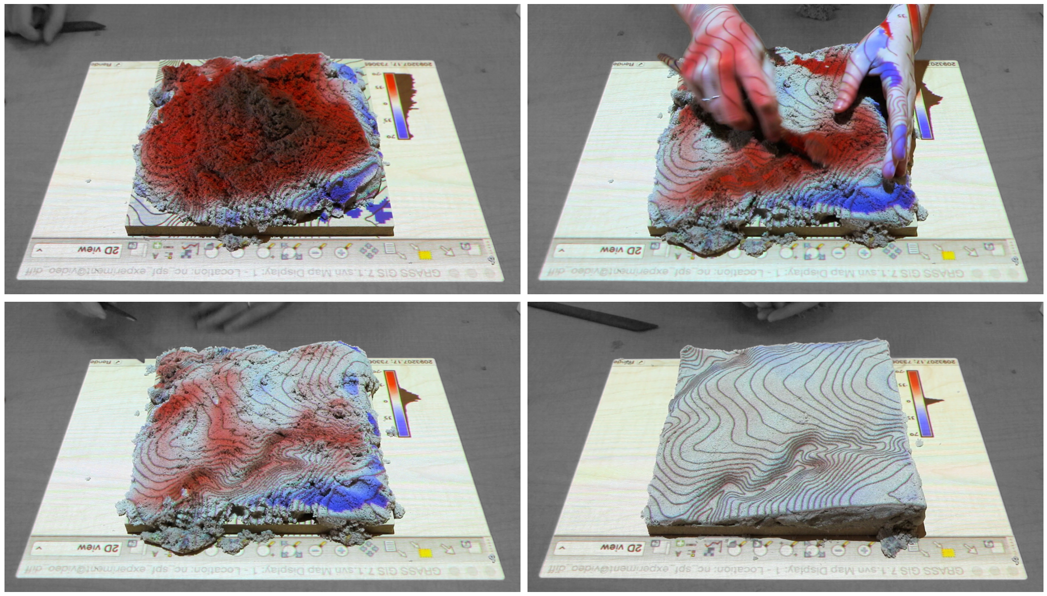


Fig. 9. Sculpting a terrain model using Tangible Landscape's difference analytic. Blue means add sand and red means remove sand.

landscape design (D.1), landscape planning (D.2), subsurface visualization (D.3), viewshed analysis (D.4), wildfire spread (D.5), and urban growth applications (D.6).

3. COUPLING EXPERIMENT

After a pilot study [Harmon 2016] we conducted an experiment to study how coupling digital and physical models of topography mediates 3D spatial performance. This experiment compared how users performed in a terrain modeling task using digital 3D modeling with Rhinoceros, analog modeling by hand, and projection-augmented modeling powered by Tangible Landscape. Digital modeling with a GUI affords precise transformations and dynamic modes of visualization such as 3D orbiting, zooming, and ray traced shading, but is not embodied. Theoretically analog modeling – modeling by hand or with tools – should be embodied, affording subconscious, kinaesthetic sensing and manipulation of form. By sensing form subconsciously with the body users should have more cognitive resources for critiquing their work and strategizing their next moves. Projection-augmented modeling couples digital mapping with physical modeling. Theoretically it should combine affordances of both – enabling enriched visualization and physical sensing and manipulation – to offer more feedback. While more feedback may help users better assess and critique their performance so they can strategize their next moves, too much feedback may be a cognitive overload resulting in distraction, frustration, and demotivation. Physical sensing and manipulation, however, should offload some of this cognitive work onto the body.

3.1. Methods

In this experiment 18 participants tried to accurately model a given study landscape digitally, by hand, and with Tangible Landscape.

Participants. All of the participants – either graduate students, faculty, or professionals in landscape architecture or geographic information science – had experience

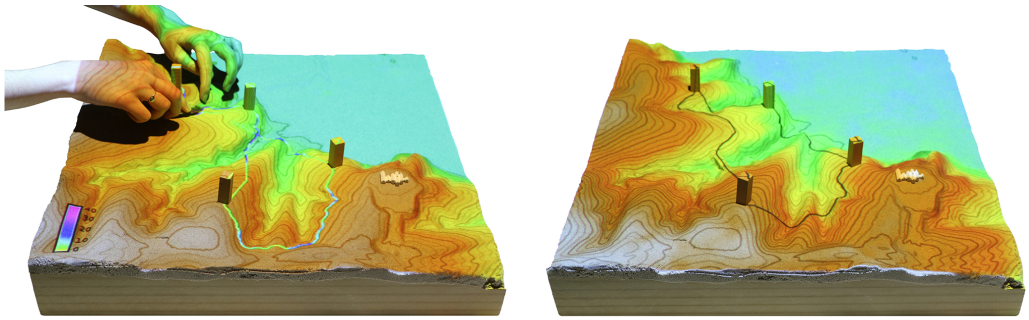


Fig. 10. Trail planning with Tangible Landscape. Users create waypoints for a trail by placing markers on the terrain model. The optimal route between the waypoints is automatically computed based on the least cost path and the solution of the traveling salesman problem. Feedback includes the slope along the trail and viewsheds from waypoints. Users can also change the topography and build bridges. Source: [Petrasova et al. 2015].

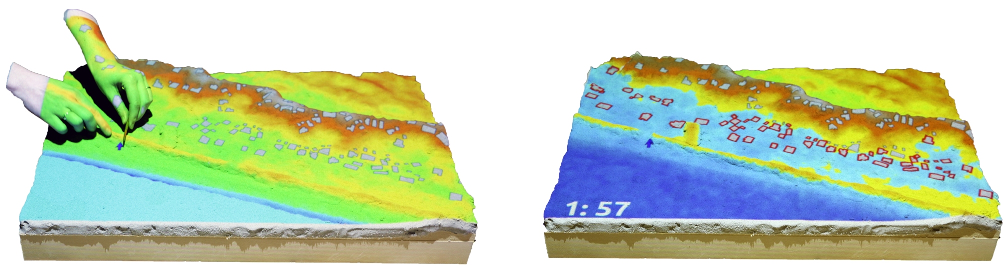


Fig. 11. Testing coastal flood defences with Tangible Landscape. Users try to save houses from coastal flooding by building coastal defenses. Given a small handful of polymer-enriched sand – their budget – they sculpt new dunes as flood defenses. The foredune is then breached at a random location and simulated storm surge is rerun, flooding any vulnerable houses.

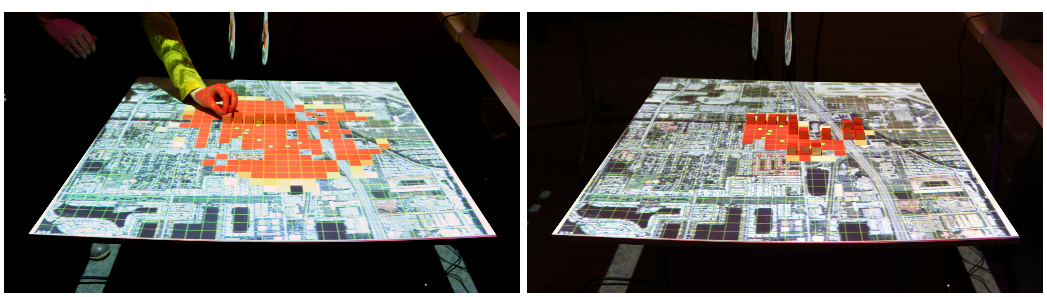


Fig. 12. Managing the simulated spread of termites through a city with Tangible Landscape by treating city blocks. After watching the simulated spread of termites across the city users place preventative treatments to try to contain the invasion. To treat a city block they place wooden cubes representing preventive treatments on the game board leveraging basic motor skills from childhood play. After they treating 10 blocks the stochastic simulation is rerun so users can see how well they contained the invasion.

Table VIII. Participants

Group	No.	GIS training	3D modeling expertise
Landscape architecture students	6	0	0
GIS students	6	6	0
Academics & professionals	6	0	2

thinking spatially. These participants were selected in order to compare the performance of novices and experts in grading (i.e. earthworking), GIS, and 3D modeling. Of the 12 graduate students 6 were in the 2nd semester of the Master of Landscape Architecture program at North Carolina State University. These students were just beginning to learn to read and manipulate contour lines in the class Landform, Site Grading, and Development Systems. They had no experience with GIS, 3 credit hours of training in digital representation, and no experience with Rhinoceros. The other 6 graduate students were in the 2nd semester of the Master of Geospatial Information Science and Technology program at North Carolina State University. They had at least 9 credits hours of training in GIS, but had no experience with contour maps, digital terrain modeling, or 3D modeling. The other 6 participants were either landscape architecture faculty with professional experience or practicing professionals in landscape architecture from around the world. Of these 2 were experts in 3D modeling with over 10 years of experience using Rhinoceros and similar programs including Maya and 3ds Max. These experts felt comfortable and proficient modeling a wide variety of geometries and had developed unique, personalized, and highly adaptable workflows (see Table VIII).

Experimental design. Participants were given three tasks – to digitally sculpt a model of a landscape using the 3D modeling program Rhinoceros, to hand sculpt a model of a landscape in polymer-enriched sand, and to sculpt a model of a landscape using Tangible Landscape. They had 10 minutes to complete each task. The time limit was calibrated based on the time it took the research team to comfortably complete each task. The modeling tasks were reordered for each participant to partially account for learning and fatigue by counterbalancing the experiment using a Latin square design. Participants were asked to model the same landscape for each task so that their performance could be quantitatively assessed using spatial modeling, statistics, analysis, and simulation. Their modeling processes were qualitatively assessed through direct observation supported by photographic and video documentation. After completing the tasks the academics and professionals were interviewed. We intended to conduct semi-structured interviews with all of the participants, but the students were too tired by the end of the experiment. Psychometric tests were not used to assess spatial ability because these do not address geographic scales, spatial relations, domain-specific knowledge and abilities [Lee and Bednarz 2009; Bednarz and Lee 2011; Wakabayashi and Ishikawa 2011], or embodied cognitive ability. See Appendix B for instructions for running the experiment and Appendix C for semi-structured interview guidelines.

We used a region of Lake Raleigh Woods in Raleigh, North Carolina as the study landscape for this experiment. A real landscape was used because computer generated landscapes often look surreal and may lack distinct landforms and clearly defined streams. This study region has distinctive, clearly defined landforms – a stream valley flanked by a ridge and sloping towards the lake. The digital elevation model for this region was derived from a 2013 airborne lidar survey using the regularized spline with tension interpolation method [Mitasova et al. 2005]. We CNC routed a model of the study landscape in Baltic birch using 2 parallel finish cuts with a 3.175 mm diameter ball-nose bit with a 1.27 mm stepover. Participants were given this model at the beginning of the experiment to use as a reference during each task.

Digital modeling. Participants had 10 minutes to digitally model the study landscape in Rhinoceros 5, a non-uniform rational basis spline (NURBS) based 3D modeling program designed for precise freeform curve and surface modeling [McNeel and Associates 2016]. After 10 minutes of training participants modeled the study landscape as a NURBS surface by vertically translating control points (Fig. 13). They started with a flat NURBS surface that was divided into a 10 x 10 grid of control points. As a reference their model space also included a locked representation of the study landscape as 3D contours. At any point participants could rebuild the surface with a higher density of control points for finer, more nuanced control. This method is relatively simple and analogous to basic actions in sculpture – pushing and pulling. We developed and tested this method as a simple, straightforward technique for digital freeform surface modeling that could be taught quickly, yet could produce an accurate model. Through testing we determined that novice users took approximately 10 minutes to model the surface with a 10 x 10 grid of control points before wanting to rebuild the surface with more control points. See Appendix E for videos demonstrating the training (E.1) and digital 3D modeling task (E.2).

Different 3D modeling programs afford very different interactions, modeling tools, data structures, and modes of representations. Developing a simple, intuitive modeling technique drove the choice of software in this study. After testing 3D modeling workflows in Rhinoceros, Vue, Maya, and SketchUp we chose Rhinoceros 5 for this task because it is popular with designers such as architects, has a wide variety of modeling tools, can precisely represent continuous surfaces, and has plugins for importing and exporting geographic data. To make a fair comparison between digital, analog, and tangible modeling, the digital modeling technique needed to be relatively analogous to hand sculpting – i.e. pushing and pulling rather than painting in 3D, drafting in 3D, or stacking voxels. There is an analogous modeling technique – pulling and pushing vertices – using the Sandbox tool in SketchUp [Trimble 2016], but this creates a triangulated irregular network (TIN) rather than a continuous NURBS surface. Vue has a terrain editor designed for intuitive 3D painting and sculpting [e-on software 2012], but it requires continual retuning of tool parameters and generates a TIN. TINs less accurately represent continuous surfaces like topography and would generate artifacts in our analyses. In another pilot study [Harmon et al. 2016c] we tested Vue's terrain editor. We found that participants tended to over-exaggerate distinct features in the landscape like stream channels, while ignoring more subtle features like slopes. We also determined that the resulting models had an obvious triangulated structure that caused exaggerated slopes and discontinuous water flow in our analyses. While voxel modeling programs like Voxel Builder and games like Minecraft [Mojang 2009] are very intuitive to use, they can also be slow to use, create blocky rather than continuous surfaces, and are not typically used in design professions like architecture and landscape architecture.

Analog modeling. After a brief explanation and demonstration participants had 10 minutes to sculpt the study landscape in polymer-enriched sand by hand or with a wooden sculpting tool (Fig. 14). They were given a CNC-routed model of the study landscape as a reference, a sculpting tool, and a 3D scale. Participants were shown how the 3D scale could be used to measure the height of the model. A lamp on the table cast shadows across the model for hillshading. See Appendix E for a video demonstrating the analog 3D modeling task (E.3).

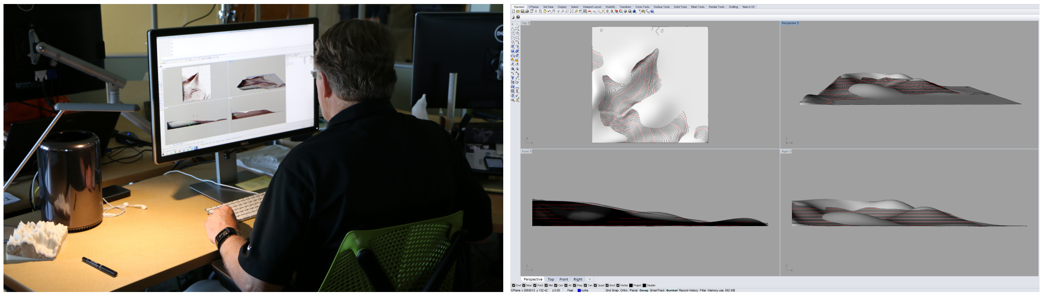


Fig. 13. Coupling experiment – digital modeling. A participant digitally sculpts the study landscape in Rhinoceros using 3D contours as guides.

Fig. 14. Coupling experiment – analog modeling by hand. A participant sculpts the study landscape by hand using a physical model as a reference.

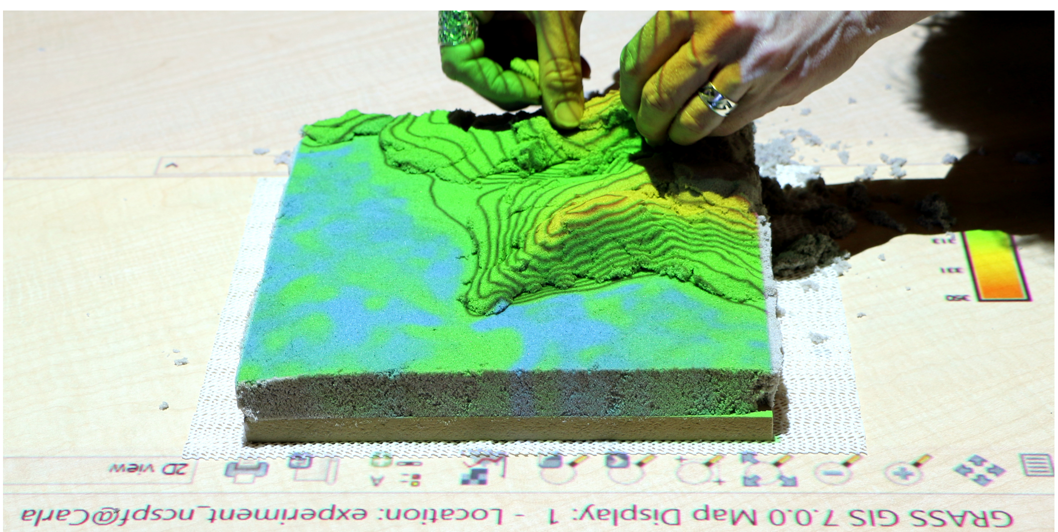


Fig. 15. Coupling experiment – projection-augmented modeling. A participant sculpts the study landscape using the projected elevation and contour maps as guides.

Projection-augmented modeling. After a minute long explanation and demonstration participants had 10 minutes to sculpt a projection-augmented, polymer-enriched sand model of the study landscape by hand or with a wooden sculpting tool (Fig. 15). Tangible Landscape was used to project an elevation map of the study landscape with contours and a legend onto participants' sand models as guide for sculpting. Participants were also given CNC routed reference model and a 3D scale ruled in map units. After an explanation of the contour map, elevation color table, and legend, participants were shown how the 3D scale could be used to measure the elevation of their scale models. See Appendix E for a video demonstrating the projection-augmented 3D modeling task (E.4).

Data collection and analysis. We used Tangible Landscape to scan the finished models built using analog hand modeling and projection-augmented modeling. The scans were captured as point clouds, interpolated as digital elevation models using the regularized spline with tension method, and stored as raster maps in a GRASS GIS database. The NURBS surfaces modeled in Rhinoceros were exported as raster elevation maps, imported into GRASS GIS, randomly resampled, re-interpolated using the regularized spline with tension method, and stored as raster maps in a GRASS GIS database. The data from Rhinoceros was randomly resampled and re-interpolated to account for differences and irregularities in resolution, data density, and point spacing. For each set of models – digital, analog, and augmented – we computed raster statistics (i.e. per cell statistics), topographic and morphometric parameters, and simulated water flow.

Mean elevation. We computed the mean elevation and standard deviation of elevation for each set with the module *r.series* [GRASS Development Team 2016d]. The mean elevation is the average of each cell of all elevation maps in a given set of models.

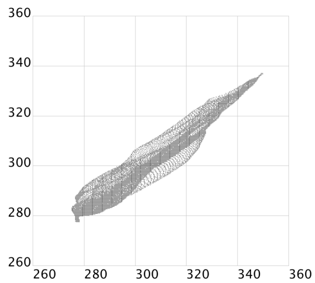
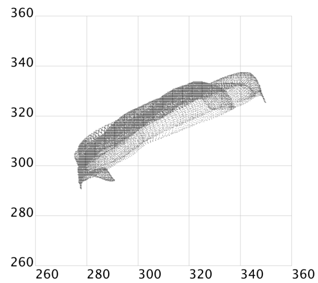
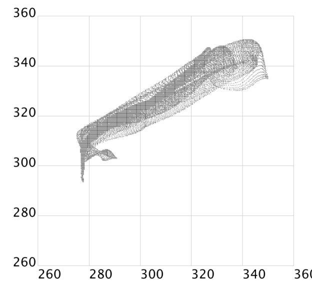
Standard deviation of elevation. The standard deviation of elevations represents the set's consistency. We computed the standard deviation of elevation for each set with the module *r.series* [GRASS Development Team 2016d]. This is the standard deviation of each cell of all elevation maps in a given set of models. We used a sequential color table from Color Brewer [Brewer 1994; Brewer and Harrower 2016].

Mean difference. In order to compare participants' modeling performance between sets we computed the difference between the linearly regressed reference elevation and the mean elevation for each set. The difference between the reference and mean elevation maps should show where the mean elevation values for each set are too low or too high, i.e. where they needed to add (blue) or remove (red) volume to match the reference. There were, however, systematic errors in the scanned models. Table IX shows the vertical shift in the hand sculpted and projection-augmented models caused by scanning and georeferencing. We used linear regression to vertically rescale and translate the reference elevation in order to account for these systematic errors in the difference calculation,

$$\Delta = (a + b * z_0) - \overline{z} \tag{1}$$

where:
Δ is the difference
z_0 is the reference elevation map
$\overline{z}$ is the mean elevation of maps in a set
a is the intercept of the regression line
b is the slope of the regression line.

Table IX. Bivariate scatterplots of elevation values

	Digital	Analog	Augmented
Mean			
	Reference	Reference	Reference

Standard deviation of difference. In order to find how consistently the models fit the reference landscape we computed the standard deviation of difference by first calculating the difference between the linearly regressed reference elevation and each modeled elevation map in a set to generate a set of difference maps. Then we calculated the standard deviation for that set of difference maps.

Mean slope. We derived the slope of the mean elevation of each set using differential geometry [Wood 1996] with the module *r.param.scale* [GRASS Development Team 2016c].

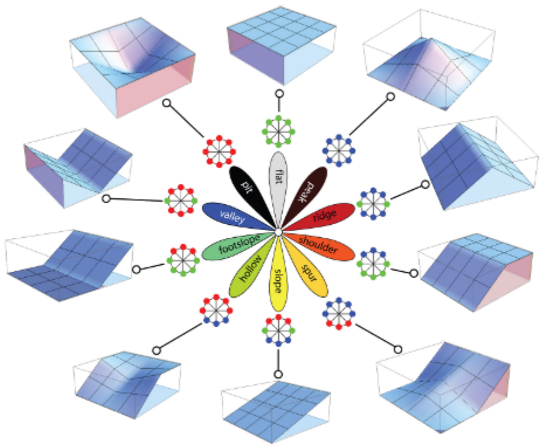
Mean landforms. We identified landforms for the mean digital elevation model for each set using geomorphons, a pattern recognition method for landform classification based on the openness of the terrain and implemented as the add-on module *r.geomorphon* [GRASS Development Team 2016b]. Geomorphon works effectively across spatial scales because the neighborhood search size for pattern recognition is spatially variable – it depends on the visibility of the cell [Jasiewicz and Stepinski 2013]. Landforms can be classified as flat, peak, ridge, shoulder, spur, slope, hollow, footslope, valley, or depression (Fig. 16).

Mean minimum distance. We computed the mean minimum distance between cells with water flow, ridges, and valleys on the models and the reference landscape as a measure of positional accuracy.

Systematic errors. Table IX shows systematic errors in the hand sculpted and projection-augmented models. These models are vertically shifted due to scanning and have low values along the borders caused by slumping sand. While we used linear regression to vertically shift and rescale the difference in elevation, we did not mitigate the systematic errors along the borders.

3.2. Results

We used pairwise comparison to study how performance varied between novices and experts (Fig. 17). After analyzing all participants performance (Table X) we compared students with academics and professionals (Table XI - XII). Then we compared landscape architecture students with GIS students (Table XIII - XIV). Last we compared academics and professionals with and without 3D modeling expertise (Table XV - XVI).



−/+	0	1	2	3	4	5	6	7	8
0	FL	FL	FL	FS	FS	VL	VL	VL	PT
1	FL	FL	FS	FS	FS	VL	VL	VL	_
2	FL	SH	SL	SL	HL	HL	VL	_	_
3	SH	SH	SL	SL	SL	HL	_	_	_
4	SH	SH	SP	SL	SL	_	_	_	_
5	RI	RI	SP	SP	_	_	_	_	_
6	RI	RI	RI	_	_	_	_	_	_
7	RI	RI	_	_	_	_	_	_	_
8	PK	_	_	_	_	_	_	_	_

Fig. 16. Landforms identified by *r.geomorphon* – 1) flat, 2) peak, 3) ridge, 4) shoulder, 5) spur, 6) slope, 7) hollow, 8) footslope, 9) valley, and 10) depression. Source: [GRASS Development Team 2016b].

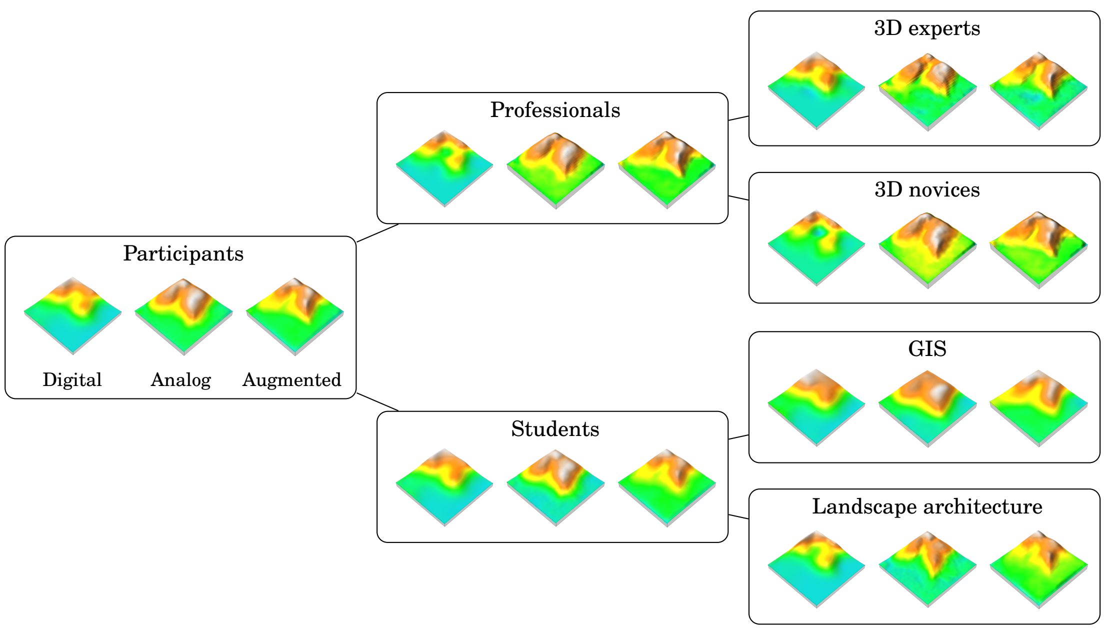
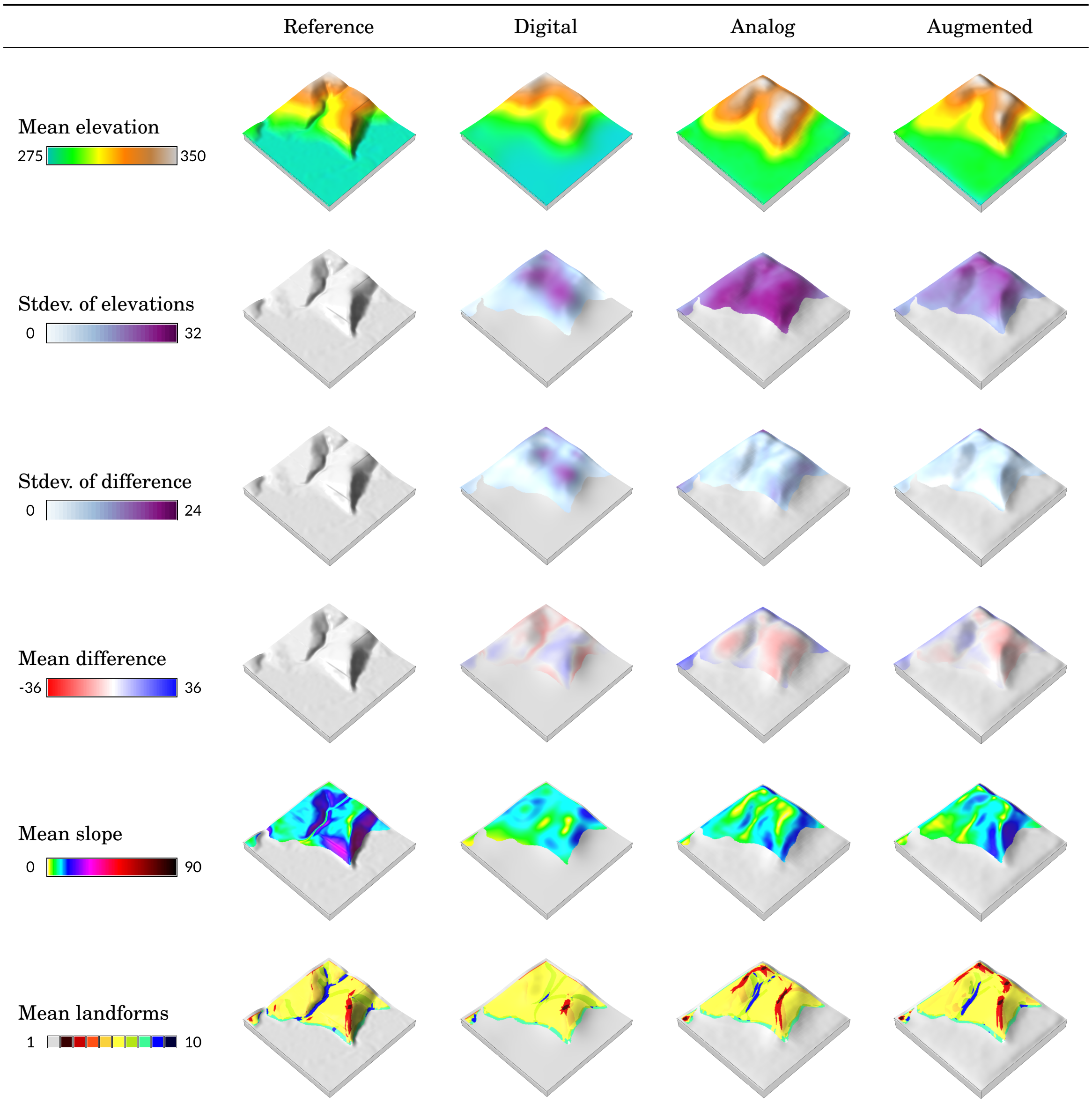


Fig. 17. Pairwise comparison of the mean digital elevation models grouped by category of participants

Overall participants performed worst with digital modeling, better with analog modeling, and best with projection-augmented modeling. Table X compares participants' performance with each technology through 3D maps of raster statistics and geospatial analyses. When digitally modeling with Rhinoceros participants tended to create very approximate massings of the topography with serious errors in the interior space and with indistinct landforms that only hinted at the morphology of the landscape. When they sculpted by hand their models tended to be descriptive – differing substantially from the reference, but accurately representing most of the landforms.

Table X. Coupling experiment: maps of per-cell statistics and geospatial analyses draped over 3D topography for all participants



Their performance improved when they sculpted projection-augmented models – the resulting models fit the reference better, had more defined topography, and accurately represented most of the landforms.

When participants are analyzed as groups – as GIS students, Landscape Architecture students, academics and professionals without 3D modeling expertise, and academics and professionals with 3D modeling expertise – these trends generally still hold, albeit with some very important exceptions. Unlike all other groups, the 3D modeling experts performed extremely well in the digital modeling task with a very low

Table XI. Students

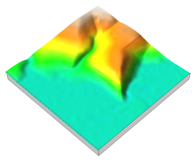
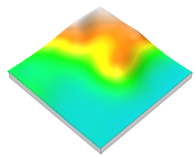
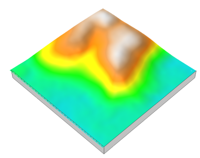
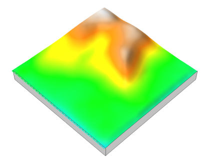
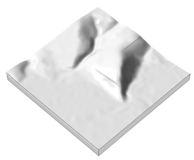
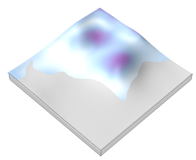
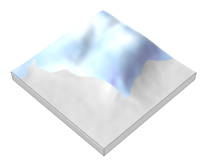
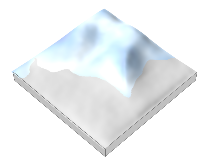
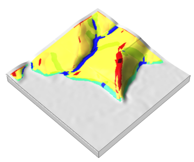
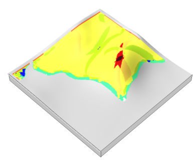
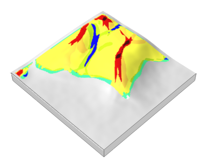
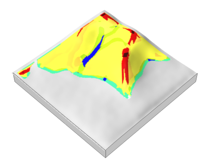
	Reference	Digital	Analog	Augmented
Mean elevation 275 350				
Stdev. of difference 0 24				
Mean landforms 1 10				

Table XII. Academics and professionals

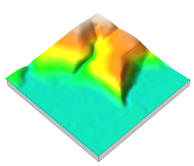
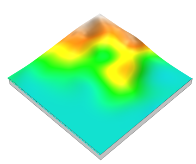
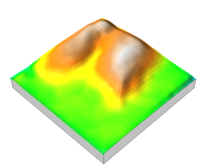
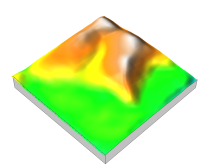
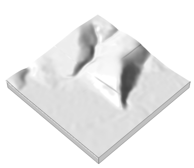
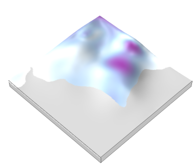
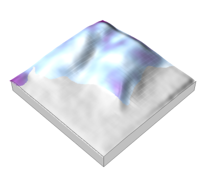
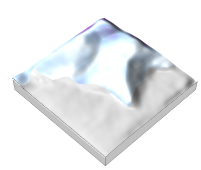
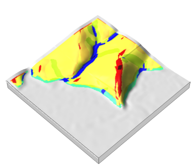
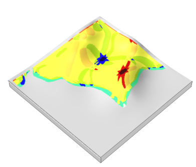
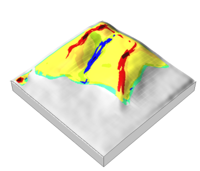
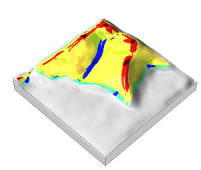
	Reference	Digital	Analog	Augmented
Mean elevation 275 350				
Stdev. of difference 0 24				
Mean landforms 1 10				

Table XIII. Landscape architecture students

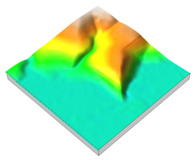
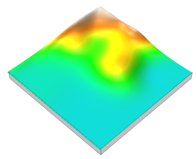
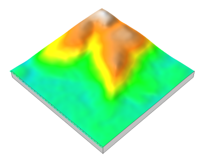
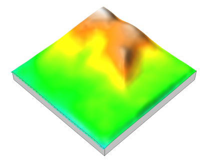
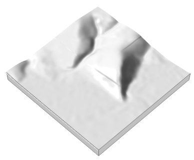
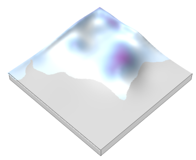
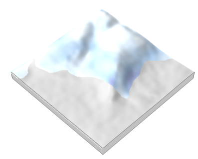
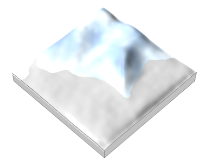
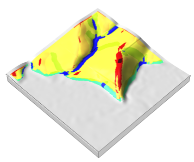
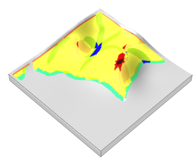
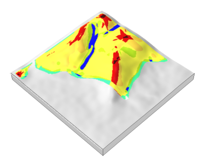
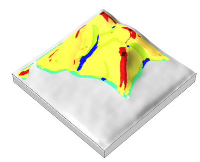
	Reference	Digital	Analog	Augmented
Mean elevation 275 350				
Stdev. of difference 0 24				
Mean landforms 1 10				

Table XIV. GIS students

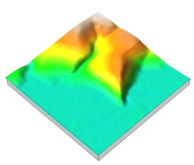
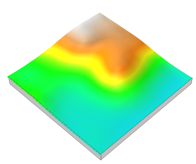
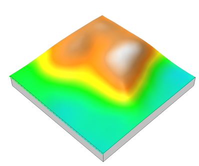
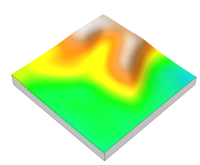
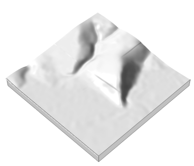
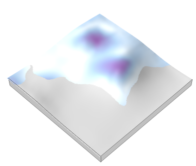
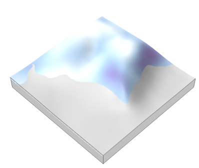
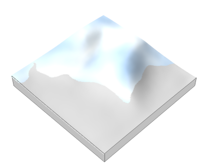
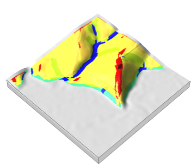
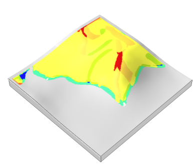
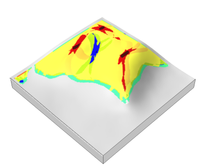
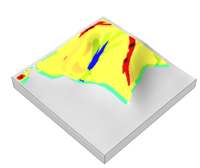
	Reference	Digital	Analog	Augmented
Mean elevation 275 350				
Stdev. of difference 0 24				
Mean landforms 1 10				

Table XV. Academics and professionals without expertise in 3D modeling

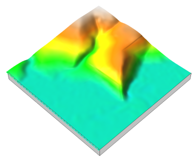
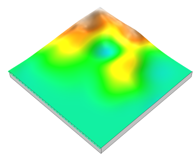
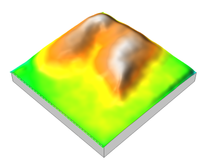
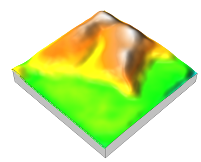
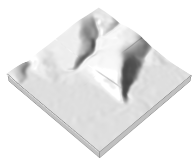
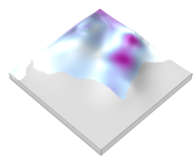
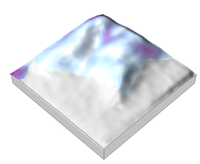
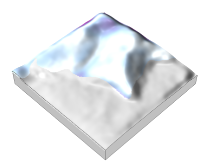
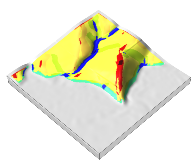
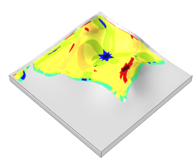
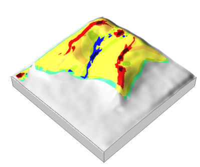
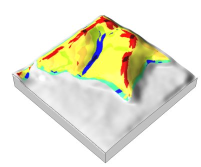
	Reference	Digital	Analog	Augmented
Mean elevation 275 350				
Stdev. of difference 0 24				
Mean landforms 1 10				

Table XVI. Academics and professionals with expertise in 3D modeling

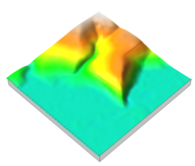
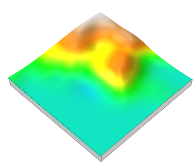
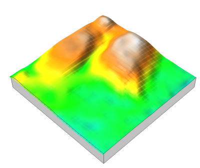
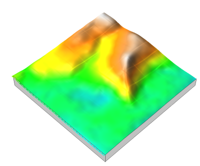
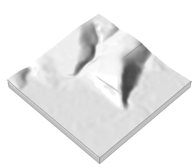
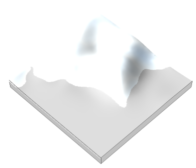
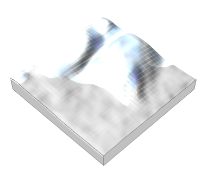
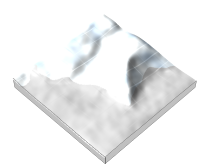
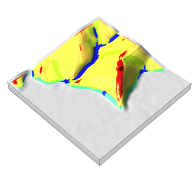
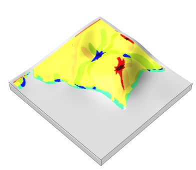
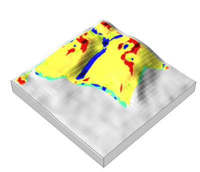
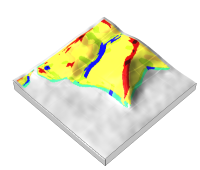
	Reference	Digital	Analog	Augmented
Mean elevation 275 350				
Stdev. of difference 0 24				
Mean landforms 1 10				

Table XVII. Coupling experiment: percent cells

Method	Concentrated flow	Ridges	Valleys
Reference	1.16	2.10	2.90
Digital	1.34	0.69	0.49
Hand	0.97	3.85	1.48
Augmented	1.05	4.18	1.63

Table XVIII. Mean minimum distance (ft) of features from reference features

Method	Concentrated flow	Ridges	Valleys
Digital	19303	105764	110017
Hand	12021	25238	70287
Augmented	11898	20110	30980

standard deviation of difference, but still only hinted at the landforms (Table XVI). This means that even for expert 3D modelers, projection-augmented modeling should be a better, faster tool for quick modeling tasks.

All participants. Tables X, XVII, and XVIII show the results for all participants. When digitally modeling with Rhino participants were relatively consistent and accurate except in the interior space. The interior space – the main valley and the ridge – tended to have serious errors. They built very abstract massing models approximating the general shape of the landscape without any detail. The slopes in these models were consistently too low and gradual. They did not have enough curvature to create distinct landforms. These models only hinted at the morphology of landscape with a small cluster of valley cells and another small cluster of ridge cells. Key features like the stream channel were not represented.

We observed that most participants had trouble judging depth and perceiving interior space when digitally modeling. We also observed most participants using similar digital modeling strategies in a relatively linear fashion. Since the reference data – the 3D contour curves – clearly represented profiles, many participants first modeled the borders of the landscape relying heavily on the front and side viewports. Then in perspective view they began to pull up relative high points to build a rough massing model of the topography. Finally they began to refine its shape by pulling down relative low points to steepen slopes and form valleys. The 3D modeling experts, however, used unique modeling strategies developing their own techniques as they worked. One worked exclusively in the perspective viewport continually orbited above and below the model in order to compare the top and the bottom as he pushed and pulled points in a very freeform, iterative process. Only the experts had time to rebuild the 10 x 10 grid of control points as a 20 x 20 grid. This meant that all of the other models had half the effective resolution and were thus more approximate representations of the landscape.

When sculpting by hand participants used very different modeling strategies and as a result they built very different models as shown by the standard deviation of elevation. While inconsistent, their models were relatively accurate and captured the key landforms. While they tended to over exaggerate the main ridge, they did represent this ridge and most of the central valley. Due to slumping sand these models tended to be too low along the edges.

We observed participants using a wide range of different modeling strategies and techniques when sculpting by hand. They tended to work in a very freeform manner – switching freely between adding, removing, pressing, pushing, pulling, or smoothing sand. Some used only their bare hands, some used only the wooden sculpting tool, and others used their bare hands to sculpt and the tool the refine details. Most participants used the 3D scale to build highest point at the right height – some even buried the 3D scale in their model building around it. Some participants instead picked up the reference model and used its edges – its profiles – to build the sides of the model. Some participants also ran their fingers over the reference model to feel its shape. A few participants, however, ignored both the 3D scale and the reference model.

We observed participants freely and rapidly switch between sculpting the sand with their whole hands, their palms, the blade of their hands, or just their fingertips depending on whether they wanted to make a big move or a fine-tuned refinement. While participants could select and transform a group of control points in Rhinoceros, their control was limited by the grid size, i.e. the number of points, and their speed by the need to continually change the selection. When we tested Vue as an alternative with 3D painting and sculpting tools with parameters like size and intensity we found that these parameters required continually tuning, which interrupted the modeling process and slowed down interaction.

See Table XXVIII for select comments from interviews. One participant said that she felt anxious when digitally modeling, but felt calmer and more relaxed when hand sculpting sand. She found hand sculpting to be more intuitive, saying that while digital modeling had 'a long learning curve,' she could read the sand model 'like braille. . . I could feel the shape with my fingers.'

Overall participants performed best with projection-augmented modeling building more accurate models that represented the major landforms. These models had the lowest mean minimum distance for cells with concentrated water flow, ridges, and valleys (see Tables XVII & XVIII). We observed participants using the same modeling techniques, strategies, and tool use as they did when sculpting by hand. They worked in the same freeform manner, but – with the aid of the projected contours and elevation – had more consistent results as shown by the standard deviation of elevations. Overall, they had more accurate results – albeit with systemic errors along the borders due to slumping sand – as shown by the mean difference and standard deviation of differences. They correctly represented the main ridge and the central valley, but tended to miss details like the y-shaped branch at the head of of the stream channel.

One participant found that with projection-augmented modeling he was able to effectively combine the affordances of hand sculpture with the extra layer of data. He described an iterative strategy of additive modeling in which the projected 'contours were just a guide' – 'My general strategy was additive. I felt with my hands to try to match the contours. If I saw concavity in the contours then I felt the sand and sculpted that concavity. Finding the relative height, however, was challenging – it was subtle.'

Students vs. academics and professionals. Table XI and Table XII compare students' results with academics and professionals. Overall the academics and professionals only performed slightly better than the students. When digitally modeling both groups built very approximate massing models that only hinted at the landforms. While the professionals and academics managed to create a small cluster of valleys cells in the central stream channel, the students tended to miss this feature. When sculpting by hand both groups' performance improved dramatically; they built more accurate models as shown by the standard deviation of difference and better represented the landforms roughly capturing the main ridge and valley. With projection augmented modeling both groups' performance increased even more as shown by the low standard deviation of difference.

Landscape architecture vs. GIS students. Table XIII and Table XIV compare landscape architecture and GIS students' results. The GIS students built more abstract, approximate models than the landscape architecture students who tended to over-exaggerate the shape of the landscape. With each technology the GIS students' performance improved; they built more and more accurate models with more distinct landforms. The landscape architecture students' performance, however, did not improve significantly between analog and projection-augmented modeling. With digital modeling both groups had major errors along the ridge, but the GIS students also had serious problems with the interior space. The GIS students missed the central valley entirely, while the landscape students hinted at it with a small cluster of valley cells. When hand sculpting both groups made major improvements. The GIS students began to form the main ridge and valley. They tended to build too large a ridge with the highest point near its tip and significant errors on its slopes. The landscape architecture students tended to hand sculpt distorted, exaggerated landscapes with extras landforms, but roughly captured the y-shaped stream. With projection augmented modeling the GIS students captured the central valley and ridge, correctly modeled steeper slopes, and had much less errors as shown by the standard deviation of difference. The landscape architecture students, however, did not make significant improvements over their hand sculpted models.

Academics and professionals with and without 3D modeling expertise. Table XV and Table XVI compare landscape architecture academics and professionals with and without 3D modeling expertise. While the other academics and professionals performed poorly with digital modeling, better with analog modeling, and best with projection augmented modeling, the expert 3D modelers built very accurate models with each technology, but represented the landforms best with projection augmented modeling. While the rest of the academics and professionals had major errors on the ridge in the digital modeling task, the expert 3D modelers built accurate models with very low mean difference and standard deviation of difference. The 3D experts worked faster and had time to rebuild denser grids of control points so that they could build more detailed, higher resolution models. Despite their accuracy their digitally sculpted models still only hinted at the landforms with small clusters of valley and ridge cells. The 3D modeling experts represented more complete landforms when sculpting by hand, capturing details like the y-shaped branch of the stream, but missed much of the ridge. With projection augmented modeling the expert 3D modelers performed even better successfully capturing the ridge, the valley, and its y-shaped branch with few anomalous features. They used the wooden modeling tool to cut clean edges around their models minimizing systematic errors caused by slumping sand.

4. DIFFERENCE EXPERIMENT

We conducted an experiment to study how the difference analytic mediates 3D spatial performance when using a tangible interface for GIS. This experiment was designed to explore how participants used the difference analytic – to study their modeling process, rather than compare their performance against other technologies.

4.1. Methods

Difference analytic. The same 18 participants were asked to use Tangible Landscape's difference analytic to model a different region of Lake Raleigh Woods with a large central ridge flanked by valleys and a smaller, secondary ridge. Participants had 10 minutes to model this region in polymer-enriched sand using Tangible Landscape with the difference analytic (Fig. XIX). The difference between the reference elevation and the participant's modeled elevation was computed in near real-time and projected onto the sand as an interactive guide. The linear regression of the reference and scanned elevation maps was used to correct shifts in scanning and georeferencing. The difference showed where sand needs to added (blue) or removed (red) in order to match the reference landscape (Fig. 9). While this feedback should show participants what to do next, it may provide too much data or be too challenging to rapidly parse. See Appendix E for a video demonstrating the 3D modeling task with the difference analytic (E.5).

Data collection and analysis. The final scan of each model was stored in a GRASS GIS database for analysis. We used raster statistics, the difference in elevation, topographic parameters, and morphometric parameters to compare the reference elevation and the set of modeled elevations. We computed the mean elevation, the standard deviation of elevations, and the standard deviation of difference for the set. To find the standard deviation of differences we first computed the difference between the reference elevation and each elevation and then used raster statistics to find the standard deviation of these differences. We also computed the difference between the reference elevation and the mean elevation for the set. The reference elevation used in the difference calculation was rescaled and shifted based on the linear regression of the reference and mean elevation. We computed the slope and landforms of the mean elevation. We also filmed each session, observed and took notes on participants' modeling processes, and interviewed landscape architecture professionals and academics.

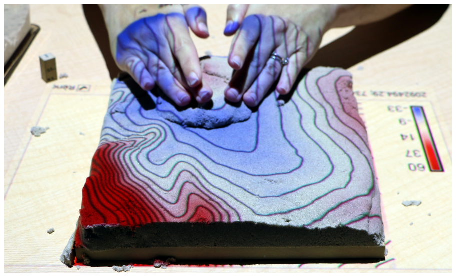
4.2. Results

Participants performed well with the difference analytic – modeling simplified, but relatively accurate approximations of the landscape. Participants with expertise in 3D modeling performed even better than other participants – more accurately modeling the elevation and slopes, but not the landforms. Since these models were sculpted in sand, their edges tend to slump. This caused systematic artifacts in the analysis like low elevation values and steep slopes along the borders. Based on interviews and observations we found that the difference analytic enabled a rapid, iterative process of modeling, learning from computational feedback, re-remodeling, etc.

Per-cell statistics. Table XX shows maps of raster statistics for this experiment. The mean elevation for this set of models has the approximate shape of the reference elevation, but is much simpler, lacking many details. The standard deviation of elevations shows that participants consistently modeled the low point at the base of the secondary ridge in the same way, but modeled the primary ridge in different ways. The standard deviation of difference shows how consistently the models fit the reference. Overall participants performed well – there was little deviation from the best fit. Participants tended to perform poorly near the edges of models, especially in the corners. They also had trouble with the valleys and the low point by the secondary ridge.

Geospatial analyses. Table XXI shows geospatial analyses for this experiment. The mean elevation difference shows that participants tended to add too little to the edges of the model, too much to primary ridge, and too much to the slope of the secondary ridge. The mean slope shows that participants tended to model overly steep slopes for the primary ridge – exaggerating its form – but tended not model steep enough slopes for the secondary ridge. The mean landforms show that participants tended to clearly capture the central ridge and its spurs and the secondary ridge and its valley, but missed the other valleys (sees Tables XXI-XXII). Hollows – transitions between slopes, footslopes, and valleys – on the mean landform map hint at these other valleys in the right locations.

Table XIX. Difference experiment: a participant sculpts the study landscape using Tangible Landscape's difference analytic, which shows where to add sand (blue) and remove sand (red).



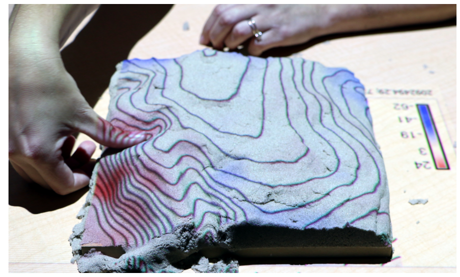


Table XX. Difference experiment: maps of per-cell statistics draped over a 3D rendering of the topography for all participants

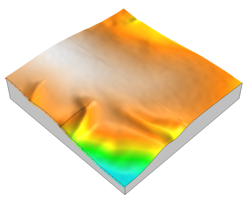
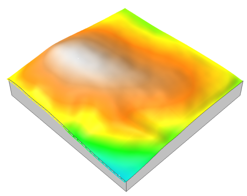
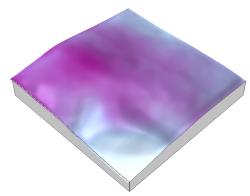
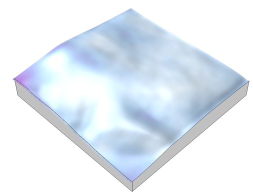
Reference elevation	Mean elevation	Stdev. of elevations	Stdev. of differences
			
277 – 365	277 – 365	0 – 32	0 – 24

Table XXI. Difference experiment: maps of geospatial analyses draped over a 3D rendering of the topography for all participants

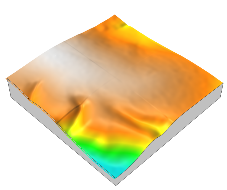
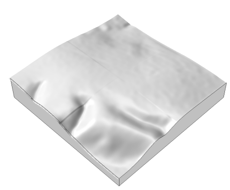
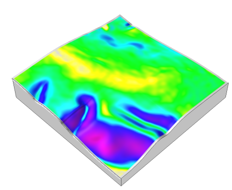
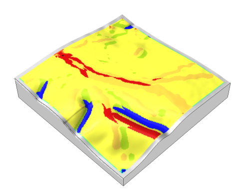
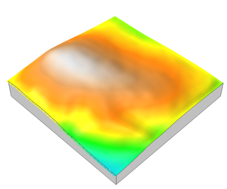
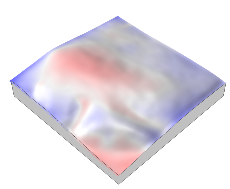
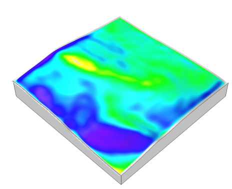
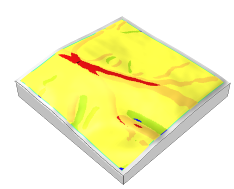
	Elevation	Elevation difference	Slope	Landform
Reference				
Mean				
	277 – 365	-36 – 36	0 – 90	1 – 10

Table XXII. Difference experiment: percent cells

Method	Concentrated flow		Ridges		Valleys	
	Reference	Mean	Reference	Mean	Reference	Mean
Difference	1.94	0.90	4.27	2.93	2.96	0.13

Table XXIII. Difference experiment: comparison of 3D modeling novices and experts

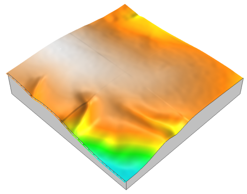
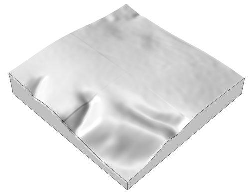
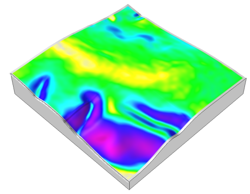
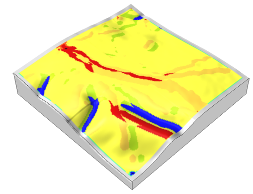
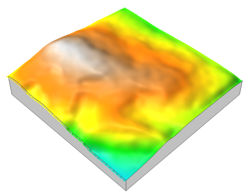
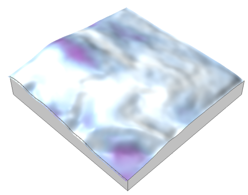
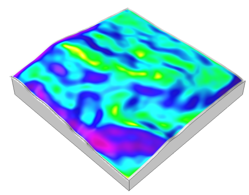
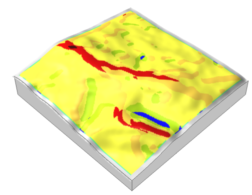
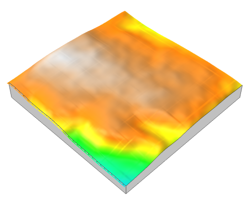
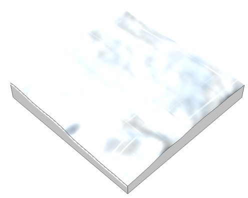
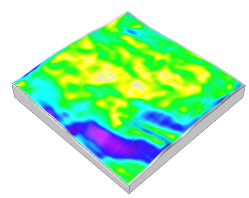
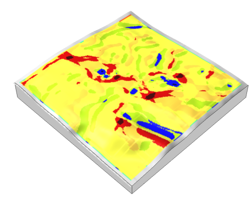
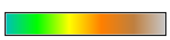
	Elevation	Stdev. of differences	Slope	Landforms
Reference				
3D novices				
3D experts				
	277  365	0  24	0  90	1  10

Table XXIII compares the performance of landscape architecture academics and professionals with and without 3D modeling experience. The 3D modeling experts built more accurate models with a lower standard deviation of differences and more accurate slopes. Since they did not, however, exaggerate the central ridge and did not smooth its slopes, they did not cleanly represent this landform. The others built more exaggerated models that more clearly captured the main ridge.

Interviews and observations. To successfully use the difference analytic participants had to think about topography as volume. They had to either add or excavate sand to make the models match. They described the process of modeling with the difference analytic as continual 'rebuilding to make it match.' They described an iterative process of continual refinement based on critical analysis – similar to Schön's reflection-in-action [Schön 1983] – but enhanced by computational feedback explaining that 'because Tangible Landscape gives immediate results it encourages an iterative process.' See Table XXVIII for select comments about this experiment.

The difference analytic is intuitive – participants were able to learn how to use it effectively without training, producing good, albeit exaggerated approximations of the landscape. Their models tended to have key morphometric characteristics – the primary ridge, its spurs, the low point, the secondary ridge, and one of the valleys – but these characteristics tended to be either exaggerated or under-exaggerated.

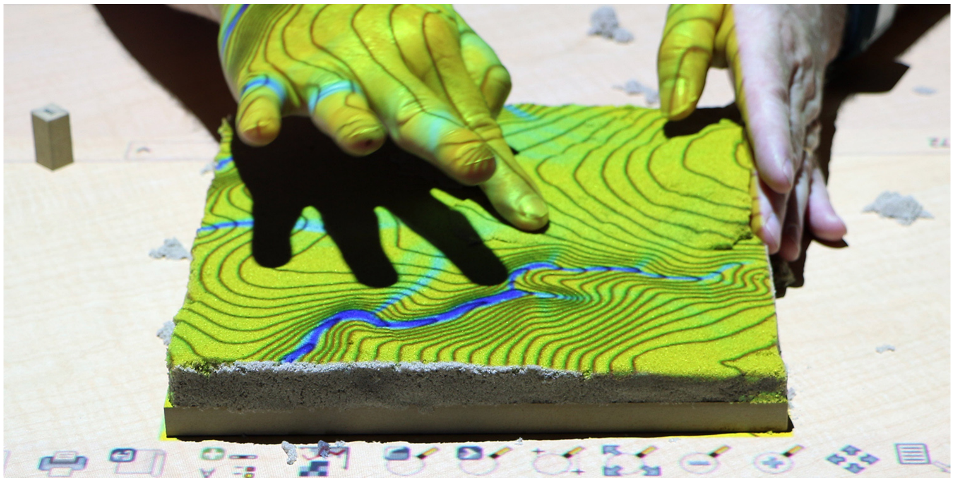


Fig. 18. Water flow experiment: A participant sculpts the study landscape using Tangible Landscape's water flow analytic.

5. WATER FLOW EXPERIMENT

After a pilot study [Harmon et al. 2016c] we conducted an experiment to study how water flow analytics mediate 3D spatial performance when using a tangible interface for GIS. This experiment was designed to study whether participants could link form and process using the water flow analytic – to assess how well they could understand the relationship between topographic form and the flow of water when using Tangible Landscape.

5.1. Methods

Water flow analytic. The same 18 participants were asked to model water flow across another region of Lake Raleigh Woods using Tangible Landscape with the water flow analytic. This region has a central ridge flanked by a large stream on one side and a small stream on the other. A third, smaller stream bisects the ridge. Participants had 10 minutes to model water flow across this region by sculpting polymer-enriched sand using Tangible Landscape with the water flow analytic. They sculpted sand models of the topography to direct the simulated flow of water. Water flow was simulated in near real-time as a diffusive wave approximation of shallow water flow. The module *r.sim.water* [GRASS Development Team 2016e] uses a path sampling technique to solve the shallow water flow continuity equation [Mitasova et al. 2004]. Participants could switch between the precomputed reference water flow – i.e. their target – and the water flow over their scanned model. See Appendix E for a video demonstrating the 3D modeling task with the water flow analytic (E.6).

Data collection and analysis. The final scan of each model was stored in a GRASS GIS database for analysis. We used raster statistics, simulated water flow, and the difference in simulated water depth to compare water flow across the study landscape and the set of models. We computed the mean elevation, the standard deviation of elevations, and the standard deviation of difference for the set. Then we simulated water flow across the mean elevation for the set of models and computed the difference between the reference and mean water flow.

Table XXIV. Water flow experiment: maps of per-cell statistics draped over a 3D rendering of the topography for all participants

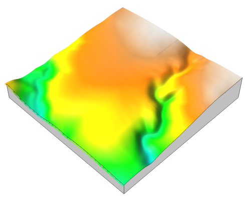
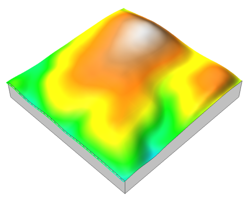
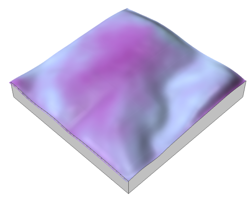
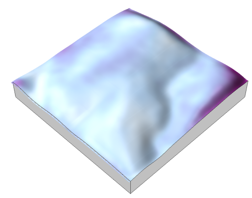
Reference elevation	Mean elevation	Stdev. of elevations	Stdev. of differences
			
280 352	280 352	0 32	0 24

Table XXV. Water flow experiment: maps of geospatial analyses draped over a 3D rendering of the topography for all participants

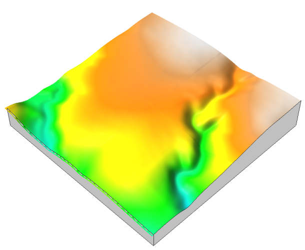
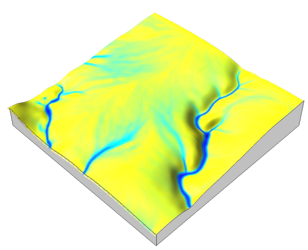
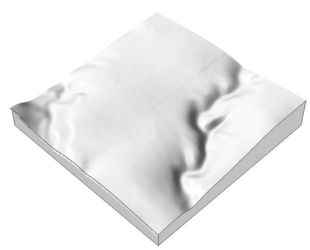
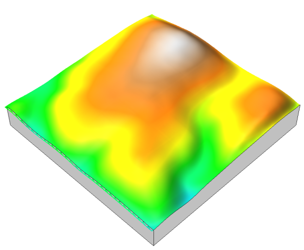
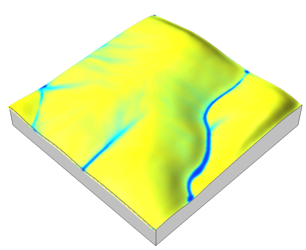
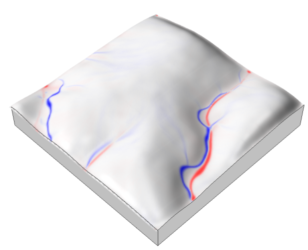
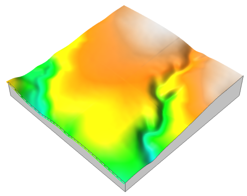
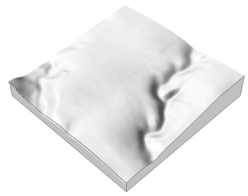
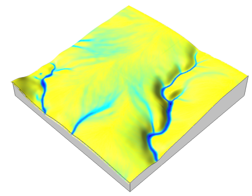
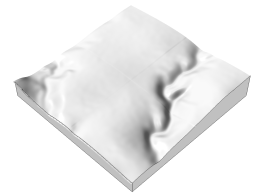
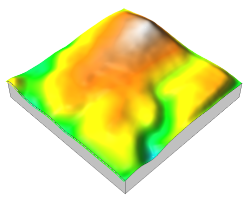
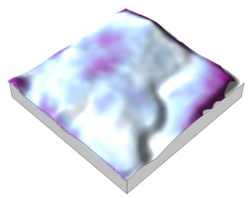
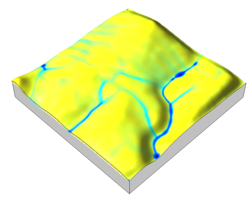
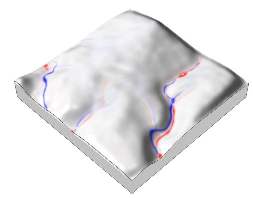
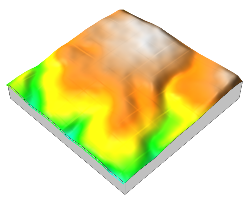
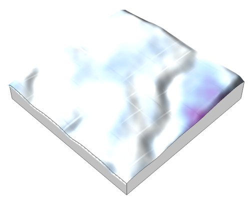
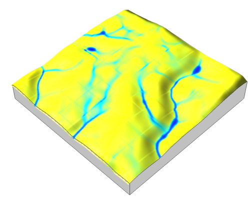
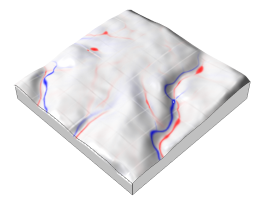
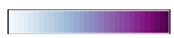
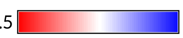
	Elevation	Water depth	Depth difference
Reference			
Mean			
	280 352	0 0.5	-0.5 0.5

Table XXVI. Water flow experiment: percent cells

method	concentrated flow		ridges		valleys	
	reference	mean	reference	mean	reference	mean
water flow	3.28	2.26	1.18	2.99	4.77	3.70

Table XXVII. Water flow experiment: comparison of 3D modeling novices and experts

	Elevation	Stdev. of differences	Water depth	Depth difference
Reference				
3D novices				
3D experts				
	280  352	0  24	0  0.5	-0.5  0.5

5.2. Results

Participants performed well with the water flow analytic – approximately modeling two of the three streams. Participants with expertise in 3D modeling performed better than the others with more accurate models that captured all three streams.

Per-cell statistics. Table XXIV shows maps of raster statistics for this experiment. The mean elevation for this set of models has under-exaggerated valleys and over-exaggerated ridges in the right places. The mean elevation has 22.43% less valley cells than the reference, but 153.40% more ridge cells (see Table XXVI). The standard deviation of elevations shows that participants consistently modeled the streams, but varied greatly in their treatment of the primary ridge. The standard deviation of difference shows that participants performed well with the greatest deviation from the reference in the corners and along the edges. Again this is to be expected as sand slumps along the borders.

Geospatial analyses. Table XXV shows geospatial analyses for this experiment. The mean water depth map shows two of the streams and hints of the third. The streams are simplified, but in the right locations. The simplified stream channels lack micro-topography and thus details. Table XXVI shows that there was substantial concentrated flow (water depth $>= 0.05$ ft) in the streams, albeit 31.10% less than in the reference. This is to be expected since water flow over the sculpted models was only computed over the model region, while the reference water flow was computed over a larger region with the entire contributing watershed in order to produce an accurate representation of water flow across the study landscape. The water depth difference map shows where water should be added (red) or removed (blue) to match the reference – i.e. where water should flow versus where it was modeled. The mean water flow tightly fit the reference, following similar, albeit simplified routes. Table XXVII compares the performance of landscape architecture academics and professionals with and without 3D modeling experience. With the water flow analytic the 3D modeling experts built more accurate models with a lower standard deviation of differences and captured all of the streams, while the others only captured two of the streams and hinted at the third.

Interviews and observations. With the water flow analytic participants focused on accurately modeling the streams, rather than the general shape of the topography. As a result the primary ridge was inconsistently modeled and over-exaggerated, while the streams were consistently modeled, had high volumes of continuous water flow, and flowed along the correct routes. This experiment required abstract spatial thinking linking form and process. Because water flow is controlled by the shape and gradient of the topography participants had to sculpt topographic form to drive water flow. This modeling process, however, helped them understand topography better because 'seeing the flow took away the mystery of topography.' We observed participants using an iterative modeling process with the water flow analytic – they *a)* sculpted the topography, *b)* observed how the water flow simulation changed, *c)* critiqued their water flow and topography, *d)* and continued to sculpt. Using the water flow analytic with this trial-and-error process participants were able to generate hypotheses, test hypotheses, and draw inferences about the way that water flows over topography. See Table XXVIII for select comments about this experiment.

6. DISCUSSION

6.1. Coupling physical and digital models

The coupling experiment was designed to test whether coupling a physical and digital model of topography can improve 3D spatial performance. We found that both novices and experts were able to take advantage of the affordances of both digital and analog modeling with projection-augmented modeling. All participants' without expertise in 3D modeling performed significantly better with projected-augmented modeling. They were able to combine the extra layers of data afforded by digital modeling with the intuitive interaction, speed, and detail afforded by analog modeling to model more accurate landscapes with distinct landforms. The expert 3D modelers performed well in the digital modeling task, but given the time constraints and limited palette of digital modeling tools were not able to form well defined morphological features. With projection-augmented modeling, however, they were able to work faster, refine their models sooner, and build distinct ridges and valleys.

While the novices' performance demonstrates that projection-augmented modeling can be intuitive – enabling high performance without training or experience – the experts' performance shows that the technology affords faster interaction. Intuitive interaction means that users are able to act, to do what they want to do, to make what they want to make quickly and reliably without training, experience, or even having to consciously think about it. The 3D modeling novices were able to build more accurate models with projection-augmented modeling. Drawing on embodied cognition they were able to feel the 3D shape of their model, while they struggled to read curvature, judge distance, and estimate size and shape based on distance visually using the graphical user interface. They were also able to work faster, knowing automatically, subconsciously how to act, how to feel and shape things with their hands, while they

Table XXVIII. Interviews

Technology	Select comments
Digital	Rhino has a long learning curve.
	Understanding how Rhino works – i.e. the underlying mathematical representation, NURBS – is very important. Once you understand that is a tension field then you understand how to shape it, how to make it do what you want.
Analog	I worked additively, then subtractively, smoothing. The sculpting tool gave sharpness – the sharp edge let me smooth in a way my fingers couldn't. It felt like drawing or laying concrete. Feeling is important – I could feel subtle changes in topography.
	My sense of touch helped me to understand the topography. I could sculpt like reading braille. I could feel the shape with my fingers. It was intuitive and calming.
	I have done lots of sculpture so I knew how to feel the shape of the model. And the desk lamp cast shadows so I could visually perceive depth.
Augmented	The contours were just a guide. My general strategy was additive. I felt with my hands to try to match the contours. If I saw concavity in the contours then I felt the sand and sculpted that concavity. Finding the relative height, however, was challenging – it was subtle. Most people don't understand contours. They have to be taught.
Tangible Landscape	We all already understand how sand works. We understand sand, but not necessarily these analytics – the difference analytic or the water flow simulation.
	The water flow analytic reminds of me of playing in creeks and grading streams as a kid.
	The difference analytic was the best. I tried to make it match. I was constantly rebuilding to make it match. The water flow analytic was useful for thinking about form, about what form does – why water flows where it does. Seeing the flow takes away the mystery of topography. Our students tend to have a linear design process. Because Tangible Landscape gives immediate results it encourages an iterative process.
	Tangible Landscape let me tinker. I could rapidly create, making new iterations. I could try something, see and feel it – directly experience it – and try again. Reinvent it. Tinkering like this is a learning process. Learning through doing. Tangible Landscape lowers the stakes so that you're not too invested. You're ready to fail. So you can intuitively explore, while reflecting on what you've done, what you're doing.

struggled to find buttons, remember keyboard shortcuts, and understand the graphical user interface.

Intuitive interaction mattered less for the 3D modeling experts because they had already acquired the knowledge and skills needed. They still performed better with projection-augmented modeling because they were able to work faster and refine their models earlier. Based on observations during the study we conclude that even without real-time analytics the tangible interface is faster for 3D modeling experts because it affords an almost instantaneous transition between tools – between fingertips, palms, the arches of hands, the blades of hands, the blade of a knife, and the tip of a knife. It is also faster because it affords more feedback by combining kinaesthetic sensing of physical form with computer graphics so users do not have to spend as much time trying to understand the space.

While previous studies of tangible interaction have shown that tangible interfaces can be faster and more reliable than graphical interfaces for simple spatial tasks [Huang 2004; Couture et al. 2008], this study shows that tangible interfaces can be more intuitive, faster, and more reliable for complex spatial tasks. While research on tangibles has focused on novices and intuition, we have found that tangible interfaces can be useful for experts as well as novices if they have the capabilities, tools, and precision that experts need. A well designed tangible interface for spatial modeling should be more effective than a digital modeling program for short exploratory modeling tasks because it affords faster modeling. With faster modeling experts can explore more ideas, rapidly iterating through many designs. This ability to work quickly and rapidly iterate is the key to ideation.

We hypothesize, however, that digital modeling becomes increasingly efficient as tasks become longer. The longer the modeling task the more the basic affordances of digital modeling – precision, zooming, layering, snapping, copying and pasting, etc. – should help make the process more and more efficient. Affordances like zooming that are challenging to develop for augmented sandbox interfaces have, however, already been implemented in shape changing interfaces like Tangible CityScape [Tang et al. 2013]. Based on our own experiences we further hypothesize that hybrid approaches combining tangible modeling and digital fabrication should be even more efficient and effective for longer, more complex problems.

6.2. How tangible geospatial analytics mediate users' 3D spatial performance

The results of the difference experiment show that the difference analytic enabled an iterative modeling process successfully combining the affordances of physical modeling with near real-time computational feedback. Participants tended to perform well without training; they managed to quickly learn and understand the analytic and successfully used it to adaptively sculpt accurate models. This suggests that they were able to offload the cognitive work of manipulation onto their bodies, while cognitively parsing a rapidly changing, graphical representation of the difference in volume.

We observed, however, that some participants had trouble understanding the color table for the difference analytic. We used a relative color table that assigned colors based on percentage of value. The color table rescaled every scan so participants had a hard time quantifying their overall performance. This caused participants to make exaggerated changes in places where only minor adjustments were needed. After the experiment we tested an absolute color table with colors assigned to specific values. The absolute color table helped – it was much easier to observe gradual, incremental progress throughout the modeling process.

The results of the water flow experiment show that the water flow simulation helped participants understand the relationship between form and process. We observed participants using an iterative process to adaptively sculpt based on the simulated water flow. Through this trial and error process participants learned how topographic form controls the flow of water. Given that they accurately represented the streams without training they must have been able to offload some of the cognitive work of sensing and manipulating 3D form onto their bodies so that they could focus on the water flow.

Tangible Landscape enabled users to model in an iterative process informed by spatial analytics. We theorize that users offloaded the cognitive work of sensing and manipulating 3D form onto their bodies, successfully parsed the projected graphics, and metacognitively adapted their modeling strategy. Given the accuracy of their models participants did not suffer from too great a cognitive overload; they were parse the analytic feedback, critique their performance, and re-strategize.

With both analytics the 3D modeling experts performed better than all of the others including other experienced academics and professionals. First of all this shows that tangible interfaces for geospatial modeling with real-time analytics can be effective tools for experts. It also suggests that advanced spatial abilities and skills developed with digital tools can be transferred to tangible interfaces. If these abilities are trans-

Fig. 19. Attendees playing games with Tangible Landscape at an interactive seminar hosted by NCSU's Library exploring how serious, analytical games can be used to explore real world problems like coastal flooding and the spread of invasive species. See Fig. 11 - 12 for examples of the serious games played at this event.

ferable, then tangible interfaces – given their intuitive, embodied nature – may be a fast and effective way to train them. Future research is needed to explore spatial learning and transfer using tangible interfaces.

6.3. Reflections on the design process

Since we began designing and developing Tangible Landscape we have demonstrated and used various iterations of the system live during lab tours, in classes such as GIS for Designers and the Landscape Dynamics Seminar in NCSU's Department of Landscape Architecture, at conferences such as FOSS4G NA 2016 [Petrasova et al. 2016a; Harmon et al. 2016b], US-IALE 2016, and ACM SIGSPATIAL 2016 [Tabrizian et al. 2016], in public exhibitions at the City of Raleigh Museum and the North Carolina Museum of Natural Sciences, and at special events such as NCSU Library's Coffee & Viz seminar on serious gaming [Harmon et al. 2016d] (Fig. 19). At these events we observed how diverse groups of users interacted with the system as we continued to develop it. During tours we observed that many users had trouble understanding how Tangible Landscape worked until they actually tried it themselves. Once users saw their own hands scanned and rendered as part of the topography with simulated water flowing between their fingers or ponding in the palms of their hands they intuitively understood how to interact with the system (Fig. 4). Early in the design process we considered arms and hands captured by the 3D sensor to be confusing, disruptive artifacts that obfuscated the real data interrupting the desired interaction. We tried to deal with these artifacts by ignoring scans with large changes (i.e. an arm reaching across the model), masking cells that were too high (i.e. a hand hovering above the model), and speeding up the system to minimize lag so that a digitized hand would not linger as topography for too long. However, after observing users' first encounters with Tangible Landscape during tours, exhibits, and other events we found that users more quickly grasped how the system worked by trying it and seeing their hands digitized as part of the topography directing the flow of water. While sculpting a depression and then seeing it fill with simulated water is an intuitive interaction with a clear cause and effect, users appeared to learn how the system worked even faster by instead cupping their hands to create simulated ponds in the hollow of their palms. This interaction is even more direct; we hypothesize that its immediacy and embodied nature helps users make the conceptual leap that the physical and digital are coupled. For users to effectively see their hands digitized as topography there needs to be a little lag – their digitized hands should trail behind their real hands by a half second or so.

We also observed that many users did not know what they should do even though they understood how to use the tangible interface. Some users hesitated to try the system, made a few indecisive moves, and then gave up, while other users happily played in the sand or with objects like markers or buildings blocks. While free, unstructured play suits some users, others would benefit from a more structured experience. Free, unstructured play is a useful way to introduce a tangible interface like Tangible Landscape, but does not engage some users for long. While Woods et al. argue that 'effective classroom use of the AR sandbox required developing student modeling exercises that took advantage of real-time feedback, virtual water, and physical modeling activities' [Woods et al. 2016], we found that some Tangible Landscape users needed an even more structured experience to learn effectively. Even during classes and workshops in which we had assigned tasks like designing a network of hiking trails many students and attendees still had trouble deciding what to do. An objective was not enough; they needed more feedback and a way to judge their performance – metrics or even a score. When we demonstrated Tangible Landscape for students or the general public we found that they needed a challenge to hold their attention and that simple rules and a score were enough to structure the experience. We designed two serious games about coastal flooding and termite invasion as prototypes and tested them in an interactive workshop as part of NCSU Library's Coffee & Viz series [Harmon et al. 2016d]. Quick rounds with scores encouraged participants to keep on playing, to try new things in hope of getting a better score. While the structured experience of these serious games worked well with the general public, experts wanted more depth, feedback, and customizability – i.e. a structured, yet open experience that would be engaging and encourage in-depth exploration. Experts need to be able to use many different modes of tangible interaction so that they can make use of their extensive, well-developed skills. Experts may also want to compare metrics rather than see a simplified score so that they can make tradeoffs between alternatives. When for example we designed applications for geographers and ecologists for managing termite invasions and controlling the spread of sudden oak death they asked for dashboards with statistics and data visualizations in addition to the projected maps so that they could study how different scenarios would affect groups of impacted stakeholders who valued different things.

The experiments helped us to refine the design of Tangible Landscape. We learned how users performed with different modes of analytic feedback, gained insight about their experiences and needs, thought critically about colors, and reaffirmed the need for speed – the importance of fast (but not too fast) feedback. This informed the development of the next generation of Tangible Landscape and led to the redesign of the difference analytic. After the experiments we developed the 3rd generation Tangible Landscape system using the OpenKinect project for drivers, the Point Cloud Library for point cloud processing, and OpenCV for computer vision. This dramatically increased the speed of the system approximately doubling the rate of feedback. Now that the analytics are faster (see Table VII) users should perform even better than they did in the experiments. As a test a member of our research team performed the task for the difference experiment using the new generation of Tangible Landscape and produced a very accurate model (see Appendix E.7).

6.4. Design guidelines

Based on our experience designing Tangible Landscape, the results of the experiments, and our observations of users during tours, workshops, classes, and other events we propose the following guidelines for designing tangible interfaces for spatial modeling:

— Modes of interaction should be analogous to ubiquitous tasks
— Design intuitive interactions with simple feedback for novices
— Design a wide variety of interactions and tools with rich feedback for experts
— Design free, playful experiences to encourage creative exploration
— Design structured experiences with objectives, rules, and feedback to encourage continued engagement
— Build on existing tools and technologies

We recommend designing tangible interactions that are analogous to ubiquitous, everyday tasks so that users will already subconsciously know what to do. When designing for novices we recommend making interactions as natural and intuitive as possible, while offering relatively simple feedback like a water flow simulation. Free, unstructured experiences will encourage creative exploration, but many users will be more engaged by more structured experiences with clear, well defined objectives, rules, feedback, and even scores. Experts, however, need a wide array of tools available so that they can intuitively use their diverse, existing skills and seamless switch between them. They need richer, more complex feedback so they can make critical, scientifically informed decisions. To efficiently develop the wide variety of tools and interactions that experts need we recommend using existing libraries for scientific computing. Using well documented, peer-reviewed, open source scientific models makes it easier to develop new tangible geospatial interactions and know if they behave properly. Building on the infrastructure of existing open source projects – on their codebase, documentation, binaries, support, and community – helps one efficiently collaborate and involve expert users in the design and development process so that they can contribute their own scientific models to the project [Petrasova et al. 2016b].

6.5. Open science

As a work of open science we invite readers to replicate or build upon this experiment by using or adapting our tangible interface, experimental methodology, code, and data. The python scripts for data processing and analysis are in Appendix F and also on GitHub at https://github.com/baharmon/tangible_topography released under the GNU General Public License (GPL). See Appendix B and the documentation in the GitHub repository for detailed instructions for replicating this experiment. The data used in this experiment and the results – including data, renderings, photographs, and interview notes – are in Appendix G and also on the Open Science Framework at https://osf.io/82gst/ under the Creative Commons Zero license. While the rest of the software used in this research is free and open source, Rhinoceros is proprietary software. Open source 3D modeling programs like Blender, however, could be substituted for Rhinoceros.

To build your own Tangible Landscape refer to Appendix A, visit the project website at http://tangible-landscape.github.io/, see the documentation in the GitHub repository including the Wiki at https://github.com/tangible-landscape/grass-tangible-landscape/wiki, and refer to the book Tangible Modeling with Open Source GIS [Petrasova et al. 2015]. GRASS GIS is available at https://grass.osgeo.org/ under the GPL. Tangible Landscape's components are available at https://github.com/tangible-landscape under the GPL.

7. FUTURE WORK

Our user experiments showed that Tangible Landscape is an effective tangible interface for geospatial modeling. Based on the user experiments and our own reflections and experiences with Tangible Landscape we have identified ways to improve the system. Our users want more tools that are natural to use so that they can do whatever they imagine with their existing skills. They want a richer, more immersive experience. They want larger models and easier, faster, cheaper ways to build models. We plan to refine existing modes of interaction with new methods for handling, processing, and filtering point clouds. By fusing color and depth data we will develop new modes of interaction including planting individual trees of a given species with a model tree and building structures with building blocks. We plan to support new VR headsets and integrate procedural plant generation, 3D tree libraries, and 3D building libraries for more immersive renderings. We plan to support arrays of multiple 3D sensors for scanning larger models. We plan to design better ways to build physical models using in-situ robotic fabrication and plan to develop GRASS GIS modules for 3D printing and CNC routing. We also plan to improve the system setup so that it is modular, lighter, more portable, more adaptable, less expensive, and more aesthetic. Through the user experiments and our own experiences we have also identified new research questions. How do tangible interfaces for geospatial modeling mediate learning? How can Tangible Landscape be used effectively in classrooms? Our design process is also highly conceptual and vision-driven. Inspired by advances in pervasive sensing, robotics, and automated construction we have developed a new vision for Tangible Landscape as a way to couple physical models and digital models of landscapes with real landscapes.

7.1. Future cognitive studies

This study focused on 3D spatial performance using geospatial analyses to assess modeling results. It did not quantitively address cognitive, affective, motivational, or metacognitive processes. Future research in embodied spatial cognition with tangible interfaces should study these processes using quantitive methods like eye tracking and biometric sensing and qualitative methods like protocol analysis. Future research should also study spatiotemporal performance using time series analysis to assess participants' modeling processes. Suitable methods for spatiotemporal analysis and visualization include space-time cubes, 3D raster statistics and map algebra, vector flow fields, contour evolution, and animation.

7.2. Robotic fabrication and autonomous construction

Emerging technologies are enabling ever closer coupling of the physical and the digital bridging real and virtual geographies. With advances in sensor networking physical things and environmental processes can be digitally tracked, sensed, and analyzed – giving the physical a digital presence [Ratti et al. 2009; Resch et al. 2012]. With advances in sensing technologies 3D forms can be digitized at scales ranging from millimeters to the entire planet. Data can be digitally fabricated with technologies such as 3D printing and robotics. Landscapes and the built environment can be digitally fabricated with technologies such as machine control for construction, earthmoving, and precision agriculture. Tangible interfaces for GIS have the potential to tie these emerging technologies together seamlessly linking physical models, digital models, and real geographies. In the future we intend to extend Tangible Landscape to seamlessly, bidirectionally link a physical model, a digital model, and a real landscape. We plan to integrate real-time streaming data, robotic fabrication, and automated construction to link real and virtual geographies via a tangible interface. We would stream real-time topographic data from sensors in the field – such as unmanned aerial vehicles – to a GIS. A robotic arm would then rapidly update the physical model based on changes to the digital elevation model. Users could then explore potential changes by sculpting the physical model and interacting with the real-time geospatial analyses and simulations. Finally, they could send a computationally optimized design to an autonomous construction vehicle or robot in the field for construction (Fig. 20).

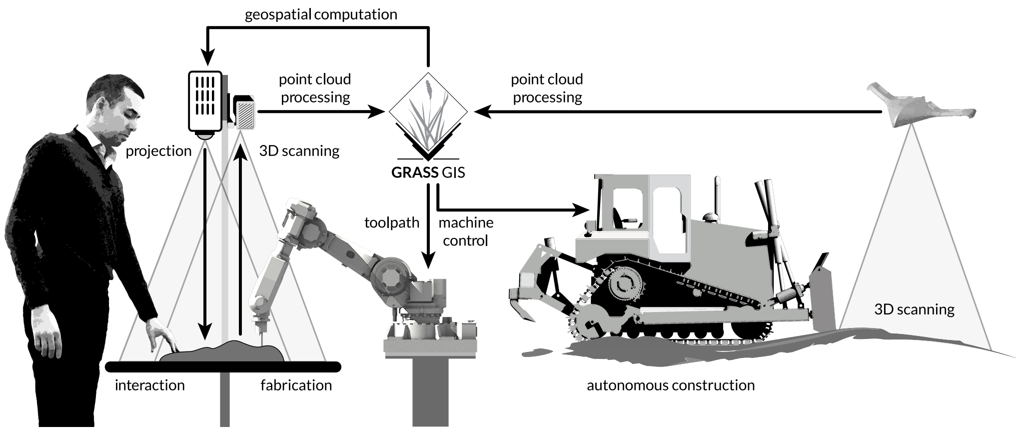


Fig. 20. Tangible Landscape with robotic fabrication, robotic construction, and streaming field data.

8. CONCLUSION

Through a series of experiments we found that tangible interfaces for spatial modeling can enhance 3D spatial performance in terms of speed, accuracy, and process. By comparing digital, analog, and projection-augmented modeling we found that coupling digital and physical models as a tangible interface can combine the affordances of digital and analog tools – enabling an embodied modeling process enriched with digital data – so that users can model intuitively, quickly, and precisely. Even 3D modeling experts performed better with the tangible interface – building more accurate models that better represented the morphology of the landscape – because they could work faster creating and refining details sooner. They were able to transfer and effectively use the spatial skills and abilities they had developed through digital modeling with the tangible interface. We also found that tangible interaction with real-time geospatial analytics can encourage iterative modeling processes. With the real-time difference analytic and water flow simulation users worked in rapid cycles of sculpting and digitally informed critical analysis to build accurate models that correctly represented the topographic and hydrologic morphology. Through this embodied process of reflection-in-action users were able to observe spatial patterns, forms, and processes, generate and test hypotheses, and draw inferences. The experiments showed that users were able to offload enough of the cognitive work of sensing and manipulating space onto their bodies that they could understand the computational analytics and adaptively re-strategize. Further experiments are needed to explore the role of spatial cognition, affect, motivation, and metacognition in tangible modeling.

The experiments show that Tangible Landscape, a tangible interface for GIS, works as theorized and designed – coupling a physical and digital model of a landscape enables users to cognitively grasp topography, intuitively shape and interact with multidimensional space, and offload enough cognitive work to understand real-time geospatial analytics. With Tangible Landscape users can intuitively interact with spatial data and scientific models using their bodies. While novices should be able to effectively learn about multidimensional space and rapidly improve their spatial abilities with Tangible Landscape, experts can effectively use it to rapidly develop, prototype, and test hypotheses about space and spatiotemporal processes.

A. HOW TO BUILD TANGIBLE LANDSCAPE

Table XXIX. Hardware

Type	Product	Cost
Computer	System 76 Oryx Pro	$1500
Projector	Epson PowerLite 1761W	$600
3D sensor	Xbox One Kinect	$100
	Kinect Adapter for Windows	$50
Stand	Avenger 40-Inch C-Stand with Grip Kit	$200
	Kupo 4 Way Clamp	$50
	Kupo Baby 5/8-Inch Receiver for 4 Way Clamp	$12
	Avenger D520L 40-Inch Extension Arm	$45
	Avenger F800 3-Inch Baby Wall Plate	$10
	Avenger F810 3-Inch Baby Wall Plate with Swivel Pin	$40
Peripherals	HDMI cable	$10
	Extension cord	$10
Modeling media	Waba Fun Kinetic Sand 11 Lbs	$50

Hardware & software. To build Tangible Landscape you will need a computer, a projector, a 3D sensor, an armature to hold the projector and sensor, and a physical model of a landscape. The computer should be running Linux or Mac OS X and have GRASS GIS,[1] the grass-tangible-landscape plugin,[2] the r.in.kinect add-on,[3] and their dependencies compiled.

Physical models. To sculpt with Tangible Landscape you need a malleable model made of a soft, deformable medium like polymer enriched sand. These models can be hand sculpted or precisely cast with digitally fabricated molds. When you are using Tangible Landscape for object detection you can use hard, rigid models such as 3D prints.

Setup. Place your physical model of a landscape on a table. Mount the Kinect sensor on baby wall plate attached to a C-stand. Adjust the height of the C-stand so that the Kinect is 50 - 100 cm above the model. Check that the Kinect is level using an instrument like a spirit level. Mount the projector on another baby wall plate attached to the other C-stand. Connect the Kinect and projector to your computer. See https://github.com/tangible-landscape/grass-tangible-landscape/wiki for more detailed instructions.

Calibration. Remove the model, clear the table, and then run Tangible Landscape's automatic calibration function to account for the relative rotation of the scanner and the table.

[1]https://grass.osgeo.org/
[2]https://github.com/tangible-landscape/grass-tangible-landscape
[3]https://github.com/tangible-landscape/r.in.kinect

Fig. 21. Download stickers from https://github.com/tangible-landscape/tangible-landscape-media

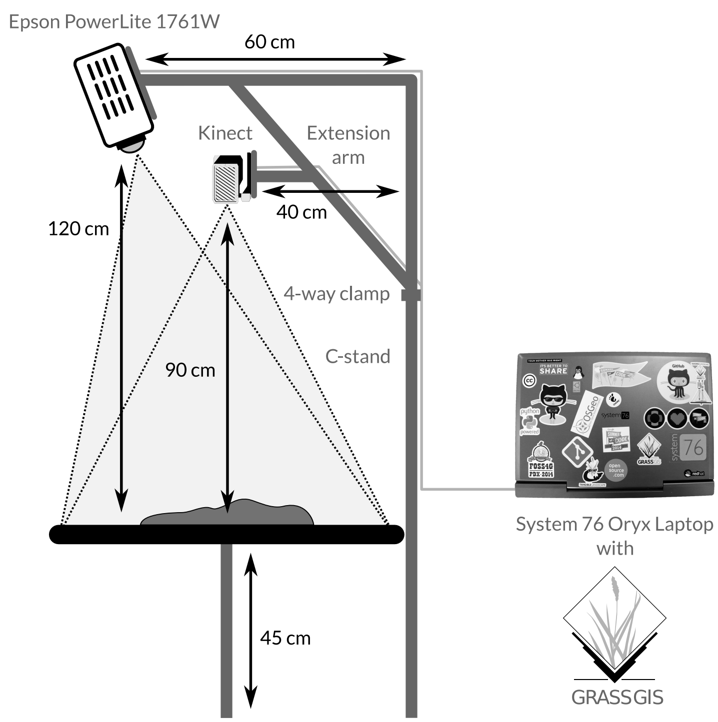


Fig. 22. System setup

B. EXPERIMENTAL PROCEDURE

B.1. Data

Acquire elevation data for your study landscape. We used a 2013 airborne lidar survey of Wake County, North Carolina. Other sources for lidar point clouds and raster elevation data include the National Elevation Dataset,[4] the United States Interagency Elevation Inventory,[5] Open Topography,[6] and the European Environment Agency's Digital Elevation Model over Europe.[7] Import lidar data in GRASS GIS as vector points using the module v.in.lidar[8] and then interpolate with the module v.surf.rst.[9] Find regions of the same size with clearly defined morphological features for each experiment.

When preparing data and running analyses use the following naming conventions. Digital modeling, analog modeling, augmented modeling, tangible modeling with the difference analytic, and tangible modeling with the water flow analytic will be experiments 1-5. For each experiment save the corresponding reference digital elevation model in the *PERMANENT* mapset with the number of the experiment (i.e. dem_1, dem_2, dem_3, dem_4, and dem_5). Save the results of each experiment in the *data* mapset with the participant's name, the type of data, and the experiment number (i.e. name_dem_number).

B.2. Experiments

Introduce the research and explain the experiment to each participants. If they agree to take part in the experiment have them sign an informed consent form. Shuffle the order of experiments for each participant.

Digital modeling. In the 1st experiment participants will sit at a computer and use Rhinoceros, a 3D modeling program, to digitally model the study landscape. They will have 10 minutes of training before they begin. Start by explaining the interface, showing them the basic controls – selecting, panning, zooming, orbiting, and transforming with the gumball – and then letting them try. Then explain how this experiment will work, show them how to vertically translate control points on a NURBS surface using the gumball, and let them try. Begin the experiment. They will have 10 minutes to model the study landscape by vertically translating control points on a NURBS surface using the gumball. They will begin with a flat surface subdivided into a 10 x 10 grid of control points. They can use the *rebuild* command to create a higher density of control points. They will raise and lower these control points with the gumball to change the surface. They can used a locked layer with 3D contours as a reference. Snapping should be disabled. When 10 minutes have elapsed save their model as a *.3dm* file and then export it as a GeoTIFF (*.tif)*. Import this *.tif* raster into GRASS GIS using r.in.gdal,[10] randomly resample it using r.random,[11] and then interpolate it using v.surf.rst to create a digital elevation model. Copy this to the *data* mapset as *name_dem_1*.

Analog modeling. In the 2nd experiment each participant will have 10 minutes to build a polymer-enriched sand model of the study landscape using a CNC-routed model as a reference. They will be given a 3D scale – a wooden block ruled with map units –

[4]https://viewer.nationalmap.gov
[5]https://coast.noaa.gov/inventory/
[6]http://www.opentopography.org/
[7]http://www.eea.europa.eu/data-and-maps/data/eu-dem
[8]https://grass.osgeo.org/grass72/manuals/v.in.lidar.html
[9]https://grass.osgeo.org/grass72/manuals/v.surf.rst.html
[10]https://grass.osgeo.org/grass72/manuals/r.in.gdal.html
[11]https://grass.osgeo.org/grass72/manuals/r.random.html

as an additional guide. They can use a wooden modeling tool or their hands to sculpt the model. A desk lamp will illuminate both models from an angle casting shadows like a hillshade. When 10 minutes have elapsed save their model by scanning it with Tangible Landscape. Copy the scanned elevation to the *data* mapset as *name_dem_2*.

Projection-augmented modeling. In the 3rd experiment each participant will have 10 minutes to build a projection-augmented polymer-enriched sand model of the study landscape. The digital elevation model and contours of the study landscape will be projected on the sand model as a reference. They should also be given a CNC-routed model and a 3D scale for additional guidance. When 10 minutes have elapsed save their model by scanning it with Tangible Landscape. Copy the scanned elevation to the *data* mapset as *name_dem_3*.

Tangible modeling with the difference analytic. In the 4th experiment each participant will have 10 minutes to build a polymer-enriched sand model of the study landscape using Tangible Landscape with the difference analytic. This experiment will use a different region of the study landscape. Use Tangible Landscape's *run_difference* function in the *current_analyses.py* script to show each participant where to add and remove sand in order to match the study landscape The difference between their model and the study landscape will be projected onto the sand model in near real-time to guide them. The contours of the study landscape should layered over the difference map. They should also be given a CNC-routed model and a 3D scale for additional guidance. When 10 minutes have elapsed save their model by scanning it with Tangible Landscape. Copy the scanned elevation to the *data* mapset as *name_dem_4*.

Tangible modeling with the water flow analytic. In the 5th experiment each participant will have 10 minutes to build a polymer-enriched sand model of the study landscape using Tangible Landscape with the water flow analytic. This experiment will use a different region of the study landscape. Each participant can choose to see either simulated water flow for the study landscape or simulated water flow for their model. When a participant asks switch between these layers in GRASS's layer manager. Use Tangible Landscape's *run_simwe* function in the *current_analyses.py* script to simulate water flow across their model in near-real time. The contours of the study landscape should layered over the precomputed reference water flow, while the contours of the scanned model should be layered over the water flow for the scanned model. They should also be given a CNC-routed model and a 3D scale for additional guidance. When 10 minutes have elapsed save their model by scanning it with Tangible Landscape. Copy the scanned elevation to the *data* mapset as *name_dem_5*.

Documentation. Record each experiment with photographs or video. Observe each participant as they work and take notes about their modeling processing.

Interviews. Interview select participants after they finish the experiments. See Appendix C for semi-structured interview guidelines.

B.3. Geospatial analysis

Copy the scanned maps from the *data* mapset to a new *analysis* mapset for processing. Open a session of GRASS GIS in the appropriate location (i.e. *tangible_topography_mapset*) with the *analysis* mapset. Create new directories *results* and *render_3d* inside the location directory. Run the script *analysis.py* in this GRASS session to analyze the data. This will generate new maps with analyses and simulations in the *analysis* mapset and will render the maps as *.png* images in the *results* directory. Then run the script *render_3d_images.py* to generate 3D renderings of the maps in the *render_3d* directory.

C. SEMI-STRUCTURED INTERVIEW GUIDELINES

C.1. Aim

Understand how tangible interfaces for geospatial modeling change how users model.

C.2. Interview goals

— Map participants' analog, hand modeling processes
— Map participants' digital modeling processes
— Map participants' augmented modeling processes
— Map participants' tangible modeling processes with the difference analytic
— Map participants' tangible modeling processes with the water flow analytic

C.3. *Topic:* Modeling process

— Please describe your modeling process with each technology
— Did you work additively or subtractively? A mix?
— Did you work in a linear or iterative, exploratory process?
— How did this technology aid you? What did it let you to do?
— Did this technology constrain you in any way?

C.4. *Topic:* Intuition

— How intuitive was it?
— Could you model what you intended?
— Did you have to think about how to modeling? Or could you just act?

C.5. *Topic:* Metacognition

— We asked you to sculpt a model of the study landscape. Please describe your thought process while sculpting.
— Did you strategize about how to model? If so what was your modeling strategy?
— Did your modeling strategy evolve as you worked?

C.6. *Topic:* perception and experience

— How did it feel to sculpt a 3D model with this technology?
— Was it stressful? Was it fun?
— Did the technology change how you perceived distance, depth, form, or volume?

D. VIDEOS: APPLICATIONS

https://www.youtube.com/playlist?list=PLiNYVMuYqTHXzgHK0Y_yQ7v9EsnnMaMwg

A collection of videos demonstrating applications for Tangible Landscape.

D.1. Landscape design with Tangible Landscape and Virtual Reality

https://youtu.be/pYbpEMjME1Y

We coupled Tangible Landscape with an immersive virtual environment so that users can virtually walk around the modeled landscape and visualize it at a human-scale. As users shape topography, draw trees, define viewpoints, or route a walkthrough, they can see the results on the projection-augmented model, rendered on a display, or rendered on a head-mounted display.

D.2. Landscape planning with Tangible Landscape

https://youtu.be/Cd3cCQTGer4

As users sculpt a physical model – building dams, forming depressions, and carving stream channels in polymeric sand – they see simulated water flow and ponding update in real-time. Computed using the modules r.sim.water and r.fill.dir in GRASS GIS.

D.3. Subsurface visualization with Tangible Landscape

https://youtu.be/__fWppH9aqQ

Users visualize subsurface properties such as the percentage of soil moisture by digging to excavate soil or placing markers to take soil core samples.

D.4. Viewshed analysis with Tangible Landscape

https://youtu.be/tGFNHFoHMYM

Users place markers on a physical model to digitize viewpoints and compute viewsheds in real-time. Viewshed are computed using the module r.viewshed in GRASS GIS.

D.5. Wildfire spread modeling with Tangible Landscape

https://youtu.be/EJc57GFJeZI

Users interact with a fire spread simulation by removing fuel from a physical model of a landscape to create firebreaks. Fire spread is computed using the modules r.ros and r.spread in GRASS GIS.

D.6. Urban growth modeling with Tangible Landscape

https://youtu.be/SeBoGwSqmRM

Users collaboratively interact with the FUTURES urban growth simulation by delineating protected areas (with green sand) and areas where they want future development to occur (with red sand). Participants can also draw new roads, which will attract more development.

E. VIDEOS: USER EXPERIMENTS

https://www.youtube.com/playlist?list=PLiNYVMuYqTHVCISj3CS9Og2Q5GZZ8o065

A collection of videos demonstrating the training and user experiments in this study.

E.1. Training for digital 3D modeling

https://youtu.be/dSyrHAuu698

E.2. Digital 3D modeling with Rhinoceros

https://youtu.be/vA1xwMSaGV4

E.3. Analog 3D modeling

https://youtu.be/STYHUHNaWdY

E.4. Projection-augmented 3D modeling with Tangible Landscape

https://youtu.be/1uEvzMJWh_E

E.5. 3D modeling with Tangible Landscape's difference analytic

https://youtu.be/VXmW9-yASVU

E.6. 3D modeling with Tangible Landscape's water flow analytic

https://youtu.be/61hsXgb3MLY

E.7. Good performance with Tangible Landscape's difference analytic

https://youtu.be/Q3elMIRCYSk

F. SCRIPTS

F.1. analysis.py

https://github.com/baharmon/tangible_topography

The python scripts for data processing, analysis, and rendering used in this experiment are available on GitHub under the GNU General Public License (GPL).

G. DATA

G.1. tangible_topography_mapset

https://osf.io/82gst/

The data used in this experiment and the results including analyses and renderings are available on the Open Science Framework under the Creative Commons Zero license. The data is stored in a GRASS GIS location with a collection of mapsets with GIS data and directories with renderings.

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