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Tangible Landscape

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Abstract

I have co-designed Tangible Landscape – a tangible user interface powered by a geographic information system – and used it to explore how technology mediates creativity and spatial cognition in a rigorous experiment.

Tangible Landscape is a continuous shape display that couples a malleable, interactive physical model of a landscape with a digital model of the landscape so that users can 3D sketch ideas and then immediately analyze them with scientific rigor. The physical and digital models are linked through a real-time cycle of interaction, 3D scanning, geospatial modeling, and projection. As we interact with a physical model of a landscape – for example by sculpting the topography – the changes are scanned into GRASS GIS, an open source geographic information system (GIS), for geospatial analysis and simulation and the resulting analytics are projected onto the physical model.

Tangible user interfaces are based on the premise that embodied cognition in computing can enhance cognitive processes. However, the ways in which embodied cognition in computing transform spatial thinking have not yet been rigorously studied.

In a terrain modeling experiment my colleagues and I studied whether Tangible Landscape can enhance spatial thinking and improve spatial performance. We used quantitive and qualitative methods to assess participants' spatial performance and creative processes using different technologies. We used geospatial analytics such as geomorphometry and geostatistics supplemented by semi-structured interviews and direct observation to analyze how visual computing with a GUI and tangible computing with a shape display mediate multidimensional spatial performance.

My initial findings suggest that: **1.** digital sculpting via a GUI is unintuitive, **2.** visual ambiguity in digital sculpting via a GUI leads to spatial misinterpretations, **3.** shape displays like Tangible Landscape can be intuitive, enhance spatial performance in novel ways, enable rapid iteration and ideation, and encourage creativity, and **4.** different analytics encourage significantly different modes of spatial thinking and strategies for modeling.

My colleagues and I have developed applications for Tangible Landscape including stormwater management, flood control, landscape management and erosion control, trail planning, viewshed analysis, solar analysis, wildfire management, disease spread management, urban growth, and sea level rise adaption.

Embodied cognition in tangible computing

Literature review

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1 Introduction

Emerging theories of cognitive science rethink how we interact with our environment, tools, and computers and have inspired new modes of computing. Based on the theories of embodied, situated, and distributed cognition researchers have theorized a physical-digital divide in human-computer interaction – positing that the high level of abstraction required to interact with a computer in a visual computing paradigm constrains how we think – and designed innovative technologies for bridging this divide such as tangible user interfaces (TUIs). TUIs are designed to enable embodied cognition by physically manifesting data so that we can kinaesthetically sense and tangibly interact with computations. More embodied cognition in computing should enhance spatial thinking and may also encourage creative thinking.

While these theories have inspired the design of novel technologies for human-computer interaction, their applied principles need to be empirically tested, critiqued, and refined in order to improve interaction design. This research studies how tangible computing mediates spatial and creative thinking in order to improve interaction design and enhance spatial performance. This literature review begins with a critical overview of emerging theories of cognitive science and the theories of human-computer interaction that they have inspired. Then the implementation of these theories of human-computer interaction is explored in a critical review of the evolution of TUIs. After a review of research on tangible interaction a research agenda is proposed.

2 The cognitive science of human-computer interaction

2.1 Embodied, situated, and distributed cognition

There is a new paradigm of cognitive science that studies 'cognition beyond the brain' (Hardy-Vallée and Payette, 2008). This new paradigm – embodied, situated, and distributed cognition – explores how cognition is functionally embedded in the body, embedded in its environment, and distributed across networks of agents and artifacts. While older paradigms of cognitive science studied the mind abstracted in isolation, this paradigm grounds cognition in its biocultural context studying how a continuous flow of information links brain, body, and environment (Hardy-Vallée and Payette, 2008).

In embodied cognition the mind is embedded in the body. It is based on bodily experience. Higher cognitive processes, the traditional realm of cognitive science, rely on lower level processes such as emotion and sensorimotor processes that link perception and action (Hardy-Vallée and Payette, 2008). Thus our bodies and actions mediate how we think. We can for example physically simulate cognitive processes, offloading cognition onto action to functionally 'think with our bodies' (Kirsh, 2013). We can cognitively grasp objects, temporarily, contingently incorporating tools into our body schema (Kirsh, 2013). This view of cognition considers feeling, action, and perception to be functionally integral to thought.

In situated cognition the mind is embedded in its environment. Situated cognition is a sociocultural process influenced by environment, society, and culture. Information not only flows into the body and thus the mind from its environment, but also from the mind via the body into the environment.

Since information can be stored in and transformed by the environment we use our environment, our artifacts, and our tools to store ideas, to offload cognitive processes, but our environment, our artifacts, and our tools also constrain and transform our ideas, mediating cognition. By storing ideas or mental states in external representations like writing or painting we can extend our memory, but – given the constrains of the medium – we can also transform the idea or state through its expression. In addition to reducing our cognitive load by offloading cognitive processes onto our bodies or our environments (Wilson, 2002) we can also enhance our cognitive performance by offloading onto technology – technology such as language, books, telecommunications, and computing (Dror and Harnad, 2008). Thus cognition is grounded in, uses, transforms, and is transformed by its environment (Hardy-Vallée and Payette, 2008; Anderson, 2008). Since from a phenomenological perspective meaning arises from interaction with the environment (Dourish, 2001) situated cognition studies how interaction and thus meaning is mediated by the environment, artifacts, and tools (Reichelt and Rossmanith, 2008).

In distributed cognition the mind is distributed across sociocultural and technological networks. It is distributed across networks of situated agents and artifacts through language, technology, society and culture (Hardy-Vallée and Payette, 2008). The means of communication, of shared thought, mediate meaning and cognition.

Some of these ideas are controversial. When we perform a task our cognition is situated in the immediate context, but when we think abstractly without a task to perform we are do not have an immediate context(Wilson, 2002). From this perspective abstract thinking is not situated. From a phenomenological perspective, however, all meaning is derived from interaction making even abstract thinking grounded – situated – in phenomenological experience (Dourish, 2001). Even from this more philosophic perspective abstract thinking should be less situated than the thinking that directs an action, the cognition for performing a task. However, even when thinking abstractly we often rely on our bodies and sometimes our environment. We may physically simulate what we imagine, representing for example a shape with our hands, measuring a distance with our bodies, or counting off a sequence with our fingers (Wilson, 2002). Spatial thinking – whether abstract or applied – is situated. We think about space visually and kinaesthetically. We visualize and feel it.

Wilson draws a distinction between online embodied cognition for immediate tasks requiring action and offline embodied cognition for tasks that are either imaginary or distant in time or space (2002). Many tasks are time sensitive and require fast thinking. The need to act quickly can cause representational bottlenecks – mental models may not be formed quickly enough for one to succeed at a task. Online embodied cognition uses the body and environment to think quickly. We can reduce our cognitive load and mental modeling time with our bodies by learning motor schema or pragmatic representations that let us automatically, subconsciously perform tasks. We can also cognitively offload by using our bodies or our environment as a proxy for memory. When an action or our environment is indexical to the task we cognitively offload online. When, however, the relationship between our environment and the task is symbolic we cognitively offload offline. When for example we draw, write, or diagram the relationship between the physical representation and the idea is symbolic and disconnected in time and sometime space. Symbolic cognitive offloading is offline and yet embodied, grounded in tools or our environment. Thus offline cognition, while often abstract, can also be embodied. Mental simulations can also be embodied as they may draw upon visual, auditory, and kinesthetic representations derived from experience (Wilson, 2002).

We can also archivally offload onto our environment by encoding ideas for example in books, maps, and places (Wilson, 2002). Basso for example describes from an anthropological perspective how meaning and cultural significance can be invested in a landscape and how the cultural values embedded in that landscape can inspire introspection and learning across generations (1996). A computer, however, is not just a tool for storage, for archiving data – it is a tool for computation, for enhancing our thinking, for augmenting our cognitive processes (Dror and Harnad, 2008). We use it to extend our thinking capacity, to process, model, simulate, and represent complex phenomena.

2.2 Embodied interaction

The theses that cognition is embodied and situated, that we sometimes understand more through acting than by watching, that tools mediate how we perceive, think, and act, and that tools like computers can extend our capacity to think (Kirsh, 2013) have inspired a new paradigm of human-computer interaction – embodied interaction.

Dourish outlined the history of human-computer interaction as an evolution from electrical to symbolic to textual to visual computing and theorized that the emerging paradigms of tangible and social computing would make interaction more embodied and situated (2001).

The dominant paradigm of computing today – visual computing, computing via a graphical user interface (GUI) – is thought to be relatively disembodied because of the high level of abstraction required to interact with the computer. The body plays a limited role in visual computing. With a GUI one uses an input device to interact with data visually represented as graphics on a display. When we use a mouse and keyboard, archetypal examples of input devices, there is a disjunction between our actions and the results – the double click of a mouse button is not indexical to its result, the opening of a folder. This arbitrary coding adds a layer of abstraction between our intention and its expression. Input devices include mice and keyboards, touch sensitive displays, and digitizing pens. Some of these, the pressure-sensitive digitizing pens for example, enable a wider range of haptic experience and enaction. The more haptic feedback a GUI offers, the closer to a TUI it becomes. Inputs are limited to keystrokes or two-dimensional translations of pointing devices like mice or digitizing pens. Feedback – save for the position of the hand on the pointing device in relation to a cursor in an abstract space – is visual (Dourish, 2001; Ishii, 2008a). Even the transitional paradigm of touch computing is limited to two-dimensional touch gestures and visual or symbolic feedback. There is a disconnect between intention, action, and feedback – our intention is translated into symbolic action, action into computation, computation into visual representation, and representation into mental model. Multiple layers of abstraction separate intention, enaction, and a critical understanding of the result. The limited forms of input and feedback in visual computing enable sophisticated, abstract thinking, but do not afford many aspects of embodied cognition like cognitive grasping, haptic shape recognition, and physical simulation.

Furthermore visual computing is thought to be relatively unsituated as it immerses users in abstract, disembodied virtual environments disconnected from their immediate, physical environments. Social interaction in virtual environments lacks the cues and affordances of natural social interaction in physical environments. Ubiquitous computing was a vision of computation embedded in our everyday, physical environment, of situating computing in our physical and social en-

vironment rather than immersing ourselves in abstract digital environments (Dourish, 2001). This vision of computationally enhanced everyday life inspired tangible computing (Ishii and Ullmer, 1997).

The relatively disembodied nature of visual computing has been described as a physical-digital divide, a disconnect between 'cyberspace and the physical environment' (Ishii and Ullmer, 1997). Human-computer interaction researchers and designers have sought to bridge the physical-digital divide with tangible computing. Tangible computing aims to embody computing by coupling physical and digital data (Dourish, 2001) – by physically manifesting digital data so that we can cognitively grasp and absorb it, so that we can think with it rather than about it (Kirsh, 2013). Ishii and Ullmer envisioned that TUIs would 'take advantage of natural physical affordances to achieve a heightened legibility and seamlessness of interaction between people and information' (1997).

Many TUIs have been designed and prototyped including the Marble Answering Machine (Poynor, 1995), Urp (Underkoffler and Ishii, 1999), the Aegis Hyposurface (Goulthorpe, 2000), FEELEX (Iwata et al., 2001), Luminous Table (Ishii et al., 2002), Illuminating Clay (Piper et al., 2002a), Sandscape (Ishii et al., 2004), the Tangible Geospatial Modeling System (Tateosian et al., 2010), Relief (Leithinger and Ishii, 2010), inFORM (Follmer et al., 2013), and the Augmented Reality Sandbox (Kreylos, 2015). Research on TUIs, however, has largely been limited to user feedback (such as Ishii et al. 2004), case studies (such as Iwata et al. 2001; Ishii et al. 2002; Tateosian et al. 2010), and small scale qualitative studies using methods like protocol analysis (such as Kim and Maher 2008).

A better understanding of the cognitive implications of embodiment and disembodiment in computing would improve interaction design. To understand how computing transforms cognition we need to study 'the complex coordination between external and internal simulation, between doing things internally and doing things externally' (Kirsh, 2013). The theory of embodied interaction needs to be rigorously tested, critiqued and refined so that we can develop more nuanced design principles that are derived from theory grounded in empirical research. The assumption that the more human-computer interaction is embodied, the more natural it will be needs to be refined and nuanced. Intermediate levels of 'realism' in embodied interaction, for example, may lead to a disconcerting 'uncanny valley' of expectation disappointed giving rise to uncertainty and misinterpretation. If some aspects of an interaction closely mirror physical reality, while others are still highly abstract, users may experience a cognitive dissonance for the appearance of reality in one aspect suggests it in another. Therefore the coherence and consistency of experience may be more important than the relative embodiment of any aspect (Cafaro et al., 2014).

Theoretically tangible computing is especially well suited to spatial applications, but it has also been used for aspatial applications such as tangible programming (Horn and Jacob, 2007). Given that visual computing already enables sophisticated abstract thinking, embodied interaction through tangible computing may not add any cognitive potential in some computing applications. A study of the coordination of internal and external simulation and processing may show which applications embodied interaction enhances and how. Furthermore we should study the degree to which abstract and embodied thinking can be coordinated by coupling visual and tangible computing.

2.3 Object-oriented action

In cognitive neuroscience actions such as reaching for, grasping, manipulating, and using an object are considered object-oriented. To interact with an object, to use a tool – to sculpt sand or move a mouse – we need to understand where the object is relative to us in space, understand its form and physical properties, and identify what we do can with it. Using a tool is a question of space, mechanics, and semiotics.

We use internal models to generate action – to predict and react to known stimuli and adapt to and learn from novel stimuli. Object-oriented action is directed by both pragmatic and semantic representations, subconscious and conscious internal models based on haptic and visual feedback (Jeannerod, 1997).

Pragmatic representations are internal models for rapidly generating action that are primarily based on haptic or tactile feedback. We use touch to directly assess the form and physical properties of objects – their size, shape, volume, weight, hardness, and texture. This haptic feedback is processed automatically, immediately, and subconsciously (Jeannerod, 1997).

Semantic representations assign meaning and cognitively signal action. They are primarily based on visual perception (Jeannerod, 1997). Vision, however, requires interpretation and is subject to illusions. Visually perceived depth is reconstructed from perspective, accommodation and vergence, interposition and shading, and motion parallax. In stereoscopic vision we derive the visual third dimension from perspective based on the difference between the two-dimensional imagery projected to each eye. Aspects of perspective include size, linear position, perceived distance, and textural perspective. Illusions can arise from misreading curvature, misjudging distance, and misapproximating size based on distance (Howard, 2012a,b; Jeannerod, 1997). Since visual feedback is cognitively processed for interpretation the derived semantic representation is subjective and mediated by knowledge. Visually perceived objects are semantically classified and identified based on their perceived, phenomenological attributes (Jeannerod, 1997).

Action can be driven by both pragmatic and semantic representations that are coordinated as they unfold on different timescales. Both types of representation are processed in parallel, exchange information, and are temporally coordinated. When for example we try to identify an object by both feeling it and seeing it we are simultaneously processing haptic and visual feedback. The pragmatic and semantic representations inform each other, but there is a temporal disjunction due to the latency in processing visual feedback so they are coordinated by a higher level temporal schema (Jeannerod, 1997).

To use a tool we need to be able to identify it and what it can do. A tool may afford many different actions; we may be able to use it in many different ways, but we may not realize all of them. The affordances of a tool – the actions we think we can do with it (Gibson, 1977) – are mediated by our knowledge and experience. Therefore knowing how to use an object can be a cognitive task based on a semiotic understanding of what it is and what it can do. It can also be a exploratory procedure based on pragmatic action (Jeannerod, 1997). Action can be informed by a continuum from innate properties to symbolic meanings.

The neuroscience of object-oriented action supports in theory the idea that TUIs can offer affordances that GUIs cannot. This design idea, proposed by Ishii and Ullmer (1997), has driven the development of tangible computing. Ishii and Ullmer criticized visual computing – arguing that

"GUIs fall short of embracing the richness of human senses and skills people have developed through a lifetime of interaction with the physical world" – and proposed a vision of TUIs "to bridge the gaps between both cyberspace and the physical environment, as well as the foreground and background of human activities" (1997). In their vision digital data would be physically embodied as tangible bits so that users could feel and not just see their data. By physically manifesting digital data they hoped to offer new affordances – the ability to touch and sense the size, shape, volume, weight, and hardness of the data; the ability to directly, physically manipulate and shape data. To, in terms of cognitive neuroscience, make pragmatic representations of digital data. This should enable rapid, intuitive action and expression in a way that was not possible in visual computing; it should fundamentally transform the way we think and act while computing.

While tangible computing is often theorized in terms of embodied cognition, embedded cognition, and embodied interaction, the neuroscience of object-oriented action offers a nuanced perspective on the role of visual and haptic feedback in computing. Since GUIs rely almost entirely on visual feedback they only cognitively afford semantic representations (save for the pragmatic, semantically conditioned representations needed for the tasks of typing and clicking). By adding haptic feedback and enabling a wider range of physical expression TUIs also afford pragmatic representations. Thus a visual computing paradigm should be well suited to more semantic tasks like word processing or programming, while a tangible computing paradigm should be better when physical and spatial properties matter. Tangible computing should help us to better understand space and shape form. The intuitive and exploratory nature of pragmatic representations means that tangible computing should also enable more creative spatial thinking. Furthermore when tangible computing combines visual feedback and haptic feedback we generate both semantic and pragmatic representations and thus benefit from a richer, fuller understanding of our data and a wider range of expression.

2.4 Embodied spatial cognition

Many conceptions and studies of spatial thinking focus on a visual, semantic understanding of space. Embodied cognition, however, highlights the importance of a kinaesthetic, pragmatic understanding of space and the enaction of spatial transformation – for the act of transforming an object changes how we think about space. As Kirsh argues, sometimes 'we know more by doing than by seeing' (2013).

Uttal et al. defined spatial thinking as 'the mental processes of representing, analyzing, and drawing inferences from spatial relations' (2013a). This definition is based on a semantic rather than pragmatic understanding of space, an understanding based on visual rather haptic, kinaesthetic feedback. In this paradigm space is imagined rather than felt and spatial transformation is imagined rather than enacted. Psychometric tests of spatial ability – the application of spatial thinking – for example study spatial visualization and mental rotation (Uttal et al., 2013a,b; Ormand et al., 2014). We, however, do not just see space – we also feel it; we use our bodies to feel size, shape, and volume. Space need not be imagined to be transformed – haptic feedback about space informs subconscious pragmatic representations that rapidly generate action (Jeannerod, 1997). Spatial thinking can be embodied.

Spatial thinking is malleable and can be improved with training. The effects of spatial training can

be durable – persisting for months – and transferable – training in a given spatial task improves performance in other untrained spatial tasks (Uttal et al., 2013a). Spatial training has been shown to improve performance in science, technology, engineering, and math (STEM). Research, however, is needed to determine which training methods will mostly effectively improve STEM performance. How can spatial training integrate domain specific knowledge? And could such applied training more effectively improve performance in a given discipline? (Uttal et al., 2013a) Embodied spatial thinking may lead to improvements in STEM performance by reducing cognitive loads with pragmatic representations and physical simulation and by enhancing perception with visual and haptic feedback.

The recent focus on STEM in education has been criticized for its lack of creativity and innovation with some educators and policy makers calling for the integration of arts and design – for STEAM – in the hope that a more creative culture may stimulate innovation (Land, 2013; Connor et al., 2015). In light of this we should also be asking what are the most effective ways to improve *creative* spatial thinking.

Since spatial thinking is mediated by technology the effectiveness of training methods will depend upon their implementation, upon the technology used. Computer gaming has been shown to improve spatial thinking and technologies like geographic information systems (GIS) can be used to integrate domain specific knowledge (Uttal et al., 2013a). Unintuitive human-computer interaction, however, may constrain spatial thinking and add cognitive costs thus reducing the effectiveness of digitally implemented training methods. Embodied and computationally enriched cognition may enhance spatial thinking in novel ways enabling and encouraging coupled creative and analytic thinking.

2.5 Conceptual blending

Creative thinking is an iterative process that can mapped as a series of conceptual blends in which two ideas are synthesized into a new idea. Conceptual blending is a fundamental subconscious cognitive process by which meaning evolves. It is the creative process by which meanings such as "categorizations, analogies, counterfactuals, metaphors, rituals, logical framing, grammatical constructions" (Fauconnier, 2000) and representation are constructed. In conceptual blending two inputs, two initial ideas are partially matched and then selectively projected into a blend. Even though the inputs may be incongruent and contradictory if they share common elements – elements of a common abstract structure or organization, a 'generic space' – then these common elements can be used as anchors for drawing connections. The two input spaces are blended or integrated by selectively projecting the anchors and other elements of the spaces together. By drawing connections between these partially mismatched concepts and then blending them together a novel conceptual structure emerges (Fauconnier, 2000) – new meaning emerges from the blend. Rapid iterations of conceptual blending have the potential to develop more novelty through the continued evolution of the emergent conceptual structure.

Through blending simple concepts can generate complex concepts. Blends of blends form integration networks generating hierarchies of complexity. Low level processes like emotion and sensorimotor processes give rise to emergent higher cognitive processes through integration networks. It is through blends that higher cognition emerges from embodied cognition, that abstract

thinking emerges from bodily experience (Jetter et al., 2014).

When we think creatively about space we iteratively develop an evolving cognitive model of the space. We blend spatial ideas together – for example synthesizing two spaces together or applying a transformation to a form. Because spatial thinking can be cognitively taxing cognitive work may be offloaded into pragmatic representations or even computational representations and processes. When spatial thinking unfolds subconsciously in conceptual blends and pragmatic representations active metacognition may play little role in creative spatial thinking. Csikszentmihalyi describes this mode of subconscious action or generative ideation in creative thinking as *flow* (1996). Subconscious creative action for example plays an important role in Chan and Zen art inspired by the Taoist concept of *wu wei* and the Zen concept of *mushin*. When, however, complex hierarchies of blends develop metacognition may play an important coordinating role in creative thinking.

2.6 Blended interaction

Blended interaction is a conceptual framework based on conceptual blending for describing the naturalness of human-computer interaction. The more conceptual blending used in a cognitive process and the denser the hierarchies of the integration network, the less natural and intuitive the process becomes. More cognitive steps mean more processing, more thinking, and thus less immediacy. Therefore interactions are intuitive and thus feel natural when they draw directly upon basic experiences and past knowledge (Jetter et al., 2014).

Blended interaction in spatial thinking Blended interaction can be used to describe and map how technologies mediate spatial thinking in visual computing and tangible computing. Spatial cognitive processes can be mapped as integration networks of successive conceptual blends. Representing space is an important cognitive process – we use spatial representations to better understand space, share ideas about space, and design space.

Representation is not pure replication – it is symbolically (Deacon, 2006) and technologically mediated (Donald, 2006). Thus it is a creative, ideational endeavor in which new meaning forms. Based on the comparator model for the regulation of action (Jeannerod, 1997), we have modeled the process of representation as an ongoing series of conceptual blends comparing sensory feedback against intention – comparing what has been represented against what was intended. To represent something we imagine what we want to make and we think about what we have, our medium. To act we blend these mental representations – what we want and what we have – into intention. Technology, the means of expression, mediates how that intention translates into action. As soon as we have acted, we feel and see the differences between our intention and our result. Again, we blend what we want and what we have into a new intention – the process repeats, an iterative sequence of blends. The complexity of this sequence of blends, this integration network depends upon the technology used.

Blending in hand modeling When we model space by hand, sculpting for example in a medium like sand or clay, we cognitively grasp our medium as a pragmatic representation that rapidly

generates action at a subconscious level – we continually, experimentally sculpt to find the form we seek. When we model by hand we both feel and see the result. We use the visual feedback to consciously analyze and critique the form we have made. There are two integration networks at play here. The haptic, pragmatic network of blends should be simple and highly intuitive, drawing on low-level, embodied cognitive processes. The visual, semantic network of blends should be more complex and less intuitive, requiring abstract, analytical thought to critique the form.

Driven by pragmatic representations the process of representing space by hand is exploratory and experimental. It unfolds in an iterative cycle of generative ideation, haptic analysis and visual analysis, and critique. By hand there is a physical, kinaesthetic immediacy that allows for coupled, simultaneous ideation and creation – for generative ideation. By immediately acting out our thoughts we can generate ideas by giving them form (Ingold, 2011). Ideation and expression can only be tightly coupled when the act of expression, of representation is highly intuitive.

The process of representing space by hand can be mapped in greater detail as an iterative sequence of successive conceptual blends. In generative ideation the thing being represented is blended with the initial concept to represent it or in subsequent iterations with the current state of the representation. Both inputs share an abstract conception of space, a datum. These inputs – the thing represented and the thing representing it mediated by the means of representation – are connected as a representation and the resulting blend is an evolving concept and form, the emerging state of the representation. This is then compared tactilely and visually with the thing being represented. In the tactile or haptic analysis the difference is felt subconsciously and immediately informs the act of representation. The immediacy of felt feedback – automatic adjustments to the fingers for examples – make drawing and sculpture fluid. The difference identified by the visual analysis is blended with the means of representation to generate a critique. The critique asks, why is there a difference? This critique informs the next act of representation, the subsequent iteration.

Mapping the analog process of representation as a conceptual blending network suggests that haptic feedback facilitates an intuitive process with rapid iterations. Visual feedback may add analytical depth by enabling a conscious critique of the process, but that depends upon the richness and perceptual legibility of visual data. For example good lighting casting distinct shadows on a model of landscape would convey rich, intuitively understood information about the 3-dimensionality of the terrain whereas as a poorly lit model might be visual illegible potentially even (mis)reading as a flat plane. This analysis suggests that haptic feedback may enable one to represent accurately up to a point, up to the limits of their kinaesthetic or embodied understanding of space and their medium. Visual feedback paired with haptic feedback may enable one to represent even more accurately by supplementing subconscious kinaesthetic experience with conscious critical judgment.

Blending in visual computing When interacting with a computer via a GUI (or a command line) intention must be translated through multiple layers of abstraction – from the hand to the keyboard and mouse, from these (input) devices to computations, from computations to a display, and from the display to the eyes. Feedback is largely visual and thus semantically processed. Based on this reasoning GUI-based technologies for representation should require highly abstract thought to use and interpret. Therefore these technologies should theoretically be unintuitive requiring substantial learning to be use as intended (Ishii, 2008a).

When we model space using a GUI it unfolds in an iterative cycle of ideation, form generation, visual analysis, and critique. Here ideation is decoupled from form generation for an additional layer of abstraction – the GUI – separates the conception of an idea from its instantiation. Graphical user interactions tend to be symbolic, arbitrary – the computation and visualization (scaling an object for example) may bear little indexical relationship to the physical act (a move of the wrist and a click of a button). This high level of abstraction tends to make digital modes of representation unintuitive as one must learn to connect arbitrary meaning to action.

The digital process of representation can be mapped as a linear sequence of successive conceptual blends. The thing represented is blended with thing representing – with the current state of the representation, initially a blank medium. This blending generates an intention to represent an image schema. This intention is blended with the means of representation to generate a form. The form, the new representation is compared with the thing represented via visual analysis. This blend generates the difference between what is represented and representing. The difference is blended with the means of representation in a critical analysis of why there is a difference. This critique informs the next iteration. The digital process when using a GUI is deprived of meaningful haptic feedback about the form represented. While one physically knows their intention has been enacted by feeling sensation of key pressed, there is no indexicality between that sensation and the resultant form. This suggests that the digital process should be less intuitive than an analog process, requiring more learning and unfolding in slower iterations. The quality of visual feedback becomes very important.

Blending in tangible computing A TUI like a shape display can be conceptualized as a blend of hand modeling and visual computing. When we model space using a TUI the cognitive processes used in hand modeling and GUI-based modeling unfold in parallel informing each other. This hybrid process should be highly intuitive and yet informed by computation; it draws on rich haptic, visual, and computational feedback.

Because the hand modeling process affords an intuitive, detailed representation of the space modeled, the computationally-derived graphical feedback need not convey the same information. Instead the computational representation can be designed to offer more analytic feedback. In this way embodied cognition could be enhanced with analytical cognition informed by computational analyses – if intuitive and analytical thinking can be coordinated. These embodied and computational blending networks unfold in parallel on different timescales. How successfully can these parallel cognitive processes be coordinated? Can analytical cognitive processes informed by computation enhance embodied cognition?

3 The evolution of tangible user interfaces

Inspired by prototypes like Durrell Bishop's Marble Answering Machine (Poynor, 1995) and concepts like Fitzmaurice et al.'s Graspable User Interface (1995) Ishii and Ullmer (1997) proposed a new paradigm of human-computer interaction – the TUI. They envisioned that TUIs could make computing more natural and intuitive by coupling digital bits with physical objects as Tangible Bits. In their vision Tangible Bits bridge the physical and digital, affording more manual dexterity and kinaesthetic intelligence and situating computing in physical space and social context (Ishii and Ullmer, 1997; Dourish, 2001). By enabling embodied cognition in human-computer interaction TUIs let us cognitively grip data as an extension of our bodies, intuitively manipulate data, and physically simulate processes. TUIs are thus especially well suited for spatial thinking and problem solving. Recently, the development of TUIs has gained momentum thanks to new developments in 3D technologies such as 3D scanning and 3D printing.

3.1 Spatial thinking with tangible user interfaces

We can easily, intuitively understand and manipulate space physically with our bodies using embodied cognition. We can also precisely and quantitatively model and analyze space computationally in ways that we cannot with just our bodies. Computer modeling via GUI in a visual computing paradigm, however, is thought to constrain spatial perception and thinking, to be less intuitive, and require more experience than physical modeling. Intuition allows us to perceive, think, and act in rapid succession; it allows us to creatively brainstorm and express new ideas. TUIs aim to make the use of computers more embodied and thus more intuitive combining the advantages of physicality and computation. By affording new ways to perceive and analyze physically and digitally layered space TUIs may change the way we think about space.

Spatial thinking plays an important role in science, technology, engineering, arts, and math. Technology mediates how we think about space in these disciplines. In the spatial sciences for example geographic information systems (GIS) are used to computationally model, simulate, and analyze space and the processes that shape it. In the design professions GIS and computer aided design (CAD) programs are used to help study, re-envision, and reshape the built environment. The limitations of technology, however, constrain how we think. Technologies like GIS and CAD are thought to be challenging to learn and use due to the unintuitive nature of understanding and manipulating 3D forms visually in 2D via a GUI (Piper et al., 2002a). Technologies that are challenging to learn and use may constrain action and restrict creativity.

Theoretically being able to interact more naturally with digital space should enhance our spatial thinking, encouraging creativity, analytical exploration, and learning. This is critical for designers as they need to intuitively understand and manipulate information in iterative, experimental processes of creation (Schön, 1983). TUIs are designed to enable users to work intuitively by hand with all the benefits of computer modeling and analytics – to couple embodied cognition with computational processing.

Physical modeling Physical models are used to represent space intuitively. With a physical model we can not only see its volume and depth just as we would perceive space in a real land-

scape, but also feel it by running our hands over the modeled terrain. By feeling and seeing a physical model we can couple pragmatic and semantic representations of the space, our sense of touch correcting the illusions in visual perception, our vision enriching our reconstruction of the 3D form with cast shadows and pattern recognition. Physical models can be built by hand or digitally fabricated. Handmade models for example, be sculpted in clay or cut as contours.

We can shape physical models intuitively – for example we can sculpt landforms by hand, place models of buildings, or draw directly on the terrain. With a physical model, however, we are constrained to a single scale, simple measurements, and largely qualitative impressions.

Digital modeling Digital models are used to visualize, quantitatively analyze, and precisely design space. With digital models we can dynamically visualize different scales and layers of information, study a space by computing geospatial analyses and simulations, and precisely edit digital models. Interacting with digital models using visual computing, however, may be unintuitive. A high level of abstraction separates us from a digital model – to interact with this digital abstraction of physical space with a GUI we must translate our intent through our hands to the computer via input devices like a keyboard and mouse and then visualize the results graphically on a display. The digital model itself is a high level abstraction of physical space represented by arrays of values or by mathematical functions. We have to think abstractly and make great conceptual leaps to work through so many layers of abstraction. Understanding and working directly with a digital model is a hard learned skill, a skill that may constrain our thinking and mediate creativity.

Coupled physical-digital modeling TUIs aim to make interaction between humans and computers more natural and intuitive by giving digital data a physical form and physical form a digital dimension. By coupling the physical and the digital through a feedback loop, we can interact with our physical data directly and very naturally with our bodies – drawing on our highly developed kinaesthetic intelligence.

There are two basic types of TUIs. Some TUIs use machine vision to recognize physical objects or tokens, pair them with the corresponding digital model, and track their movement or manipulation. Shape displays, the other basic type of TUI, represent space as an interactive surface or volume enabling users to directly feel and manipulate space with their bodies. Shape displays can integrate other types of tangible user interactions such as object recognition and tracking.

With a shape display space can be intuitively modeled, creatively explored, dynamically computed, richly layered with data, and rigorously analyzed. It can have all of the advantages of physical landscape models, geospatial models, and CAD combined. With shape displays we can shape a coupled physical-digital model naturally with our hands to creatively explore ideas as if sketching in multiple dimensions. With a physical model we are constrained to modeling in three-dimensions, to modeling for example topographic form. With a hybrid landscape model we are not limited to modeling topographic form – we can dynamically explore and compute many dimensions of geospatial data in rapid succession with the same model (Fig. 1).

Figure 1: Physical, digital, and hybrid physical-digital modeling processes

3.2 Dynamic shape displays

Dynamic shape displays or shape changing displays – a type of TUI – are computer controlled, interactive, physically responsive surfaces. As we interact with the physical surface it changes the digital model and, conversely, as we interact with the digital model the physical surface changes (Ishii, 2008a; Poupyrev et al., 2007). Dynamic shape displays tend to be arrays of pistons and actuated pins that form kinetic, 2.5D surfaces (Petrie, 2006) although there is experimental research into continuous, moving surfaces made of shape changing materials driven by heat, magnetic, or electrical stimuli (Coelho and Zigelbaum, 2010).

Aegis Hyposurface The Aegis Hyposurface, an early example of a dynamic shape display, is a generative art installation that uses pneumatic actuators to move a triangulated mesh surface according to an algorithm. It can be either preprogrammed or interactive, moving in response to sensed sound, light, or movement. As it was designed and built at an architectural scale the Aegis Hyposurface has a very coarse resolution for an actuated shape display (Goulthorpe, 2000).

FEELEX The resolution of actuated shape displays is constrained by the size and arrangement of the piston motors and piston rods or pins that move the surface. Project FEELEX, another early dynamic shape display, used linear actuators to deform a rubber plate. The size of the motors – 4 cm – meant that the resolution of the shape display was very coarse. Since the motors are larger than the pins, FEELEX 2 used a piston-crank mechanism to achieve a relatively high 8 mm

resolution by clustering the pins while offsetting the motors below. A rubber sheet was stretched over the array of pins to create a 2.5D display for projection. When a user touched the surface they would depress the pins and the pressure of their touch would be recorded as a user interaction (Iwata et al., 2001).

Dynamic Sand Table & Terrain Table The XenoVision Mark III Dynamic Sand Table, developed in 2004, and the Northrop Grumman Terrain Table, developed in 2006, were actuated shape displays that represented topography in 2.5D. In the Terrain Table thousands of pins driven by a motor shaped a silicone surface held taut by suction from a vacuum below into a terrain. The Terrain Table recorded touches as user interactions such as panning and zooming. As users panned, zoomed, or loaded new geographic data, the actuated surface would automatically reshape within seconds (Petrie, 2006).

Relief Relief is a relatively low-cost, scalable, 2.5D actuated shape display based on open source hardware and software. Given the complexity and thus the cost, maintenance, and unadaptability of earlier dynamic shape displays like FEELEX and the Northrop Grumman Terrain Table, Leithinger and Ishii (2010) aimed to design a simpler, faster system that was easier to build, adapt, scale, and maintain. In the first prototype of Relief an array of 120 actuated pins driven by electric slide potentiometers stretch a Lycra sheet into a shape display. Users can reshape the shape display by pressing or pulling on the actuated pins. The actuators are controlled with open source Arduino boards and a program written in the open source language Processing controls, senses, and tracks all of the pins and their relation to the digital model (Leithinger et al., 2009; Leithinger and Ishii, 2010). The transparency and freedom of open source solutions should make it relatively easy to reconfigure and adapt this system.

Recompose While Relief was initially designed for a simple, highly intuitive interaction – direct physical manipulation (Leithinger and Ishii, 2010) – its next iteration, Recompose, added gesture recognition (Leithinger et al., 2011; Blackshaw et al., 2011). While with Relief users can only directly sculpt the shape display with their hands, with Recompose they can also use gestures to select, translate, rotate, and scale regions of the display. The size and coarse resolution of the actuated shape display mean that only small datasets or subsets of larger datasets can be modeled with useful fidelity. Furthermore, Leithinger et al. (2011) found that only a very limited range of touch interactions could be recognized at the same time and that it can be challenging to manipulate individual pins as they may be out of reach. They augment touch with gestures by adding a Kinect as a depth camera so that users can easily change the context and explore larger datasets. While gestures are less precise than direct physical manipulation, they greatly expand the scope of possible interactions (Blackshaw et al., 2011). Interactions via external devices such as a mouse may be less ambiguous than gestures, but Leithinger et al. argue that they draw users' focus away from the shape display. Therefore they choose to combine touch interactions with gestures rather than pointing devices so that the transition from sculpting to selection, translation, rotation, and scaling would be fluid and seamless given the physical directness of both modes of interaction (Leithinger et al., 2011).

Tangible CityScape Tangible CityScape, a system built upon Recompose, is an example of how this type of TUI can be applied to a specific domain – urban planning. It used a 2.5D dynamic shape display to model and study urban massing. Building masses were modeled by clusters of pins and the model dynamically reshaped as users panned or zoomed with gestures (Tang et al., 2013).

inFORM With inFORM Follmer et al. (2013) developed a dynamically changing user interface capable of diverse, rich user interactions. Building on the Relief and Recompose systems, they developed a 2.5D actuated shape display that supports object tracking, visualization via projection, and both direct and indirect physical manipulation. The shape display is moved by a dense array of pins linked by connecting rods to a larger array of actuators below (Fig. 2). The pins, pushing and pulling with variable pressure, offer nuanced haptic feedback to users. A Kinect depth sensor is used to track objects and users' hands. The actuated surface – a grid of pins – can be manipulated directly by pushing and pulling pins. Furthermore, users can interact with the system indirectly via object tracking. The surface can respond to interactions – both direct and indirect – and reshape itself. The actuated surface can also move objects placed on it, enabling indirect physical manipulations. Follmer et al. used this system to explore how shape-changing displays can dynamically model content and offer novel modes of interaction based on dynamically changing constraints and opportunities. As a responsive physical user interface inFORM enables rich and varied mode of interaction such as responsive sculpting, moving passive objects, painting changes, and physically instantiated UI elements like buttons (Follmer et al., 2013).

Dynamic shape display that can be shaped both by touch and computation enable physical interactions from human to computer and computer to human. With a dynamic shape display the digital model is physically instantiated and this shape changing physical model is used for both input and output. When a user changes the surface of the shape display the computer reads the changes; when the computer changes the surface the user sees and feels the changes. Hypothetically this should radically reduce the level of abstraction in human-computer interaction. This novel mode of bidirectional, tangible interaction should be highly intuitive because it is so direct – human and computers communicate via the same medium. However, while dynamic shape displays may be highly intuitive, they have a relatively coarse resolution, are expensive, maintenance intensive, and hard to transport, all due to the actuators. The resolution of the display for example is constrained by the size of the actuators that make the display kinetic. The coarse resolution makes these displays' representations approximate and abstract, limiting their possible applications.

3.3 Continuous shape displays

Continuous shape displays couple a continuous physical model with a digital model through a cycle of sculpting, 3D scanning, computation, and projection. We can sculpt the display and then see the resulting computation projected onto the model in near real-time. The feedback from digital modeling is visual – unlike dynamic shape displays, these shape display are passive and do not physically respond to computations. Because there are no actuators the model can be built of a malleable, continuous material such as sand or clay that can be easily sculpted and can accurately represent forms such as landscapes (Ishii et al., 2004; Ishii, 2008b).

Figure 2: inFORM: a 2.5D actuated shape display designed by the MIT Media Lab (image source: `http://tangible.media.mit.edu/project/inform/`)

Projection Augmented Relief Models Currently continuous shape displays rely on projection for representing digital data. While projected imagery has long been used to augment physical terrain models, the approach has recently been dubbed Projection Augmented Relief Models (Priestnall et al., 2012). This approach enhances a static physical representation of a landscape with a dynamic visual representation of digital data.

Illuminating Clay With Illuminating Clay (Piper et al., 2002a) – an early continuous shape display from the MIT Media Lab – a clay model of a landscape was continuously scanned with a laser to generate a point cloud of x, y, and z coordinates which were then binned into a digital elevation model (DEM). The DEM or a derived topographic parameter such as slope, aspect, or cast shadow was then projected back onto the clay model so that users could see the impact of their changes in near real-time. Illuminating Clay's library of geospatial analyses was limited as it used custom implementations of elevation, aspect, slope, cast shadow, profile, curvature, viewshed, solar irradiation, and drain direction algorithms. Because Illuminating Clay used a laser scanner the scans were relatively fast – 1.2 seconds each – and accurate to less than 1 mm, but the system was very expensive (Piper et al., 2002a,b). Piper et al. (2002a) also tried to use TUI elements based on object tracking to select algorithms and parameters, but found that too many parameters were involved in geospatial modeling for this approach to be feasible, so they ultimately used standard graphical user interactions with a mouse and keyboard.

Sandscape In an effort to make a more affordable continuous shape display Ishii et al. (2004) designed a system called Sandscape based on infrared depth sensing. In Sandscape a 'sandbox' filled with 1 mm glass beads was lit from beneath by infrared LEDs; an infrared camera above the 'sandbox' captured the intensity of infrared light passing through the glass beads. A DEM based on the light intensity was projected back onto the 'sandbox' so that users would have real-time feedback as they sculpted. While this system was very fast and much less expensive than Illuminating Clay, the scans were low resolution and the physical medium – glass beads – could only be coarsely sculpted (Ishii et al., 2004; Ishii, 2008b).

Augmented Reality Sandbox SandyStation (Altman and Eckstein, 2014), developed in 2011, and the Augmented Reality Sandbox (Kreylos, 2015), developed in 2012, are continuous shape display sandboxes. Kreylos's Augmented Reality Sandbox, inspired by the Czech SandyStation, couples a sandbox with a DEM through a real-time cycle of 3D scanning, modeling and simulation, and projection. As users sculpt the sand a Kinect sensor continually scans the sand surface generating a stream of depth maps. The depth stream is filtered to remove noise and the user's hands. A DEM, contours, and simulated water flow are computed from the depth and projected back on the sandbox. The water flow simulation is a custom implementation based of the shallow water flow equations. The Augmented Reality Sandbox is powered by Kreylos's Kinect 3D Video Capture Project and Vrui VR Toolkit, open source software released under the GNU General Public License. The system is highly intuitive and very fast with each cycle of scanning, processing, and simulation completing in just a couple seconds. However, given that the system only models elevation, contours, and water flow on an abstract landscape it is limited in its scope of potential applications.

(a) Multiple users interacting

(b) The shape display paired with a 3D rendering

(c) The hardware setup with a laser scanner mounted above the model

Figure 3: The Tangible Geospatial Modeling System: a continuous shape display powered by GRASS GIS

Tangible Geospatial Modeling System The Tangible Geospatial Modeling System (TanGeoMS) extended the concept of Illuminating Clay by integrating GRASS GIS (Fig. 3). Integrating a full GIS into a continuous shape display gave users a wide range of sophisticated, scientific tools for geospatial modeling and visualization in a highly intuitive environment. By combining freeform hand modeling with geospatial modeling, simulation, and visualization users could easily explore how changes in topographic form affect landscape processes (Mitasova et al., 2006). Like Illuminating Clay the system used a laser scanner to 3D scan a clay model. The scanned point cloud was then interpolated as a DEM, select geospatial analyses or simulations were computed from the DEM, and the results were projected back onto the clay model (Tateosian et al., 2010) (Fig. 3b).

Tangible Landscape The next generation of TanGeoMS – Tangible Landscape – was designed to intuitively 3D sketch landscapes. This continuous shape display is more tightly integrated with GRASS GIS GIS and has new modes of interaction based on object recognition so that users cannot only sculpt, but also sketch in 3D – rapidly exploring ideas while learning from near real-time feedback (Fig. 5). Tangible Landscape is more affordable than its predecessors because it uses a Kinect sensor to 3D scan physical models. As a continuous shape display with object recognition a wide range of media can be used such as polymer-enriched sand, clay, 3D prints, CNC-machined models, and architectural models. It is more tightly integrated with GIS, using a GRASS GIS plugin to automatically scan, process, georeference, import, and analyze the model. Because it is so tightly integrated with GRASS GIS users can also use the GUI, the command line, and scripting as advanced controls for tasks not suited to a TUI (Petrasova et al., 2014).

Conceptually, Tangible Landscape couples a physical model with a digital model in a real-time feedback cycle of 3D scanning, geospatial modeling and simulation, and projection. For example, by sculpting the terrain of the physical model, one can see how the changes affect processes like the flow of water, flooding, erosion, and solar irradiation. Thus one can easily and rapidly test ideas while being guided by scientific feedback, exploring a much a larger solution space and make more creative and informed decisions. And since many users can interact with the physical model at once, Tangible Landscape encourages collaboration and interdisciplinary exchange (Fig. 6). Tangible Landscape combines real-time interaction with extensive scientific tools for modeling, analysis, and visualization at the precision needed for real-world design and planning applications. Tangible Landscape can be used for applications such as grading landforms, analyzing topography, modeling water flow and soil erosion, analyzing viewsheds, planning trail networks, analyzing solar radiation dynamics, simulating and managing fire, and modeling inundation and flooding.

Tangible Landscape is inexpensive, portable, adaptable, and easy to implement. As a high resolution continuous shape display it can be used for both rapid ideation and precise modeling. However, unlike a dynamic shape display the physical model is passive and cannot be changed computationally in real-time – trading real-time response for precision, simplicity, and affordability. Rapid prototyping can be used to precisely shape or reshape the physical model allowing users to work with real world landscapes and easily reset the conditions. Since Tangible Landscape is powered by GRASS GIS it can easily be adapted to new uses. New applications can be rapidly developed using the extensive GIS modules for data management, geospatial modeling, and visualization.

(a) Orthoimagery

(b) Water flow

(c) Sculpting a check dam

(d) Updated water flow

Figure 4: 3D sketching a check dam with Tangible Landscape

(a) A dammed valley with water flow simulated with *r.sim.water*

Figure 5: 3D sketching a check dam with Tangible Landscape

Figure 6: Collaboratively sculpting a retention pond

3.4 Tangible interaction research

Research on TUIs has been more focused on the design and development of the technology than empirically testing the use and effects of the technology. Rasmussen et al. for example discusses the focus on the design and development of shape displays rather than empirical research about the use of shape displays (2012). While the design of TUIs has been inspired by theories of cognitive science such as embodied cognition, the effectiveness of the technology should be rigorously tested and the applied design theories should be critiqued, refined, and validated. Research on tangible interaction has focused on user experience and to a lesser degree user performance. Few studies have explored creative spatial cognition in tangible interaction.

Research methods for evaluating user experience in TUIs include qualitative photographic and video analysis (Ishii et al., 2002; Horn and Jacob, 2007), video analysis for coding and mapping (Bakker et al., 2011), direct observation (Horn and Jacob, 2007), participant observation (Fielding-piper, 2002), and semi-structured interviews (Fielding-piper, 2002; Horn and Jacob, 2007). Research methods for evaluating user performance with TUIs include informal user feedback (Underkoffler and Ishii, 1999; Leithinger and Ishii, 2010) and small-scale experiments with metrics like precision (Iwata et al., 2001) and task time completion (Leithinger et al., 2013). Methods for evaluating user performance and experience with object recognition and tracking based TUIs focus on interaction with discrete objects or tokens and their constraints (Esteves, 2012). Metrics include topology, translation, events, task time, and attention. Shape displays require different methods since they have continuous, changeable surfaces rather than discrete features.

Protocol analysis has been used to assess creativity and spatial cognition with TUIs (Kim and Maher, 2008). Protocol analysis, a method for collecting and analyzing data on behavior, is often used to assess problem solving and creative thinking in design (Dorst and Cross, 2001). In protocol analysis subjects verbalize their thoughts while performing a task (Ericsson and Simon, 1980, 1993). Since verbal self-reporting or 'thinking aloud' is a conscious process that draws on short term memory it is not a useful method for analyzing subconscious cognitive processes like pragmatic representations. Thus it is unlikely to reveal much about embodied cognition given the importance of subconscious representations and low-level sensorimotor processes.

While researchers have proposed conceptual frameworks for designing TUIs (Hornecker and Buur, 2006), systematic research is still needed to study how TUIs mediate cognition and performance (Esteves, 2012). This research requires methods that are suitable for embodied cognition – methods that do not sideline or ignore subconscious and sensorimotor processes. Research methods for analyzing key aspects of embodied cognition like spatial thinking and creativity are needed to empirically study, assess, and improve tangible interaction.

4 Conclusion

Aim To study how shape displays mediate spatial and creative thinking.

Tangible computing should help us to better understand digital space and shape digital form by making pragmatic representations of digital data. The intuitive and exploratory nature of pragmatic representations means that tangible computing should also enable more creative spatial thinking in a way that was not possible with visual computing. Furthermore when tangible computing combines visual feedback and haptic feedback we generate both semantic and pragmatic representations and should therefore benefit from a richer, fuller understanding of our data and a wider range of expression.

With a shape display the hand modeling process affords an intuitive, detailed representation of the space modeled so the computationally-derived graphical feedback need not convey the same information. Instead the computational representation can be designed to offer more analytic feedback. In this way embodied cognition can be enhanced with analytical cognition informed by computational analyses. These embodied and computationally enriched analytical processes unfold in parallel on different timescales. How successfully can these parallel cognitive processes be coordinated? Can embodied and computationally enriched cognition enhance spatial thinking in novel ways enabling and encouraging coupled creative and analytic thinking? If so what computational analytics most effectively improve spatial performance?

Because spatial cognition is malleable spatial training can improve spatial performance. How can spatial training integrate domain specific knowledge – such as the ability to read topography and model terrain – for a given discipline – like geography or landscape architecture? How for example can we learn to better model topography? Can geospatial analytics enhance the process and if so which analytics?

Research questions

Our goal is to develop, test, and refine an empirically grounded theory of how technology mediates spatial cognition that can inform spatial education and human-computer interaction design. To do this we will study how shape displays mediate spatial and creative thinking.

1. How do shape displays mediate spatial and creative thinking?
2. How successfully can parallel embodied and computationally enriched analytical processes be coordinated?
3. Can embodied and computationally enriched cognition enhance spatial thinking in novel ways by blending generative and analytic thinking?
4. What computational analytics most effectively improve spatial performance?

Testable hypotheses

We hypothesize that

1. Limited feedback constrains spatial performance
2. Ambiguity and illusions in 3D space in visual computing reduce spatial performance
3. Computational analytics like differencing and flow simulations can enhance spatial performance
4. Computationally enriched analytical thinking can be coordinated with embodied thinking
5. Tangible computing can enable rapid iterations of exploratory, generative form-finding

We intend to test these hypotheses using qualitative methods including semi-structured interviews, direct observation, and case studies and quantitive methods including geospatial modeling, analysis, simulation, and statistics. Rather than studying basic spatial cognitive abilities that can not easily or usefully be disentangled in applied use, we will study applied spatial cognitive processes using the metrics and parameters of the given application. We will study how participants perform in a time constrained terrain modeling exercise using hand modeling, visual computing, and tangible computing. We will assess their performance with each technology using spatial statistics, topographic parameters, morphology, process-form interactions, and differencing. We will use a fast, fluid, iterative process as a proxy for creative thinking that can be assessed through interviews, observation, geospatial analyses, and spatial statistics.

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Embodied spatial thinking in tangible computing

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Contribution

My colleagues in the NCSU Open Source Geospatial Research and Education Lab (`http://geospatial.ncsu.edu/osgeorel/`) Anna Petrasova, Vaclav Petras, Helena Mitasova, and Ross Meentemeyer contributed to this research by collaboratively designing Tangible Landscape and helping to run the experiment.

Embodied Spatial Thinking in Tangible Computing

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ABSTRACT
Tangible user interfaces are based on the premise that embodied cognition in computing can enhance cognitive processes. However, the ways in which embodied cognition in computing transform spatial thinking have not yet been rigorously studied. I have co-designed Tangible Landscape – a continuous shape display powered by a geographic information system – and used it to explore how technology mediates spatial cognition in a rigorous experiment.

In this terrain modeling experiment I use geospatial analytics to analyze how visual computing with a GUI and tangible computing with a shape display mediate multidimensional spatial performance.

My initial findings suggest that: **1.** digital sculpting via a GUI is unintuitive, **2.** shape displays like Tangible Landscape can be intuitive, enhance spatial performance, and enable rapid iteration and ideation, and **3.** different analytics encourage significantly different modes of spatial thinking and strategies for modeling.

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation (e.g. HCI): User Interfaces – Evaluation/methodology; Interaction styles; Prototyping; Theory and methods

Author Keywords
Human-computer interaction; tangible user interfaces; tangible interaction; embodied cognition; spatial thinking; 3D modeling

INTRODUCTION
In embodied cognition the mind is embedded in the body. Higher cognitive processes rely on lower level processes such as emotion and sensorimotor processes that link perception and action [2]. Thus body and action mediate thought. Cognitive processes can be physically simulated with cognition offloaded onto action. Objects such as tools can be cognitively grasped and temporarily, contingently incorporated into ones body schema [5]. This view of cognition considers feeling, action, and perception to be functionally integral to thought.

Based on the theory of embodied cognition researchers have theorized a physical-digital divide in human-computer interaction – positing that the high level of abstraction required to interact with a computer via a graphical user interface (GUI) in a visual computing paradigm constrains how we think – and designed innovative technologies for bridging this divide such as tangible user interfaces (TUIs) [3, 1]. TUIs are designed to physically manifest digital data as tangible bits that afford the ability to directly, physically feel and manipulate data [3]. TUIs make pragmatic representations of digital data. Pragmatic representations are conceptual models for rapidly generating action that are primarily based on tactile feedback and are processed automatically, immediately, and subconsciously [4]. By physically manifesting data so that we can pragmatically interact with computations, TUIs should enable rapid, intuitive action and expression in a way that was not possible in visual computing. By enabling embodied cognition in human-computer interaction TUIs should let us cognitively grip data as an extension of our bodies, intuitively manipulate data, and physically simulate processes. This should enhance spatial thinking.

Research on TUIs has been more focused on the design and development of the technology than empirically testing the use and effects of the technology. Rasmussen et al. for example discuss the focus on the design and development of shape displays rather than empirical research about their use. [7]. Research on tangible interaction has focused on user experience and to a lesser degree user performance using methods such as participant observation, semi-structured interviews, video analysis, and small-scale experiments.

While the theory of embodied cognition has inspired the design of novel technologies for human-computer interaction, its applied principles need to be empirically tested, critiqued, and refined in order to improve interaction design. The aim of this research is to study how tangible computing mediates spatial thinking in order to improve interaction design, enhance spatial performance, and improve spatial education.

Testable hypotheses
I hypothesize that:

1. limited feedback constrains spatial performance,
2. misinterpretations of 3D space in visual computing reduce spatial performance,

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3. computational analytics like differencing and flow simulations can enhance spatial performance,

4. computationally enriched analytical thinking can be coordinated with embodied thinking,

5. tangible computing that computationally enhances embodied spatial thinking can improve spatial performance, and

6. tangible computing can enable a rapid iterative process of exploratory, generative form-finding that can improve spatial performance.

METHDOLOGY

I have conducted a rigorous experiment using geospatial analytics to compare spatial performance in analog modeling by hand, in tangible computing using Tangible Landscape, and in visual computing using 3D modeling programs via a GUI. Tangible Landscape is a continuous shape display tightly integrated with GRASS GIS that was designed to intuitively 3D sketch landscapes (Figure 1). Conceptually, Tangible Landscape couples a physical model with a digital model in a real-time feedback cycle of 3D scanning, geospatial modeling and simulation, and projection (Figure 1a) [6].

I have begun to test my hypotheses using quantitative methods Rather than studying basic spatial cognitive abilities that can not usefully be disentangled in applied use, I am studying applied spatial cognitive processes using the metrics and parameters of the given application. I am studying how participants perform in a series of time constrained terrain modeling exercises using analog modeling, visual computing, and tangible computing. 6 landscape architects and 6 geospatial analysts have participated in this pilot study. I am assessing their performance with each technology using spatial statistics, topographic parameters, morphology, process-form interactions, and differencing.

Terrain modeling experiment

The 1st exercise tests spatial performance in analog modeling to establish the baseline spatial ability of each participant. In this exercise participants sculpt a given terrain in polymeric sand using their hands with a CNC routed model for reference.

The 2nd exercise tests spatial performance in projection augmented analog modeling to establish a baseline for spatial performance in tangible computing. In this exercise participants sculpt a given terrain in polymeric sand using a projected map of the given elevation and contours as a guide.

The 3rd-5th exercises test spatial performance in tangible computing augmented with different analytics. In the 3rd exercise participants use Tangible Landscape to sculpt a given terrain in polymeric sand using the given and scanned contours as a guide. In the 4th exercise participants use Tangible Landscape to sculpt a given terrain in polymeric sand using the difference between the given and the scanned landscape as a guide. In the 5th exercise participants use Tangible Landscape to sculpt a given terrain in polymeric sand using the simulated water flow over the scanned landscape as a guide in order to study 4D thinking.

The 6th and 7th exercises test spatial performance in visual computing. In the 6th exercise participants digitally sculpt a given terrain in Rhinoceros, a 3D modeling program, using the given 3D contours as a guide. In the 7th exercise participants digitally sculpt a given terrain in VUE, a 3D modeling program designed for intuitive terrain sculpting, with a CNC routed model for reference.

Data collection and analysis

In the 1st-5th exercises the resulting physical models are 3D scanned, imported into GRASS GIS as point clouds, and interpolated as DEMs for analysis. In the 6th and 7th exercises the resulting digital models are exported as point clouds, imported into GRASS GIS, and interpolated as DEMs for analysis. For each model I compute the elevation and its histogram and bivariate scatterplot, the slope, the difference and its histogram, the simulated water flow, and morphology. For each exercise I compute a map of the coefficient of variance of all the of DEMs, bivariate scatterplots of the covariance and correlation matrix of all the of DEMs, and the mean and the absolute value of the mean of the differences between the the reference terrain and the modeled terrain.

Code

As a work of open science the data and the python scripts for data analysis are publicly available on GitHub at https://github.com/baharmon/tangible_topography released under the GNU General Public License version 2. Both GRASS GIS and Tangible Landscape are open source projects released under the GNU General Public License version 2. Tangible Landscape is available on GitHub at https://github.com/ncsu-osgeorel/grass-tangible-landscape.

PRELIMINARY RESULTS

Select results for one participant in the pilot study are shown in Figures 3, 4, and 5.

In the 1st exercise participants tended to model the overall form well, but exaggerated the slopes and misplaced the main ridge. In the 2nd exercise participants tended to model the landscape very well, accurately capturing the ridge and valley, but missing the saddle of the valley (Figure 2a). In the 3rd exercise participants tended to model the overall form well, but approximately with indistinct landforms and a lot of roughness. Many participants used a layered *pancake*-modeling strategy here. The 4th exercise tended to have the best results. Participants used a rapid iterative process to accurately model the landscape. In the 5th exercise participants tended to model the overall form well, but exaggerated the slopes of the stream channels. In the 6th exercise most participants modeled the form very poorly especially the interior space (Figure 2b) – either modeling only the edges or modeling very approximate massings of the main ridge and peak. Expert 3D modelers, however, modeled the form better, but still missed much of the interior space. In the 7th exercise participants tended to model the landscape suggestively in the x- and y-dimensions, but underestimated and grossly distorted the z-dimension.

The pilot study suggests that **1.** analog sculpting by hand can be highly intuitive, but the lack of analytical feedback limits

(a) (b) (c) (d)

Figure 1. 3D sketching with Tangible Landscape: (a) a cycle of scanning and projection couples a physical and digital model, (b) the differencing analytic with blue where sand should be added and red where sand should be removed, (c) a participant adding sand, and (d) the updated differencing analytic.

ones ability to critique the model and refine its form, **2.** shape displays like Tangible Landscape can be intuitive, enhance spatial performance, and enable rapid iteration and thus creative spatial learning. **3.** digital sculpting via a graphical user interface is unintuitive and visually ambiguous leading to misinterpretations of depth, height, and interior space.

(a) (b)

Figure 2. Standard deviations of the differences for all participants: (a) in Ex. 2 using projection augmented modeling and (b) in Ex. 6 using Rhinoceros.

FUTURE WORK

The full study will have approximately 40 participants. Based on the results of the study I hope to develop a theory of how technology mediates spatial cognition. In the long-term I plan to expand this study of embodied spatial cognition in tangible computing as a collaborative research project with psychologists using spatial analytics, eye tracking, biometric sensors, and EEGs.

CONCLUSIONS

This study is unique in applying geospatial analyses to asses spatial performance in tangible interaction. My initial findings suggest that shape displays like Tangible Landscape can with the right computational analytics enhance performance in novel ways and enable rapid iterations of generative form-finding and critical analysis. Different analytics encourage significantly different modes of spatial thinking and strategies for modeling. The differencing analytic leads to significant improvements in spatial performance and enables an iterative process.

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My colleagues in the NCSU Open Source Geospatial Research and Education Lab (http://geospatial.ncsu.edu/osgeorel/) Anna Petrasova, Vaclav Petras, Helena Mitasova, and Ross Meentemeyer contributed to this research by collaboratively designing Tangible Landscape and helping to run the experiment.

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(a)

(b)

(c)

Figure 3. **Reference model:**
(a) the digital elevation model (DEM),
(b) the difference between the reference DEM and the reference DEM, and
(c) the bivariate scatterplot of the difference between the reference DEM and the reference DEM.

(a)

(b)

(c)

Figure 4. **Participant's model for Ex. 2 using projection augmented modeling:**
(a) the DEM,
(b) the difference between the participant's DEM and the reference DEM, and
(c) the bivariate scatterplot of the difference between the participant's DEM and the reference DEM.

(a)

(b)

(c)

Figure 5. **Participant's model for Ex. 6 using digital sculpting with Rhinoceros:**
(a) the DEM,
(b) the difference between the participant's DEM and reference DEM, and
(c) the bivariate scatterplot of the difference between the participant's DEM and the reference DEM.

Tangible Landscape: cognitively grasping the flow of water

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Contribution

My colleagues in the NCSU Open Source Geospatial Research and Education Lab (`http://geospatial.ncsu.edu/osgeorel/`) Anna Petrasova, Vaclav Petras, and Helena Mitasova contributed to this research by collaboratively designing Tangible Landscape and helping to run the experiment. Ross Meentemeyer in NCSU's Center for Geospatial Analytics contributed to this research with advice, guidance, and support.

TANGIBLE LANDSCAPE: COGNITIVELY GRASPING THE FLOW OF WATER

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KEY WORDS: embodied cognition, spatial thinking, physical processes, water flow, hydrology, tangible user interfaces, user experiment, 3D

ABSTRACT:

Complex spatial forms like topography can be challenging to understand, much less intentionally shape, given the heavy cognitive load of visualizing and manipulating 3D form. Spatiotemporal processes like the flow of water over a landscape are even more challenging to understand and intentionally direct as they are dependent upon their context and require the simulation of forces like gravity and momentum. This cognitive work can be offloaded onto computers through 3D geospatial modeling, analysis, and simulation. Interacting with computers, however, can also be challenging, often requiring training and highly abstract thinking. Tangible computing – an emerging paradigm of human-computer interaction in which data is physically manifested so that users can feel it and directly manipulate it – aims to offload this added cognitive work onto the body. We have designed Tangible Landscape, a tangible interface powered by an open source geographic information system (GRASS GIS), so that users can naturally shape topography and interact with simulated processes with their hands in order to make observations, generate and test hypotheses, and make inferences about scientific phenomena in a rapid, iterative process. Conceptually Tangible Landscape couples a malleable physical model with a digital model of a landscape through a continuous cycle of 3D scanning, geospatial modeling, and projection. We ran a flow modeling experiment to test whether tangible interfaces like this can effectively enhance spatial performance by offloading cognitive processes onto computers and our bodies. We used hydrological simulations and statistics to quantitatively assess spatial performance. We found that Tangible Landscape enhanced 3D spatial performance and helped users understand water flow.

INTRODUCTION

Understanding physical processes

Physical processes like the flow and dispersion of water are challenging to understand because they unfold in time and space, are controlled by their context, and are driven by forces like gravity and momentum. The flow of water across a landscape is controlled by the morphological shape and gradient of the topography. It is challenging to understand how water will flow across a landscape because one must not only understand how the shape and gradient of the terrain control the flow and dispersion of water locally, but also how water will flow between shapes and gradients – how the morphology is topologically connected. Understanding a physical process requires thinking at and across multiple spatial scales simultaneously.

This cognitive work can be offloaded onto computers through 3D geospatial modeling, analysis, and simulation. Interacting with computers, however, can also be challenging, requiring training and highly abstract thinking that adds a new cognitive burden.

Tangible interfaces for GIS

Tangible interfaces are designed to make interaction with computers easier and more natural by physically manifesting digital data so that users can cognitively grasp it as an extension of their bodies, offloading cognition onto their bodies. In embodied cognition higher cognitive processes are built upon and grounded in sensorimotor processes – upon bodily action, perception, and experience – so thinking can be performed subconsciously through action and extended with tools (Kirsh, 2013). Tangible interfaces have been developed for geographic information systems (GIS) to ease the cognitive burden of complex spatial reasoning, spatial visualization, and human-computer interaction by embodying these processes. Theoretically tangible interfaces for GIS should help users understand environmental processes by giving multidimensional geospatial data an interactive, physical form that they can cognitively grasp and kinaesthetically explore in space and time.

In a seminal paper Ishii and Ullmer envisioned tangible user interfaces that would 'bridge the gap between cyberspace and the physical environment by making digital information (bits) tangible' (Ishii and Ullmer, 1997). They described 'tangible bits' as 'the coupling of bits with graspable physical objects' (Ishii and Ullmer, 1997). Tangible interfaces like Urp (Underkoffler and Ishii, 1999), Illuminating Clay (Piper et al., 2002a), and SandScape (Ratti et al., 2004) enriched physical models of urban spaces and landscapes with spatial analyses and simulations like wind direction, cast shadow, slope, aspect, curvature, and water direction in order to enhance and streamline spatial thinking, design, and decision-making.

Many of the analyses used in Illuminating Clay were adapted from the open source GRASS GIS project (Piper et al., 2002b) and eventually Illuminating Clay was coupled with GRASS GIS to draw on its extensive libraries for spatial computation. The aim of coupling Illuminating Clay with GRASS GIS was to 'explore relationships that occur between different terrains, the physical parameters of terrains, and the landscape processes that occur in these terrains' (Mitasova et al., 2006). The effort to couple a physical landscape model with GRASS GIS led to the development of the Tangible Geospatial Modeling System (Tateosian et al., 2010) and Tangible Landscape (Fig. 1) (Petrasova et al., 2014, Petrasova et al., 2015).

Tangible Landscape Tangible Landscape – a tangible user interface powered by 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 near real-time (Fig. 2). The physical model is often made of polymer-enriched sand so

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Figure 1: Tangibly modeling the flow of water with Tangible Landscape

that users can easily sculpt forms in a medium that will hold its shape, has good plasticity, and has a familiar feel and aesthetic. As users sculpt the physical model the model is 3D scanned and interpolated in GIS 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 near real-time. Conceptually, this enables users to hold a GIS in their hands – feeling the shape of the earth, sculpting its topography, and directing the flow of water. This should enable users to naturally model topography and interact with simulated physical processes in a rapid, iterative process of observation, hypothesis generation and testing, and inference.

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

Cognitively grasping spatial processes

The aim of this research was to study how tangible interfaces for GIS mediate spatial thinking about landscape processes like water flow. Theoretically a tangible interface for a GIS that enables intuitive digital sculpting while providing analytical feedback should allow users to dynamically explore how topographic form influences landscape processes. With a physical model one can cognitively grasp topographic form, offloading the cognitive work of understanding and shaping topographic form onto the body. A GIS can offload the cognitive work of simulating complex physical processes like the flow of water through computation. With these physical and computational affordances combined in a tangible interface for GIS users should be able to more easily understand and shape spatial processes. We empirically tested how a tangible interface for GIS mediated spatial performance in a water flow modeling experiment.

METHODS

We conducted a terrain and water flow modeling experiment in which participants tried to recreate a given landscape. We quantitatively assessed their spatial performance using hydrological simulation, summary statistics, and cell-by-cell statistics.

Flow modeling experiment

In the experiment 11 participants were asked to sculpt a given landscape using different technologies – first using Vue, a triangulated irregular network based 3D modeling program designed for intuitive terrain sculpting, and then using Tangible Landscape. The participants were asked to model a real landscape – a region of Lake Raleigh Woods in Raleigh, North Carolina – using each technology. We selected a region of the landscape with distinctive, clearly defined landforms – a central ridge flanked by two stream valleys (see Fig. 3). The digital elevation model (DEM) for this region was derived from a 2013 airborne lidar survey using the regularized spline with tension interpolation method.

In the 1st exercise each participant had 10 minutes to digitally sculpt the topography of the study landscape in Vue's terrain editor using a physical model as a reference (see Fig. 4a). Participants were given a 2 minute introduction to terrain sculpting in Vue and then 10 minutes to experiment and become familiar with the interface before beginning the exercise. Vue's terrain editor was designed to emulate sculpting by hand – there are tool brushes that are analogous to basic actions in sculpture including pushing, pulling, and smoothing.

In the 2nd exercise each participant had ten minutes to sculpt the study landscape in polymer enriched sand using Tangible Landscape's water flow simulation as a guide (see Fig. 4b). As participants sculpted they could switch between projected maps of either the *a)* simulated water flow across the given landscape that they were trying to replicate *b)* or the simulated water flow across the scanned landscape.

Figure 3: Our reference landscape with simulated water flow

(a) (b)

Figure 4: (a) Digitally sculpting with Vue in the 1st exercise and (b) tangibly sculpting with Tangible Landscape in the 2nd exercise

Implementation

We used GRASS GIS both for geospatial computation with Tangible Landscape and for the analysis of the results of the experiment. The algorithms used in GRASS GIS are based on peer-reviewed scientific publications and have been transparently implemented with free, publicly available, version controlled source code. Open, transparent algorithms are needed to fully reproduce computational science (Rocchini and Neteler, 2012). In this experiment we used the overland flow hydrologic simulation using a path sampling method (SIMWE) implemented in GRASS GIS as the module r.sim.water.

Shallow overland flow We simulated shallow overland water flow controlled by spatially variable topography, soil, landcover, and rainfall parameters using the SIMWE model to solve the continuity and momentum equations for steady state water flow with a path sampling method. Shallow water flow can be approximated by the bivariate form of the St Venant equation:

$$\frac{\partial h(\mathbf{r},t)}{\partial t} = i_e(\mathbf{r},t) - \nabla \cdot \mathbf{q}(\mathbf{r},t) \tag{1}$$

where:

$\mathbf{r}(x,y)$ is the position [m]

t is the time [s]

$h(\mathbf{r},t)$ is the depth of overland flow [m]

$i_e(\mathbf{r},t)$ is the rainfall excess [m/s]
(rainfall − infiltration − vegetation intercept)

$\mathbf{q}(\mathbf{r},t)$ is the water flow per unit width [m^2/s].

By integrating a diffusion term $\propto \nabla^2[h^{5/3}(\mathbf{r})]$ into the solution of the continuity and momentum equations for steady state water flow diffusive wave effects can be approximated so that water can flow through depressions.

$$-\frac{\varepsilon(\mathbf{r})}{2}\nabla^2[h^{5/3}(\mathbf{r})] + \nabla \cdot [h(\mathbf{r})\mathbf{v}(\mathbf{r})] = i_e(\mathbf{r}) \tag{2}$$

where:

$\varepsilon(\mathbf{r})$ is a spatially variable diffusion coefficient.

This equation is solved using a Green's function Monte Carlo path sampling method (Mitasova et al., 2004).

Data collection and analysis

We used summary and cell-by-cell statistics to compare the results of each exercise using the reference landscape as a baseline. The digital models sculpted in the 1st exercise were manually georeferenced and imported into GRASS GIS as point clouds for modeling and analysis. The final state of the physical models sculpted in 2nd exercise were automatically 3D scanned, georeferenced, and imported into GRASS GIS as points clouds with Tangible Landscape for modeling and analysis. All of the point clouds were randomly resampled and interpolated as DEMs using the regularized spline with tension interpolation method (Mitasova et al., 2005). For each model we simulated shallow overland water flow, identified depressions, and computed the difference between the modeled and reference water flow depth. To compute the difference we subtracted the modeled values from the initial, reference values. We identified and computed the depth of depressions by generating a depressionless DEM and then calculating the difference between the DEM from the depressionless DEM. Then we computed the mean, sum, and maximum of the water depths, the depressions, and the difference in water depths for each exercise in the experiment. We visually assessed the spatial pattern of water flow and continuity using these maps. In order to quantitatively compare how well the modeled streams matched the reference stream we computed the distance between cells with concentrated water flow in the reference depth map and mean of the modeled depth maps. First we extracted points for each cell with high water depth values ($>= 0.05$ ft) in the reference water depth raster and the mean water depth raster for each exercise. Then we calculated the minimum distance between the reference points and the nearest points from each exercise. In order to quantitatively compare the continuity of flow we computed the percentage of cells with depressions for each exercise.

Code and data

As a work of open science we invite you 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 used in this experiment are available on GitHub at `https://github.com/baharmon/tangible-water-flow` released under the GNU General Public License (GPL). See the documentation in the GitHub repository for detailed instructions for replicating this experiment. The data used in this experiment are available on the Open Science Framework at `osf.io/zv3t6` under the Creative Commons Zero license.

GRASS GIS is available at https://grass.osgeo.org/ under the GNU GPL. Tangible Landscape is available at https://github.com/ncsu-osgeorel/grass-tangible-landscape under the GNU GPL. To build your own Tangible Landscape see the documentation in the GitHub repository and refer to the book Tangible Modeling with Open Source GIS (Petrasova et al., 2015).

While the rest of the software used in this research is free and open source, Vue [1] is proprietary software. We used Vue's terrain editor for this study because it was designed specifically for intuitive terrain modeling, but open source 3D modeling programs like Blender [2] could be substituted for Vue.

RESULTS

The models sculpted with Tangible Landscape more accurately replicated the flow of water over the study landscape. The digitally sculpted models tended to have more diffuse water flow and more water pooling in depressions, whereas the tangibly sculpted models tended to have more concentrated flow in stream channels and less pooling in depressions. Furthermore, the spatial distribution of water flow on the tangibly sculpted models more closely fit the distribution of water flow on the reference landscape.

Exercise	Mean	Max	Sum
Reference	0.01	0.47	786.25
Digital	0.21	1.83	3.60
Tangible	0.27	2.31	4.60

Table 1: Highest mean, maximum, and summed water depths (ft)

Exercise	Mean	Sum
Digital	21.13	29244
Tangible	18.59	25724

Table 2: The minimum distances from reference stream cells to the nearest modeled cell with concentrated flow (ft)

Exercise	Max	Sum
Reference	0.10	0.62
Digital	24.5	53
Tangible	22.2	44

Table 3: Highest max and summed depth of depressions (ft)

Exercise	Cells
Reference	0%
Digital	44%
Tangible	17.66%

Table 4: Percent of cells with depressions (3 ft ^{2})

The models sculpted with Tangible Landscape had more concentrated flow in stream channels with higher mean, maximum, and summed water depths (see Table 1). Fig. 6 shows that water flow in the 2nd exercise was spatially concentrated in the upper stream channel, the lower stream channel, and the nascent swale to the right.

Furthermore the water flow across models sculpted with Tangible Landscape more closely fit the reference. Fig. 8 and the details in Fig. 9 show that water flow in the 1st exercise was more spatially diffuse and dispersed, whereas water flow in the 2nd exercise was a better fit. Fig. 10 - 11 show how well the flow of the digitally and tangibly sculpted models fit the reference flow. The digitally sculpted models tended to loosely fit the upper stream with fewer, more dispersed clusters of concentrated flow at further distances from the reference on average. They also tended to have very few clusters at considerable distance from the swale on the right and small, dispersed clusters that tightly fit the lower stream. The tangibly sculpted models, however, tended to more densely, tightly fit the upper stream and the swale on the right. The tangibly sculpted models tended to miss or misplace the lower stream channel (siting it too far southeast). The near-real time water flow analytic was not very useful for modeling the lower stream segment because there was not enough contributing area on the model to generate much concentrated flow. Water flow over the sculpted models was only computed over the model, whereas the reference water flow was computed over the entire watershed. Overall the tangibly sculpted models fit the reference flow 8.32% better than the digitally sculpted models (see Table 2).

The digitally sculpted models had higher max and summed water depth in depressions (see Table 1). Furthermore the depressions covered 26.34% more area of the digitally sculpted models than the tangibly sculpted models (see Table 4, Fig. 5, and Fig. 7). The presence of large depressions on the central ridge in the 1st exercise reveals concave topographic morphology where there should be convex morphology. The pervasive presence of depressions in the stream channels in both exercises reveals disrupted flows with broken continuity where water should be flowing.

DISCUSSION

The modeling results show that participants tended not to clearly understand how topography directs water flow, but began to learn about the importance of curvature and continuity with the aid of the tangible interface.

When digitally sculpting participants typically focused on making the streams lower than the surrounding topography, but not on draining water into the streams or directing a continuous flow downstream. In the 1st exercise participants made low points approximately where the streams should be, but tended not to grade smooth slopes with appropriate curvature. The participants use of concave rather than convex morphology on the central ridge reveals that some did not understand how topographic curvature controls water flow. The extensive depressions distributed widely across the terrain demonstrate that participants tended not understand the importance of topographic curvature and continuity for water flow.

With the tangible interface they typically focused on directing water into streams, but did not tend focus on directing a continuous flow downstream. In the 2nd exercise participants tended to grade smoother slopes with fewer depressions whose curvature directed water towards channels, concentrating it in streams. They, however, did not tend to grade the channels to continuously slope downstream. While participants performance improved substantially in the 2nd exercise, the pervasive presence of depressions in the stream channels in both exercises demonstrates that participants did not fully understand the morphology of streams by the end of the experiment.

We observed participants using an iterative modeling process with the tangible interface – they *a)* sculpted, *b)* studied the updated water flow simulation, *c)* critiqued the form of their model, *d)* and continued to sculpt. The substantial improvement in participants'

[1] http://www.e-onsoftware.com/products/vue/
[2] https://www.blender.org/

performance in the 2nd exercise shows that they successfully integrated the tangible interface's water flow analytic into their modeling process. To improve their performance they must have been able to successfully manage the added cognitive load of the analytical feedback. The tangibility of the interface may have let them offload some of the cognitive work of sensing and shaping 3D form onto their bodies so that they could focus on water flow.

While their performance did improve in the 2nd exercise, it may still have been adversely affected by emotions like frustration. If the cognitive load of simultaneously modeling 3D form and water flow became too great – if participants were unable to fluidly connect cause (topographic form) and effect (flow) – they might become frustrated and demotivated. Future research should investigate the role of affect, motivation, and metacognition in tangible interaction.

More analytics may enhance participants' understanding of water flow and stream morphology. Identifying and computing the depth of depressions highlighted the role of topographic curvature and continuity in water flow. While topographic parameters such as curvature and slope would highlight important aspects of the morphology, an additional step of reasoning and imagination is required to link these parameters to water flow. The ponding of water in depressions directly links topographic controls and water flow and thus should be a more intuitive analytic. We propose combining shallow overland water flow with ponding in depressions as an analytic to help users understand how water flows.

CONCLUSION

Tangible Landscape's water flow analytic enabled an iterative cycle of form-finding and critical assessment that helped participants learn how form controls process. Seeing the water flow simulation update in near real-time enabled participants to generate hypotheses, test hypotheses, and draw inferences about the way that water flows over topography. As one participant said, 'seeing the flow takes away the mystery of topography.' Physically manifesting topographic data enables users to cognitively grasp the terrain. Coupling tangible topography with the simulated flow of water lets users understand the simulation with their body.

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(a) (b) (c)

Figure 5: (a) The depth of simulated water flow across the reference landscape, (b) the mean depth using digital modeling, (c) and the mean depth using tangible modeling

(a) (b) (c)

Figure 6: (a) The depth of depressions in the reference landscape, (b) the maximum depth of depressions using digital modeling, (c) and the maximum depth of depressions using tangible modeling

(a) (b) (c)

Figure 7: (a) The difference of the reference landscape, (b) the mean of digitally sculpted models, (c) and the mean of tangibly sculpted models *from the reference landscape*

(a) (b)

Figure 8: Detail of the difference of (a) the mean of digitally sculpted models and (b) the mean of tangibly sculpted models *from the reference landscape*

Figure 9: The lines represent the minimum distance between blue points with high concentrated flow from the reference and red points with high concentrated flow from the mean depth of digitally sculpted models

Figure 10: The lines represent the minimum distance between blue points with high concentrated flow from the reference and red points with high concentrated flow from the mean depth of tangibly sculpted models

Tangible Landscape

Contribution

My colleagues in the NCSU Open Source Geospatial Research and Education Lab (`http://geospatial.ncsu.edu/osgeorel/`) Anna Petrasova, Vaclav Petras, and Helena Mitasova contributed to this research by collaboratively designing Tangible Landscape and helping to run the experiment. Ross Meentemeyer in NCSU's Center for Geospatial Analytics and Eugene Bressler and Art Rice in NCSU's Department of Landscape Architecture contributed to this research with advice, guidance, and support.

Embodied Spatial Cognition in Tangible Computing

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We have designed Tangible Landscape – a tangible interface powered by a geographic information system – that gives spatial data an interactive, physical form so that users can naturally feel it, see it, and shape it. Our aim was to iteratively design and empirically test a tangible interface that augments spatial thinking and improves spatial performance. Spatial thinking can be embodied – people can functionally think about space with their bodies by cognitively grasping objects and physically simulating spatial transformations. Tangible interfaces enable embodied cognition so that interaction will be natural and intuitive, cognitive processes can be offloaded onto the body, and cognitive processes can be computationally augmented. We designed Tangible Landscape to physically manifest geographic data so that users can cognitively grasp the data as an extension of their bodies and automatically, immediately, and subconsciously interact with it. We conducted a series of experiments using quantitative methods including geospatial modeling, analysis, and simulation and qualitative methods including semi-structured interviews and direct observation to study how tangible interfaces mediate spatial performance. Then as a case study we ran a serious gaming event in which attendees used Tangible Landscape to solve complex spatial problems. As they played the games attendees naturally steered sophisticated simulations of environmental processes, iteratively exploring and learning how the processes behave.

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

Fig. 1. Tangibly modeling the flow of water with Tangible Landscape

We present Tangible Landscape – a tangible interface for geographic information systems (GIS). Spatial thinking can be challenging – it is multidimensional and can involve vast amounts of data. Spatial analyses and simulations, however, can be computed efficiently in GIS.

...

Tangible interfaces are designed to enable natural interaction with computers by physically manifesting data so that users can feel and manipulate it with their bodies. This means that people with little or no computer experience can intuitively, collaboratively explore data and scientific models and rapidly test ideas while learning from computational feedback. Through tangible interaction with GIS users can simulate, learn about, and design complex spatiotemporal processes naturally with their bodies while being situated in a collaborative, social context. Tangible interfaces for GIS have the potential to fluidly, seamlessly combine computational science with exploratory modes of creative thinking.

...

(Fig. 1)

1.1. Spatial thinking and computation

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 like recognizing things, manipulating things, interacting with others, and way-finding. Spatial thinking is also used extensively in science, technology, engineering, the arts, and math for tasks like diagramming concepts, visualizing data, simulating physical processes, mapping and manipulating molecules, designing circuits, designing buildings, shaping sculpture, and studying topology. Given the importance of spatial thinking – personally, academically, and professionally – how can we effectively improve our spatial performance, our ability to perform tasks that require spatial thinking?

Many spatial tasks can be performed computationally enabling us 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 spatial forms. In scientific computing spatial patterns and processes can be mathematically modeled, simulated, and optimized. Geographic information systems, for example, can be used to computationally store, model, analyze, simulate, and represent geospatial patterns and processes. The open source Geographic Resource Analysis Support System (GRASS) GIS for example supports 'geospatial data management and analysis, image processing, graphics and maps production, spatial modeling, and visualization' [GRASS Development Team 2016].

Computing mediates and transforms spatial thinking, expanding, but also constraining what is possible. While spatial computing can augment spatial thinking – distributing or offloading cognitive processes through digital computation – the logic of implementation, the limits of what is computationally possible, and the modes of input and output constrain how we reason. Furthermore, when it is difficult to interact with a computer, to input commands and parse the resulting output, one has to think harder and risks frustration and demotivation.

Unintuitive modes of human-computer interaction constrain thought and add cognitive and emotional costs. The paradigmatic modes for interacting with computers today – command line interfaces (CLI) and graphical user interfaces (GUI) – require physical input from 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 should make interaction less intuitive [Dourish 2001; Ishii 2008]. Furthermore, it can be challenging to parse data that is only presented visually. Spatial data – especially 3D spatial data – presented graphically can require sophisticated spatial reasoning skills such as mental rotation [Shepard and Metzler 1971], spatial visualization, and spatial perception [Linn and Petersen 1985] to parse and understand, much less manipulate.

1.2. Tangible interaction

Tangible interfaces – interfaces that couple physical and digital data [Dourish 2001] – are designed to physically manifest digital data so that we can cognitively grasp and absorb it, so that we can think with it rather than about it [Kirsh 2013]. Ishii and Ullmer envisioned that tangible interfaces would 'take advantage of natural physical affordances to achieve a heightened legibility and seamlessness of interaction between people and information' [Ishii and Ullmer 1997]. With a tangible interface both input and output are physical. Data can be felt as well as seen; data can be directly, physically manipulated, leveraging highly developed motor skills. Thus intention, action, and feedback should be seamlessly connected enabling automatic, subconscious, and intuitive interaction.

Tangible interfaces let users interact with computers while (functionally) thinking with their bodies. By thinking with their bodies, by embodying cognition users may be able to reduce their cognitive loads by offloading cognitive tasks like spatial perception and manipulation onto the body and physically simulating processes. In embodied cognition higher cognitive processes are grounded in, built upon, and mediated by bodily experiences such kinaesthetic perception and action [Hardy-Vallée and Payette 2008]. When people use tools they temporarily, contingently incorporate them into their body schema, feeling the perimeter, weight, and balance of the tool, sensing resistance when the tool touches something, as if the tool was an extension of the body [Maravita and Iriki 2004]. Because tools can be cognitively gripped and absorbed in ones body schema, they mediate embodied cognition – affording new bodily experience and action and thus extending ones capacity for thought. Tangible interfaces are designed to make computation tangible so that it can be cognitively gripped and absorbed, so that computation can be understood with the body.

It can be challenging and cognitively taxing to visually perceive and parse space, to for example visually judge distances and imagine volumetric form. Distance and physical properties like size, shape, volume, weight, hardness, and texture, however, can be automatically and subconsciously assessed kinaesthetically with the body [Jeannerod 1997]. By affording physical feedback tangible interfaces should, therefore, reduce the cognitive load needed to judge spatial distances, relationships, patterns, and forms.

Furthermore, some cognitive processes can be physically simulated, offloading the cognitive work onto the body [Kirsh 2013].

Architects massing models Office of Metropolitan Architecture foam massing models [Yaneva 2009] or Frank Gehry's creative process of thinking through the movement of gestural drawing and exploratory form finding with massing models [Gehry 2004; Pollack 2006]

Professionals like designers develop creative ideas through 'reflection-in-action,' an iterative, exploratory process of framing the problem, ideation or making, and critical reflection [Schön 1983]. This exploratory process may unfold in an instant in action, repeated continually through acts like drawing or model making. Frank Gehry for example develops his designs through exploratory form finding with massing models and by thinking through the movement of gestural drawing [Gehry 2004; Pollack 2006].

An ethnography of the Office of Metropolitan Architecture showed that architects in the firm used practices like reuse, adaption, and exploratory modeling to develop designs through iterative processes [Yaneva 2009]. The architects, for example, explored form by carving foam massing models with hot-wire cutters, reflecting on each model as they carved, while building up a library of forms. Ideas and forms set aside and unused in one project might show up in other projects, recycled and adapted [Yaneva 2009].

When tangible interactions are designed to be analogous to everyday, physical tasks like unscrewing a bottle top [Kirsh 2013], picking up and placing objects, or sculpting sand... users may already understand what to do. Such interaction should be highly intuitive, drawing on existing motor schema and cultural knowledge.

...

1.3. Aim and objectives

1.4. Research questions

2. METHODOLOGY

2.1. Tangible Landscape

Concept. Tangible interfaces for GIS should ease the cognitive burden of visualizing, interacting with, 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 near real-time. Conceptually Tangible Landscape physically manifests geospatial 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.

Evolution. Tangible Landscape evolved from Illuminating Clay [Piper et al. 2002a] and the Tangible Geospatial Modeling System (TanGeoMS) [Tateosian et al. 2010]. 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. 2004]. 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 to integrate it with GRASS GIS in order to draw on GRASS GIS's 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 TanGeoMS [Tateosian et al. 2010]. TanGeoMS 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 assess to a sophisticated library for spatial modeling, simulation, visualization, 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. Tangible Landscape – the next generation of this system – was inspired by the open source Augmented Reality Sandbox [Kreylos 2012] which couples a sandbox with a digital model of a landscape through a real-time cycle of 3D scanning with a Kinect sensor, spatial modeling and simulation, and projection. While TanGeoMS used an expensive terrestrial lidar scanner for 3D scanning [Tateosian et al. 2010], Tangible Landscape uses a low-cost 3D sensor like the Kinect 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], and the 2nd generation of Tangible Landscape [Petrasova et al. 2015] used the 2nd generation Kinect with time-of-flight sensing [Bamji et al. 2015] .

Design. Tangible Landscape was designed to let users naturally explore spatial data, models, and simulations in an engaging, playful way by 3D sketching (Fig. 3). As users sculpt 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 simula-

tions, which are then projected back onto the physical model – all in near real-time (Fig. 2). This enables users to tangibly interact with digital models and simulations either by shaping topography with their hands or by placing markers that are identified through object detection. As the digital models and simulations update the results are projected back onto the model for the users to see.

Because the model is continually scanned users hands will be digitized as they sculpt or place objects. Scanning users' hands as topography can be distracting; it also, however, helps users understand how the system works – by seeing how direct interaction is – and encourages play. Users can, for example, cup their hands over the model and see them fill with simulated water.

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

Fig. 3. Naturally exploring subsurface soil moisture and soil types with Tangible Landscape

Fabrication. The physical model is often made of polymer-enriched sand so that users can easily sculpt forms in a medium that will hold its shape, has good plasticity, and has a familiar feel and aesthetic.

Tangible Landscape typically uses familiar, everyday materials – like sand and wooden blocks – for modeling. Interactions – sculpting sand and moving wooden blocks – are analogous to everyday tasks so users should subconsciously knows 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 model so that users can easily sculpt forms in a medium that will hold its shape, has good plasticity, and has a familiar feel and aesthetic. Because polymeric sand can easily be cast in molds and will be hold its form, we use computer-numeric control (CNC) machined or 3D printed molds to cast polymeric sand into precise models (Fig. 4.

Fig. 4. Casting polymeric sand with 3D printed molds

Applications. Landscape planning applications include stormwater management, flood control, landscape management and erosion control, trail planning, viewshed analysis, the assessment of solar potential, and subsurface visualization. Landscape change applications including urban planning, sea level rise adaption, wildfire management, disease management, and invasive species management [Petrasova et al. 2015]. These applications draw upon GRASS GIS's libraries of sophisticated models and simulations such as the FUTure Urban – Regional Environment Simulation – a patch-based, stochastic, multi-level land change modeling framework [Meentemeyer et al. 2013; Petrasova et al. 2016].

2.2. Coupling experiment

2.3. Analytics experiment

2.4. Case studies

We hosted a participatory modeling workshop using Tangible Landscape as part of North Carolina State University Library's Coffee & Viz series. In this interactive seminar participants explored complex environmental problems by playing serious games. In the games participants used simple tangible interactions to computationally steer simulations, to drive simulated environmental processes. In one game participants managed the spread of termites across a city by treating city blocks. To treat a city block they placed wooden cubes representing preventive treatments on the game board leveraging basic motor skills from childhood play (Fig. 5). In the other game participants tried to save houses from coastal flooding by building coastal defenses. To build defenses they sculpted dunes out of polymeric sand again leveraging motor skills from childhood play (Fig. 6). Participants were able to naturally interact with a statistical epidemiological model and a flood simulation. Because the interactions were so simple

they were able to iteratively explore the behavior of multidimensional environmental processes unfolding in time and space.

Fig. 5. Managing the simulated spread of termites through a city with Tangible Landscape

Fig. 6. ...

3. RESULTS

4. DISCUSSION

4.1. Design guidelines

[Wilson et al. 2014]

5. FUTURE WORK

Figure 7 . . .

Fig. 7. Tangible Landscape with robotic fabrication, robotic construction, and real-time field data

6. CONCLUSION

APPENDIX

In this appendix . . .

ELECTRONIC APPENDIX

The electronic appendix for this article can be accessed in the ACM Digital Library.

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Online Appendix to:
Embodied Spatial Cognition in Tangible Computing

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A. HOW-TO-BUILD

A.1. Hardware

Table I. Hardware

Type	Product	Cost
Computer	System 76 Oryx Pro	$1500
Projector	Optoma ML750 WXGA 700 DLP LED	$500
3D sensor	Xbox One Kinect	$100
	Kinect Adapter for Windows	$50
Stand	Avenger 40-Inch C-Stand with Grip Kit	$200
	Avenger 40-Inch C-Stand with Grip Kit	$200
	Avenger F800 3-Inch Baby Wall Plate	$10
	Avenger F800 3-Inch Baby Wall Plate	$10
Peripherals	HDMI cable	$10
	Extension cord	$10
Modeling media	Waba Fun Kinetic Sand 11 Lbs	$50

A.2. Data sources

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DOI: 0000001.0000001

Table II.
Data
sources

Data type	Data source	Link
Lidar	United States Interagency Elevation Inventory	http://coast.noaa.gov/inventory/
	Earth Explorer	http://earthexplorer.usgs.gov/
	Digital Coast	http://coast.noaa.gov/dataviewer/
	Open Topography	http://www.opentopography.org/
Digital Elevation Models	National Elevation Dataset	http://viewer.nationalmap.gov/viewer/
Orthoimagery	USGS EROS Orthoimagery WMS	http://raster.nationalmap.gov/

Tangible Modeling with Open Source GIS

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Contribution

This book was a collaborative effort with my colleagues in the NCSU Open Source Geospatial Research and Education Lab (`http://geospatial.ncsu.edu/osgeorel/`) Anna Petrasova, Vaclav Petras, and Helena Mitasova. I was the sole author of chapter 1 and chapter 3. I co-authored chapter 7 and chapter 10 being responsible for approximately half of the content. I also contributed extensively to the Appendix being responsible again for approximately half of the content. My co-authors and I extensively edited the content, imagery, style, and structure of the entire book.

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Tangible Modeling with Open Source GIS

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Acronyms

2D	Two-dimensional
2.5D	Two-and-a-half-dimensional
3D	Three-dimensional
API	Application programming interface
CAD	Computer aided design
CAM	Computer aided manufacturing
CLI	Command line interface
CNC	Computer numerical control
DEM	Digital elevation model
DSM	Digital surface model
GIS	Geographic information system
GNU GPL	GNU General Public License
GRASS	Geographic Resources Analysis Support System
GUI	Graphical user interface
HCI	Human-computer interaction
MDF	Medium density fiberboard
NCSU	North Carolina State University
NURBS	Non-uniform rational b-spline
RST	Regularized spline with tension
USLE	Universal Soil Loss Equation
SDK	Software development kit
SED	Simplified erosion and deposition
TanGeoMS	The Tangible Geospatial Modeling System
TIN	Triangulated irregular network
TSP	Traveling salesman problem
TUI	Tangible user interface
UNC	University of North Carolina
USGS	United States Geological Survey
USDA	United States Department of Agriculture
UI	User interface

Chapter 1
Introduction

The complex, 3D form of the landscape—the morphology of the terrain, the structure of vegetation, and built form—is shaped by processes like anthropogenic development, erosion by wind and water, gravitational forces, fire, solar irradiation, or the spread of disease. In the spatial sciences geographic information systems (GIS) are used to computationally model, simulate, and analyze these processes and their impact on the landscape. Similarly in the design professions GIS and computer aided design (CAD) programs are used to help study, re-envision, and reshape the built environment. However, because of the unintuitive nature of understanding and manipulating 3D forms in abstract, digital space via a graphical user interface (GUI), technologies like GIS are often so challenging to learn and use that they restrict creativity. The limitations of the technology constrain how we think. Being able to interact more naturally with digital space enhances our spatial thinking, encouraging creativity, analytical exploration, and learning. This is critical for designers as they need to intuitively understand and manipulate information in iterative, experimental processes of creation. With tangible user interfaces (TUIs) like Tangible Landscape one can work intuitively by hand with all the benefits of computer modeling and analytics. This chapter discusses the evolution of TUIs and the development of Tangible Landscape, exploring its motivations, applications, and future directions. This chapter also describes the organization of this book.

1.1 The Evolution of Tangible User Interfaces

Inspired by prototypes like Durrell Bishop's Marble Answering Machine (Poynor 1995) and concepts like Fitzmaurice et al.'s Graspable User Interface (1995) Ishii and Ullmer (1997) proposed a new paradigm of human-computer interaction—the TUI. They envisioned that TUIs could make computing more natural and intuitive by coupling digital bits with physical objects as Tangible Bits. In their

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vision Tangible Bits bridge the physical and digital, affording more manual dexterity and kinaesthetic intelligence and situating computing in physical space and social context (Dourish 2001; Ishii and Ullmer 1997). Recently, the development of TUIs has gained momentum thanks to new developments in 3D technologies such as 3D scanning and 3D printing.

1.1.1 The Principles of Tangible User Interfaces

We can easily, intuitively understand and manipulate space physically, but our understanding is largely qualitative. We can also precisely and quantitatively model and analyze space computationally, but this tends to be less intuitive and requires more experience. Intuition allows us to perceive, think, and act in rapid succession; it allows us to creatively brainstorm and express new ideas. TUIs like Tangible Landscape aim to make the use of computers more intuitive combining the advantages of physicality and computation.

Physical models are used to represent landscapes intuitively. With a physical model we can not only see its volume and depth just as we would perceive space in a real landscape, but also feel it by running our hands over the modeled terrain. We can shape physical models intuitively—for example we can sculpt landforms by hand, place models of buildings, or draw directly on the terrain. With a physical model, however, we are constrained to a single scale, simple measurements, and largely qualitative impressions.

Digital models are used to visualize, quantitatively analyze, and precisely design landscapes. With digital models we can dynamically visualize different scales and layers of information, study the landscape by computing geospatial analyses and simulations, and precisely edit digital models. Digital models, however, can be unintuitive. A high level of abstraction separates us from a digital model—to interact with this digital abstraction of physical space with a GUI we must translate our intent through our hands to the computer via input devices like a keyboard and mouse and then visualize the results graphically on a display. The digital model itself is a high level abstraction of physical space represented by arrays of values or by mathematical functions. We have to think abstractly and make great conceptual leaps to work through so many layers of abstraction. Understanding and working directly with a digital model is a hard learned skill, a skill that constrains our thinking and transforms creativity.

Tangible user interfaces aim to make interaction between humans and computers more natural and intuitive by giving digital data a physical form and physical form a digital dimension (Fig. 1.1). By coupling the physical and the digital through a feedback loop, we can interact with our physical data directly and very naturally with our bodies—drawing on our highly developed kinaesthetic intelligence.

A landscape modeled as a physical-digital hybrid through a TUI such as Tangible Landscape has the potential to be intuitively modeled, creatively explored, dynamically computed, richly layered with data, and rigorously analyzed. It can have

Fig. 1.1 Tangible Landscape: simulated water flow projected over a physical model of a landscape

Fig. 1.2 Physical, digital, and hybrid physical-digital modeling processes

all of the advantages of physical landscape models, geospatial models, and CAD combined. With Tangible Landscape we can shape a hybrid model naturally with our hands to creatively explore ideas as if sketching in multiple dimensions. With a physical model we are constrained to modeling in three-dimensions, to modeling for example topographic form. With a hybrid landscape model we are not limited to modeling topographic form—we can dynamically explore and compute many dimensions of geospatial data in rapid succession with the same model (Fig. 1.2).

1.1.2 Dynamic Shape Displays

Dynamic shape displays or shape changing displays—another type of TUI—are computer controlled, interactive, physically responsive surfaces. As we interact with the physical surface it changes the digital model and, conversely, as we interact with the digital model the physical surface changes (Ishii 2008a; Poupyrev et al. 2007). Dynamic shape displays tend to be arrays of pistons and actuated pins that form kinetic, 2.5D surfaces (Petrie 2006) although there is experimental research into continuous, moving surfaces made of shape changing materials driven by heat, magnetic, or electrical stimuli (Coelho and Zigelbaum 2010).

Aegis Hyposurface The Aegis Hyposurface, an early example of a dynamic shape display, is a generative art installation that uses pneumatic actuators to move a triangulated mesh surface according to an algorithm. It can be either preprogrammed or interactive, moving in response to sensed sound, light, or movement. As it was designed and built at an architectural scale the Aegis Hyposurface has a very coarse resolution for an actuated shape display (Goulthorpe 2000).

FEELEX The resolution of actuated shape displays is constrained by the size and arrangement of the piston motors and piston rods or pins that move the surface. Project FEELEX, another early dynamic shape display, used linear actuators to deform a rubber plate. The size of the motors—4 cm—meant that the resolution of the shape display was very coarse. Since the motors are larger than the pins, FEELEX 2 used a piston-crank mechanism to achieve a relatively high 8 mm resolution by clustering the pins while offsetting the motors below. A rubber sheet was stretched over the array of pins to create a 2.5D display for projection. When a user touched the surface they would depress the pins and the pressure of their touch would be recorded as a user interaction (Iwata et al. 2001).

Dynamic Sand Table and Terrain Table The XenoVision Mark III Dynamic Sand Table, developed in 2004, and the Northrop Grumman Terrain Table, developed in 2006, were actuated shape displays that represented topography in 2.5D. In the Terrain Table thousands of pins driven by a motor shaped a silicone surface held taut by suction from a vacuum below into a terrain. The Terrain Table recorded touches as user interactions such as panning and zooming. As users panned, zoomed, or loaded new geographic data, the actuated surface would automatically reshape within seconds (Petrie 2006).

Relief Relief is a relatively low-cost, scalable, 2.5D actuated shape display based on open source hardware and software. Given the complexity and thus the cost, maintenance, and unadaptability of earlier dynamic shape displays like FEELEX and the Northrop Grumman Terrain Table, Leithinger and Ishii (2010) aimed to design a simpler, faster system that was easier to build, adapt, scale, and maintain. In the first prototype of Relief an array of 120 actuated pins driven by electric slide potentiometers stretch a Lycra sheet into a shape display. Users can reshape the shape display by pressing or pulling on the actuated pins. The actuators are

controlled with open source Arduino boards and a program written in the open source language Processing controls, senses, and tracks all of the pins and their relation to the digital model (Leithinger et al. 2009; Leithinger and Ishii 2010). The transparency and freedom of open source solutions should make it relatively easy to reconfigure and adapt this system.

Recompose While Relief was initially designed for a simple, highly intuitive interaction—direct physical manipulation (Leithinger and Ishii 2010)—its next iteration, Recompose, added gesture recognition (Blackshaw et al. 2011; Leithinger et al. 2011). While with Relief users can only directly sculpt the shape display with their hands, with Recompose they can also use gestures to select, translate, rotate, and scale regions of the display. The size and coarse resolution of the actuated shape display mean that only small datasets or subsets of larger datasets can be modeled with useful fidelity. Furthermore, Leithinger et al. (2011) found that only a very limited range of touch interactions could be recognized at the same time and that it can be challenging to manipulate individual pins as they may be out of reach. They augment touch with gestures by adding a Kinect as a depth camera so that users can easily change the context and explore larger datasets. While gestures are less precise than direct physical manipulation, they greatly expand the scope of possible interactions (Blackshaw et al. 2011). Interactions via external devices such as a mouse may be less ambiguous than gestures, but Leithinger et al. argue that they draw users' focus away from the shape display. Therefore they choose to combine touch interactions with gestures rather than pointing devices so that the transition from sculpting to selection, translation, rotation, and scaling would be fluid and seamless given the physical directness of both modes of interaction (Leithinger et al. 2011).

Tangible CityScape Tangible CityScape, a system built upon Recompose, is an example of how this type of TUI can be applied to a specific domain—urban planning. It used a 2.5D dynamic shape display to model and study urban massing. Building masses were modeled by clusters of pins and the model dynamically reshaped as users panned or zoomed with gestures (Tang et al. 2013).

inFORM With inFORM Follmer et al. (2013) developed a dynamically changing user interface capable of diverse, rich user interactions. Building on the Relief and Recompose systems, they developed a 2.5D actuated shape display that supports object tracking, visualization via projection, and both direct and indirect physical manipulation. The shape display is moved by a dense array of pins linked by connecting rods to a larger array of actuators below (Fig. 1.3). The pins, pushing and pulling with variable pressure, offer nuanced haptic feedback to users. A Kinect depth sensor is used to track objects and users' hands. The actuated surface—a grid of pins—can be manipulated directly by pushing and pulling pins. Furthermore, users can interact with the system indirectly via object tracking. The surface can respond to interactions—both direct and indirect—and reshape itself. The actuated surface can also move objects placed on it, enabling indirect physical manipulations. Follmer et al. used this system to explore how shape-changing displays can

Fig. 1.3 inFORM: a 2.5D actuated shape display designed by the MIT Media Lab (image source: http://tangible.media.mit.edu/project/inform/)

dynamically model content and offer novel modes of interaction based on dynamically changing constraints and opportunities. As a responsive physical user interface inFORM enables rich and varied mode of interaction such as responsive sculpting, moving passive objects, painting changes, and physically instantiated UI elements like buttons (Follmer et al. 2013).

Dynamic shape displays that can be shaped both by touch and computation enable physical interactions from human to computer and computer to human. With a dynamic shape display the digital model is physically instantiated and this shape changing physical model is used for both input and output. When a user changes the surface of the shape display the computer reads the changes; when the computer changes the surface the user sees and feels the changes. Hypothetically this should radically reduce the level of abstraction in human-computer interaction. This novel

mode of bidirectional, tangible interaction should be highly intuitive because it is so direct—human and computers communicate via the same medium. However, while dynamic shape displays may be highly intuitive, they have a relatively coarse resolution, are expensive, maintenance intensive, and hard to transport, all due to the actuators. The resolution of the display for example is constrained by the size of the actuators that make the display kinetic. The coarse resolution makes these displays' representations approximate and abstract, limiting their possible applications.

1.1.3 Continuous Shape Displays

Continuous shape displays couple a continuous physical model with a digital model through a cycle of sculpting, 3D scanning, computation, and projection. We can sculpt the display and then see the resulting computation projected onto the model in near real-time. The feedback from digital modeling is visual—unlike dynamic shape displays, these shape display are passive and do not physically respond to computations. Because there are no actuators the model can be built of a malleable, continuous material such as sand or clay that can be easily sculpted and can accurately represent forms such as landscapes (Ishii et al. 2004; Ishii 2008b).

Projection Augmented Relief Models Currently continuous shape displays rely on projection for representing digital data. While projected imagery has long been used to augment physical terrain models the approach has recently been dubbed Projection Augmented Relief Models (Priestnall et al. 2012). This approach enhances a static physical representation of a landscape with a dynamic visual representation of digital data.

Illuminating Clay With Illuminating Clay (Piper et al. 2002a)—an early continuous shape display from the MIT Media Lab—a clay model of a landscape was continuously scanned with a laser to generate a point cloud of x, y, and z coordinates which were then binned into a digital elevation model (DEM). The DEM or a derived topographic parameter such as slope, aspect, or cast shadow was then projected back onto the clay model so that users could see the impact of their changes in near real-time. Illuminating Clay's library of geospatial analyses was limited as it used custom implementations of elevation, aspect, slope, cast shadow, profile, curvature, viewshed, solar irradiation, and drain direction algorithms. Because Illuminating Clay used a laser scanner the scans were relatively fast—1.2 s each—and accurate to less than 1 mm, but the system was very expensive (Piper et al. 2002a,b). Piper et al. (2002a) also tried to use TUI elements based on object tracking to select algorithms and parameters, but found that too many parameters were involved in geospatial modeling for this approach to be feasible, so they ultimately used standard graphical user interactions with a mouse and keyboard.

Sandscape In an effort to make a more affordable continuous shape display Ishii et al. (2004) designed a system called Sandscape based on infrared depth sensing. In Sandscape a 'sandbox' filled with 1 mm glass beads was lit from beneath by infrared LEDs; an infrared camera above the 'sandbox' captured the intensity of infrared light passing through the glass beads. A DEM based on the light intensity was projected back onto the 'sandbox' so that users would have real-time feedback as they sculpted. While this system was very fast and much less expensive than Illuminating Clay, the scans were low resolution and the physical medium—glass beads—could only be coarsely sculpted (Ishii et al. 2004; Ishii 2008b).

Augmented Reality Sandbox SandyStation (Altman and Eckstein 2014), developed in 2011, and the Augmented Reality Sandbox (Kreylos 2015), developed in 2012, are continuous shape display sandboxes. Kreylos's Augmented Reality Sandbox, inspired by the Czech SandyStation, couples a sandbox with a DEM through a real-time cycle of 3D scanning, modeling and simulation, and projection. As users sculpt the sand a Kinect sensor continually scans the sand surface generating a stream of depth maps. The depth stream is filtered to remove noise and the user's hands. A DEM, contours, and simulated water flow are computed from the depth and projected back on the sandbox. The water flow simulation is a custom implementation based of the shallow water flow equations. The Augmented Reality Sandbox is powered by Kreylos's Kinect 3D Video Capture Project and Vrui VR Toolkit, open source software released under the GNU General Public License. The system is highly intuitive and very fast with each cycle of scanning, processing, and simulation completing in just a couple seconds. However, given that the system only models elevation, contours, and water flow on an abstract landscape it is limited in its scope of potential applications.

Tangible Geospatial Modeling System The Tangible Geospatial Modeling System (TanGeoMS) extended the concept of Illuminating Clay by integrating GRASS GIS (Fig. 1.4). Integrating a full GIS into a continuous shape display gave users a wide range of sophisticated, scientific tools for geospatial modeling and visualization in a highly intuitive environment. By combining freeform hand modeling with geospatial modeling, simulation, and visualization users could easily explore how changes in topographic form affect landscape processes (Mitasova et al. 2006). Like Illuminating Clay the system used a laser scanner to 3D scan a clay model. The scanned point cloud was then interpolated as a DEM, select geospatial analyses or simulations were computed from the DEM, and the results were projected back onto the clay model (Tateosian et al. 2010) (Fig. 1.4b).

1.2 Tangible Landscape

The next generation of TanGeoMS—Tangible Landscape—was designed to intuitively 3D sketch landscapes. This continuous shape display is more tightly integrated with GRASS GIS and has new modes of interaction based on object recognition so that users cannot only sculpt, but also sketch in 3D—rapidly

Fig. 1.4 The Tangible Geospatial Modeling System: a continuous shape display powered by GRASS GIS. (**a**) Multiple users interacting. (**b**) The shape display paired with a 3D rendering. (**c**) The hardware setup with a laser scanner mounted above the model

exploring ideas while learning from near real-time feedback (Fig. 1.5). Tangible Landscape is more affordable than its predecessors because it uses a Kinect sensor to 3D scan physical models. As a continuous shape display with object recognition

Fig. 1.5 3D sketching a check dam with Tangible Landscape: (**a**) orthoimagery, (**b**) water flow, (**c**) sculpting a check dam, (**d**) updated water flow, and (**e**) a dammed valley with water flow simulated by *r.sim.water*. http://grass.osgeo.org/grass70/manuals/r.sim.water.html

a wide range of media can be used such as polymer-enriched sand, clay, 3D prints, CNC-machined models, and architectural models. It is more tightly integrated with GIS, using a GRASS GIS plugin to automatically scan, process, georeference,

Fig. 1.6 Collaboratively sculpting a retention pond

import, and analyze the model. Because it is so tightly integrated with GRASS GIS users can also use the GUI, the command line, and scripting as advanced controls for tasks not suited to a TUI (Petrasova et al. 2014).

Conceptually, Tangible Landscape couples a physical model with a digital model in a real-time feedback cycle of 3D scanning, geospatial modeling and simulation, and projection. For example, by sculpting the terrain of the physical model, we can see how the changes affect processes like the flow of water, flooding, erosion, and solar irradiation. Thus we can easily and rapidly test ideas while being guided by scientific feedback, exploring a much a larger solution space and make more creative and informed decisions. And since many users can interact with the physical model at once, Tangible Landscape encourages collaboration and interdisciplinary exchange (Fig. 1.6). Tangible Landscape combines real-time interaction with extensive scientific tools for modeling, analysis, and visualization at the precision needed for real-world design and planning applications. Tangible Landscape can be used for applications such as grading landforms (Chap. 3), analyzing topography (Chap. 4), modeling water flow and soil erosion (Chap. 5), analyzing viewsheds (Chap. 6), planning trail networks (Chap. 7), analyzing solar radiation dynamics (Chap. 8), simulating and managing fire (Chap. 9), and modeling inundation and flooding (Chap. 10).

Tangible Landscape is inexpensive, portable, adaptable, and easy to implement. As a high resolution continuous shape display it can be used for both rapid ideation and precise modeling. However, unlike a dynamic shape display the physical model is passive and cannot be changed computationally in real-time—trading real-time response for precision, complexity, and cost. Rapid prototyping can be used to precisely shape or reshape the physical model allowing users to work with real world landscapes and easily reset the conditions.

Fig. 1.7 3D sketching a levee breach with feedback on the resulting extent of flooding: (**a**) a flooded landscape, (**b**) breaching the levee, and (**c**) updated flooding

1.2.1 Modes of Interaction

There are many ways to 3D sketch with Tangible Landscape. It combines a couple modes of tangible user interaction. As a continuous shape display—a 2.5D interface that physically instantiates and displays continuous data in real-time—we can use it sculpt surfaces and volumes. It can also use object recognition to detect and compare changes, model volumes, designate points, select data, and sketch lines. By sculpting a physical model made of polymeric sand we can intuitively model topography (Fig. 1.7), forest canopy, buildings, and cost surfaces. We can also explore volumes such as subsurface soil moisture by digging the into polymeric sand. With change detection we can visualize the difference between models to study how we have changed it. With object recognition we can place makers to create points such as observer points for viewshed analysis, lines such as section cuts for visualizing volumes, and polylines such as the least cost path between points for route analysis. Since Tangible Landscape has so many modes of interaction and draws on GRASS GIS' extensive modules for data management, geospatial modeling, and visualization, it can easily be adapted to new uses. Since both Tangible Landscape and GRASS GIS are open source projects we can easily develop new modes of interaction and new analyses.

1.2.2 Developing Tangible Landscape

Tangible Landscape is a free, open source project with source code hosted on GitHub.[1] The system is constantly evolving in response to new developments in its hardware and software components and the needs of its expanding range of applications. Enhanced point cloud processing, optimization of the core functions, and migration to more efficient hardware and operating systems will improve real-time interaction and allow us to incorporate more sophisticated dynamic

[1] https://github.com/ncsu-osgeorel/grass-tangible-landscape

modeling. User interaction and experience can be further improved with dashboards and steered simulations. Computationally controlled shape generation with in-situ digital fabrication will combine the advantages of dynamic and continuous shape displays. By providing Tangible Landscape as a free, open source project, along with this book, we aim to build a community of developers and users of this technology for the benefit of education, research and collaborative decision making in communities worldwide.

1.3 The Organization of This Book

This book describes tangible geospatial modeling using open source GIS and its applications. For each application we explain the underlying theory and algorithms, provide the workflows used, and describe case studies. Simple GRASS GIS workflows consisting of module calls are presented in boxes with green backgrounds, while more complex workflows written in Python are presented in boxes with blue backgrounds. 3D modeling workflows in Rhinoceros are presented in boxes with grey backgrounds.

Chapter 2 describes how Tangible Landscape works and how it is set up. This chapter details the 3D scanning technology, the hardware and software used, and the physical setup of the system. It provides information about where to download GRASS GIS and the Tangible Landscape plugin and explains how to read and use the workflows. Chapter 3 explains how to build physical models for use with Tangible Landscape. This chapter covers handmade modeling techniques, digital fabrication techniques, and techniques for molding and casting models. Chapter 4 covers the basic processes of scanning, interpolating, and analyzing a terrain model. The following chapters describe a range of scientific applications for Tangible Landscape. Each chapter first covers the relevant theory and algorithms and then demonstrates the application in a case study. Chapter 5 covers surface water flow and soil erosion, Chap. 6 covers viewsheds, Chap. 7 covers trail planning, Chap. 8 covers solar irradiation dynamics, Chap. 9 covers the spread of wildfire, and Chap. 10 covers coastal inundation and flooding. The Appendix includes case studies of additional applications of Tangible Landscape, a summary of the data used in this book with download links, a list of useful on-line data sources, and a guide to getting started with GRASS GIS.

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Chapter 2
System Configuration

The setup of the Tangible Landscape system consists of four primary components: (a) a physical model that can be modified by a user, (b) a 3D scanner, (c) a projector, and (d) a computer installed with GRASS GIS for geospatial modeling and additional software that connects all the components together. The physical model, placed on a table, is scanned by the 3D scanner mounted above. The scan is then imported into GRASS GIS, where a DEM is created. The DEM is then used to compute selected geospatial analyses. The resulting image or animation is projected directly onto the modified physical model so that the results are put into the context of the modifications to the model.

2.1 Hardware

Tangible Landscape can be built with affordable, commonly available hardware: a 3D scanner, a projector and a computer. We describe some of the current hardware options while noting that the technology develops rapidly and alternative, more effective solutions may emerge.

2.1.1 3D Scanner

In the Tangible Landscape workflow the 3D scanner captures the physical model as it is modified by users. Therefore it is important that the device scans as accurately as the technology allows. Few affordable 3D scanners are currently available. However, due to growing demand this technology is developing rapidly and new, improved 3D scanners may become available soon. The Tangible Landscape system was developed using the Kinect for Windows v2 and thus has the disadvantage of

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being bound to the Microsoft Windows operating system. Being bound to a specific operating system limits the choice of environment in which to run the application. Therefore, the selection of the 3D scanner may change in the future as new, more flexible technologies become available.

The Technology Behind 3D Scanning We describe the basic principles behind current 3D depth sensing technologies in order to explain both the potential and the limitations of current scanning devices. More detailed information can be found for example in Mutto et al. (2012).

Several currently available depth sensors such as Apple Primesense Carmine, Asus Xtion PRO LIVE,[1] and Kinect for Windows v1, are based on a Primesense proprietary light-coding technique. This technique uses triangulation to map 3D space in manner similar to how the human visual system senses depth from two slightly different images. Rather than using two cameras it triangulates between a near-infrared camera and a near-infrared laser source. Corresponding objects need to be identified in order to triangulate between the images. A light coding (or structured light) technique is used to identify the objects. The laser produces a pseudo-random dot pattern which is then used to find the matching dot pattern in the projected pattern. In this way the final depth image can be constructed.

Optical triangulation is also used by high resolution 3D scanners such as SCANIFY by Fuel3D (2015). The scanner acquires a series of stereoscopic photographs with different lighting directions. When scanning multi-color objects with some texture this technology can create highly accurate 3D models with high levels of detail. The major limitation is that only relatively small models that can be scanned making it unsuitable for most applications using physical landscape models. These models usually need to be relatively large to clearly represent relief at a landscape scale without too much vertical exaggeration.

Kinect for Windows v2 uses *time-of-flight*, a technique widely used in lidar technology. Kinect v2 has a sensor that indirectly measures the time it takes for pulses of near-infrared laser light to travel from a laser source, to a target surface, and then back to the image sensor. Time-of-flight sensors are generally considered to be more precise, but also more expensive.

Since the scanning and 3D modeling algorithms and their implementations for most sensors are proprietary, the specific behavior and precision of particular sensors is subject to many experimental studies. Generally, sensors using near-infrared light are sensitive to lighting conditions, so outdoor usage is typically not recommended. The depth resolution decreases with the distance from the sensor and also at close range (i.e. between a couple of millimeters to tens of centimeters). The range and field of view of the sensors can vary; Tangible Landscape requires short range sensors with a minimum distance of 0.5 m to keep the highest possible resolution. When scanning with one sensor the size of the physical model is limited by the required accuracy because the sensor must be far enough away to

[1] https://www.asus.com/us/Multimedia/Xtion_PRO_LIVE/

capture the entire model in the sensor's field of view, which for the Kinect for Windows v2 is 60° vertical by 70° horizontal. Detailed information about accuracy and precision of Kinect for Windows v1 and v2 can be found in Andersen et al. (2012); Lachat et al. (2015) and a comparison to Asus Xtion can be found in Gonzalez-Jorge et al. (2013).

2.1.2 Projector

The projector projects the background geospatial data and results of analyses onto the the 3D physical model. Therefore it is important to select a projector with sufficient resolution and properties that minimize distortion and generate a bright image.

Resolution and brightness are two important criteria to be considered. We recommend higher resolution projectors offering at least WXGA (1280 × 800). The brightness depends upon where Tangible Landscape is used and whether the room's ambient light can be reduced for the sake of brighter projected colors. We recommend brighter projectors (at least 3000 lumens) since we project on a variety of materials which are not always white and reflective.

There are two important types of projectors—standard and short-throw projectors. They differ in throw ratio values, which are defined as the distance from the projector's lens to the screen, divided by the width of the projected image (short throw and ultra short throw projectors have ratios 0.3–0.7, while the standard projectors have throw ratio values around 2). At the same distance the projector with a lower throw ratio can display a larger image. In other words a projector with a lower throw ratio (short-throw) can project an image of the same size as the higher throw ratio projector, but from a shorter distance. Tangible Landscape can be set up using both types of projectors; each has advantages and disadvantages.

The placement and configuration of the projector is important because it affects the coverage, distortion, and visibility of the projected data. For example in some setups the 3D scanner may be caught in the projection and would thus cast a shadow over the model. Therefore it can be practical to use a short-throw projector because it can be placed to the side of the physical model at a height similar to the 3D scanner (Figs. 2.1b and 2.2). Since the projection is cast from the side the projection beam does not cross the 3D scanning device and no shadow is cast. However, with a short-throw projector there is a certain level of visible distortion when projecting on a physical model that has substantial relief. The distortion occurs because the light rays reach the model at a very acute angle. The horizontal position at which the projected light intersects the model is shifted from the position at which it would intersect with a flat surface. Larger differences in height increase the distortion. Theoretically we can remove the distortion by either warping the projected data itself or using the projector to automatically warp the projected image. The first solution would require an undistorted dataset for geospatial modeling and a warped copy of that data for projecting. That is impractical especially when working with

Fig. 2.1 Possible placements of the projector and scanner according to projector type. (**a**) Standard projector mounted in the ceiling. (**b**) Standard short throw projector. (**c**) Short throw projector capable of projecting above the center. (**d**) Short throw projector tilted to project above the center with keystone correction

many different raster and vector layers. The other solution requires the projector itself to warp the image; while this technology exists, it is only offered by a few projector manufacturers and such projectors are typically more expensive. Moreover, as the landscape is modified, the warping pattern should change as well. Currently it is not possible to find this feature in the off-the-shelf projectors.

With standard projectors the distortion is usually negligible since the incidence angle of the rays is relatively small. A standard projector needs to be placed much

Fig. 2.2 Mobile system setup: projector, scanner, model and laptop

higher above the model than a short-throw projector does due to the difference in throw ratios (Figs. 2.1a and 2.3). This creates several challenges. It is hard to mount and manipulate the projector when is it so high above the model. Furthermore it is challenging to align projector and the 3D scanner without casting a shadow. Since the 3D scanner has a limited field of view it must be placed close to the horizontal center of the model. When the projector is mounted above the scanner, the scanner is caught in the projector's beam, casting a shadow over part of the model. For small to mid sized models, depending on the particular setup and the height of the scanner and projector, this may not be a problem.

The shadow of the scanner can also be avoided with specialized short throw projectors that allow greater installation flexibility through lens shifting. These projectors (for example Canon WUX400ST) are capable of projecting from the horizontal center of the projected area at the same height as the scanner (Fig. 2.1c). A device which combines the scanner and projector would make this setup easy; an appropriate device, however, was not available at the time of writing.

To minimize the distortion when using projectors with lower throw ratios, we can project from the center by tilting the projector and correcting the resulting keystone distortion (Fig. 2.1d). With this setup we recommend projectors that have throw ratios around 1.0 (for example Epson PowerLite 1700 Series) as a lower ratio can result in additional distortion. When testing the projector setup it is useful to project the rectangular grid on a flat surface in order to quickly check if there is any distortion.

Fig. 2.3 Laboratory system setup with the projector mounted in the ceiling

2.1.3 Computer Requirements

System requirements depend largely upon the sensor and its associated library or software development kit (SDK). Certain sensors, such as Kinect for Windows, are designed to work only on specific operating systems. The computer should be configured for 3D scanning and geospatial modeling, both of which are performance- and memory-intensive processes. The hardware requirements are very similar to the requirements for gaming computers: a multi-core processor, at least 4 GB of system memory and a good graphics card are necessary to achieve real-time interaction with the model. The specific parameters required for the scanner device should be reviewed on the manufacturer's website.

2.1.4 Physical Setup

The setup for Tangible Landscape system is quite flexible. However, there are some crucial components and some specifics that make a setup more usable. When building Tangible Landscape in the laboratory or when bringing it to the community the following items are necessary:

- a table for a model
- a laptop or desktop computer with a table
- a scanner
- a projector
- 1–2 stands for a projector and a scanner
- 3–4 power plugs (and/or extension cable)

Ideally the table should be either a 90 cm × 90 cm table with rounded corners, a rounded table 100 cm in diameter, or a teardrop table of similar size. To freely interact with the model a person should be able to almost reach the other side of the table; this is not possible with larger tables. Smaller tables, on the other hand, have less space for tools, additional sand, and application windows. Ideally application windows with additional information should be projected onto the table beside the model. A large model can be placed on top of a smaller table or stand, provided that this base is stable. In this case if any application windows are needed, they have to be projected directly onto the model.

A round table is quite advantageous because people can stand at equal distances from the model and can easily move around the table. Unfortunately, one side of the table is typically occupied by the metal stands for projector and scanner since ceiling mounts are rarely possible and render the system immobile. The table should be stable enough to hold sand and models and sturdy enough to withstand their manipulation. We recommend putting the computer on a separate table so that the modeling table is not cluttered. The more space there is around the modeling table, the more access users have to the model. The computer, however, needs to be situated so that its operator has easy access to the model as well.

An alternative is to use a rectangular table (ideally with rounded corners) that is 140 cm × 90 cm for both the model and the laptop. A narrow table that is 150 cm × 75 cm may work as well. This setup makes the model less accessible as at least two sides of the model are blocked. However, the whole model should be accessible from any of the remaining sides, so this setup does not necessarily limit interaction, but rather the number of users.

Sometimes it is advantageous to have a large screen showing additional data or 3D views to enhance users' understanding of the processes. However, such screen should not limit access to the physical model. Tangible Landscape could be also extended with additional devices such as 3D displays, head-mounted displays, and hand-held devices.

There should be at least 80 cm of space on each side of the modeling table so that there is room for walking, standing, and placing the stands. The whole area required is about 2.5 m × 2.5 m but in practice the area is often larger depending on the size

of the tables and the surroundings. Generally, it is better to have a larger open space. With more space people can easily come and cluster around Tangible Landscape spreading around the different sides of the setup.

The projector and scanner can be mounted on one or two stands according to projector's capabilities as discussed in detail in Sect. 2.1.2. Two separate stands or arms give enough flexibility to accommodate various types of projectors. In any case, the stand for the projector must be robust because some of the projectors with adequate parameters can be heavy. However, there exist some portable projectors weighting less than 2 kg as well. A mobile setup with two separate stands and two separate tables is shown in Fig. 2.2. For permanent setups the projector can be mounted in the ceiling as shown in Fig. 2.3.

2.2 Software

The software for Tangible Landscape consists of several different components: a scanning program dependent upon the Kinect for Windows SDK libraries, GRASS GIS for processing scans and running geospatial analyses, and a custom library that automates the entire process. Here we briefly describe the software components with the main focus on GRASS GIS as the processing engine of Tangible Landscape. Tangible Landscape software is available in the GitHub repository[2] under the GNU GPL license.

2.2.1 GRASS GIS

GRASS GIS (Neteler and Mitasova 2008) is a general purpose, cross-platform, open-source geographic information system with raster, vector, 3D raster and image processing capabilities. It includes more than 400 modules for managing and analyzing geographical data and many more user contributed modules available in the add-on repository. GRASS GIS modules can be run using a command-line interface (CLI) or a native graphical user interface (GUI) called wxGUI which offers a seamless combination of GUI and CLI native to the operating system.

Modules are organized based on the data type they handle and they follow naming conventions explained in Table 2.1. Each module has a set of defined options and flags which are used to specify inputs, outputs, or different module settings. Most core modules using GRASS GIS C library are written in C for performance and portability reasons. Other modules and user scripts are written in Python using the GRASS GIS Python Scripting Library which provides a Python interface to GRASS GIS modules.

[2] https://github.com/ncsu-osgeorel/grass-tangible-landscape

Table 2.1 Naming conventions for GRASS GIS modules with examples

Name	Data type	Examples
g.*	General data management	g.list, g.remove, g.manual
r.*	Raster data	r.neighbors, r.viewshed, r.cost
r3.*	3D raster data	r3.colors, r3.to.rast, r3.cross.rast
v.*	Vector data	v.net, v.surf.rst, v.generalize
db.*	Attribute data	db.tables, db.select, db.dropcolumn
t.*	Temporal data	t.register, t.rast.aggregate, t.vect.extract
i.*	Imagery data	i.segment, i.maxlik, i.pca

GRASS GIS software can be downloaded freely from the main GRASS project website.[3] The download web page offers easy to install binary packages for GNU/Linux, Mac OS X, and Microsoft Windows as well as the source code. The GRASS GIS website also provides additional documentation including manual pages, tutorials, information about the externally developed modules (add-ons) and various publications. Support for developers and users is provided by several mailing lists. The following tutorial provides a quick introduction to GRASS GIS: http://grass.osgeo.org/grass70/manuals/helptext.html.

2.2.2 GRASS GIS Python API

GRASS GIS provides several Python application programming interfaces (API) to access different functionalities and accommodate many different use cases. Tangible Landscape uses the GRASS GIS Python Scripting Library to easily build new workflows by chaining together existing GRASS GIS modules. We will show an example how to use this library to automate tasks and build new functionality.

GRASS GIS modules are called with the following command syntax:

$$\underbrace{\texttt{r.colors}}_{\text{module name}}\quad \underbrace{\texttt{-e}}_{\text{flag}}\quad \underbrace{\texttt{raster}}_{\text{option name}}\texttt{=}\underbrace{\texttt{elev_state_500m}}_{\text{option value}}\quad \texttt{color=elevation}$$

This command assigns a predefined color ramp `elevation` to the raster map `elev_state_500m`. It can be executed in a GRASS GIS session from a terminal or from a GRASS GIS GUI command console. The same command looks very similar when written using the Python Scripting Library—it is just adjusted to Python syntax. To run it we have to be in a GRASS GIS session and must first import the necessary library.[4] We will use the function `run_command` to call individual modules:

[3] http://grass.osgeo.org

[4] All further Python code snippets assume the library is already imported to avoid code duplication.

```
import grass.script as gscript
gscript.run_command('r.colors', flags='e',
    raster='elev_state_500m', color='elevation')
```

Besides `run_command`, other important functions are `read_command` for reading the raw module output, `parse_command` for reading module output already parsed into a Python dictionary, and `write_command` for passing strings from standard input. All GRASS GIS modules can be called using these functions. However, for some commonly used modules the library conveniently provides wrappers simplifying the syntax, such as the `mapcalc` function, a wrapper for the *r.mapcalc* module.

The following code snippet provides a more complex example using these functions. Here, we extract low-lying areas from a DEM where the elevation z is lower than the difference $z_{mean} - z_{stddev}$:

```
import grass.script as gscript

def main():
   input_raster = 'elevation'
   output_raster = 'low_areas'
   stats = gscript.parse_command('r.univar', map=input_raster,
       flags='g')
   mean = float(stats['mean'])
   stddev = float(stats['stddev'])
   low = mean - stddev
   gscript.mapcalc('{out} = {inp} <
       {lim}'.format(out=output_raster, inp=input_raster,
       lim=low))

if __name__ == "__main__":
   main()
```

More information on writing Python scripts in GRASS GIS can be found in the online GRASS GIS Python Scripting Library documentation. [5]

2.2.3 Scanning Component

The scanning component is currently a C++ application derived from the sample application KinectFusionExplorer shipped with the Kinect for Windows SDK. It reconstructs a mesh based on multiple scans using the KinectFusion algorithm (Newcombe et al. 2011) and writes the point cloud as a text file. It allows us to set the scanning properties such as the resolution of the reconstructed mesh and to limit the volume of the mesh. We recommend using a higher volume resolution such

[5] GRASS GIS Python Scripting Library documentation: http://grass.osgeo.org/grass70/manuals/libpython/script_intro.html

Fig. 2.4 A mesh with a resolution of 512 voxels/m constructed using the KinectFusion algorithm. The mesh captures a sand model, the area outside of the model including a pile of sand and a modeling tool, and the hands of a person interacting with the model

as 512 or 640 voxels/m. It is important to make the volume of the mesh as small as possible to increase processing speed and decrease memory demands. Since the size of the mesh can only be controlled in predefined steps we cannot limit the scanned area to the model area in this way—further processing of the point cloud to filter the points outside of the model area is needed (Fig. 2.4).

2.2.4 Tangible Landscape Plugin for GRASS GIS

The Tangible Landscape plugin connects the scanning component with GRASS GIS and automates the loop of scanning, importing scans, and geoprocessing in the GRASS GIS environment. It has a graphical user interface which allows the adjustment of the different processing parameters that are necessary to properly georeference and extract the model. First it can perform an initial calibration. Then with each new scan the plugin performs the following basic steps:

1. acquiring the scan as a point cloud,
2. extracting only relevant points from the point cloud (filtering points outside the model area)
3. georeferencing (horizontal rotation, horizontal and vertical scaling, translation) the scanned data to known geographic coordinates on the edges of the model,
4. importing the point cloud into GRASS GIS and creating a digital elevation model,
5. running selected geospatial analyses, and
6. re-rendering the resulting raster or vector data that are projected on top of the model.

The conversion from the scanned point cloud to a DEM is an automated process; the details and assumptions that have to be met to produce good results are described in the following paragraphs.

Fig. 2.5 Even slight angular deviation from the vertical scanner axis will cause a tilted scan as seen in (**a**) on a scan of a flat plane with a small angular deviation of 1.7°. A calibration based on the initial scan of a flat plane can compensate for such angular deviations resulting in a horizontally aligned scan as shown in (**b**) although a small radial distortion will still be present

Calibration During scanning the scanner axis should be oriented precisely perpendicular to the table with the model in order to avoid a tilted scan. Even a small deviation of 1° can cause centimeters of height difference depending on the size of the model (see Fig. 2.5a). Therefore, we first calibrate the system by scanning the empty table and computing the angular deviation. We then use this information to automatically rotate each scanned point cloud.

From the scan of the empty table, we compute the plane that best fits the scan by applying the linear regression in 3D. We compute the angular deviation between the unit vector along the scanner axis and the vector perpendicular to the plane. We then use Rodrigues' rotation formula (Wikipedia 2015) to derive a rotation matrix to rotate the point cloud by this angular deviation around a vector given as a cross product of the two vectors. After calibration, the derived rotation matrix is used for rotating every scan resulting in perfectly horizontal scan, see Fig. 2.5b. If the scanner is moved the calibration must be repeated.

For more precise results, we can also minimize the radial distortion of the scanner visible in Fig. 2.5b. The simplest way to do this is to acquire a scan of a flat surface with the dimensions of the physical model and then subtract it from the raster representation of the model.

Model Extraction Since the size of the scanned area cannot be easily limited to just the physical model (see Fig. 2.4), we need to find the boundaries of the model in order to georeference the scanned data.

The first part of the process is to identify points that represent the underlying table. These points have very similar (but due to noise nonidentical) low values of z coordinates. If enough of the table is captured in the scan, we can find the interval of z coordinates containing the points of the table as a first local maximum in a histogram of z values. These points can then be discarded.

After removing these points, we attempt to remove points outside of the model area such as leftover sand or arms reaching over the model in Fig. 2.4. This can be successfully done when the model is rectangular, since we can estimate the horizontal dimensions of the model from the scan and then trim the areas that do not contain enough of points from each side. If the model is not rectangular we can manually choose how many centimeters to trim from each side. Manual trimming, however, requires adjustments anytime that the model is moved even slightly.

Georeferencing Georeferencing the scanned model is an important step when we need to combine it with our geographic data and to ensure that any geospatial analyses are performed on a DEM with real-world dimensions. We need to designate the DEM raster map that the model represents and specify the vertical exaggeration of the physical model to scale the elevation values properly. The scale factors S_x, S_y and S_z are computed:

$$S_x = \frac{Y_{north} - Y_{south}}{y_{max} - y_{min}}, \quad S_y = \frac{X_{north} - X_{south}}{x_{max} - x_{min}}, \quad S_z = \frac{(S_x + S_y)/2}{e} \tag{2.1}$$

where X, Y are DEM (real-world) coordinates, x, y are coordinates on the physical model and e is the specified vertical exaggeration. The vertical scale of the model typically differs from the horizontal because we vertically exaggerate the physical model to enhance our perception of the landscape and simplify our interaction with the model. Since Tangible Landscape users usually interact with the physical model from the side opposite to the scanner we have to rotate the scan by 180°. We can georeference the point cloud with the following equation:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} S_x & 0 & 0 \\ 0 & S_y & 0 \\ 0 & 0 & S_z \end{bmatrix} \cdot \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} \tag{2.2}$$

which rotates the points around the z axes by angle α in the counterclockwise direction, scales to real-world dimensions, and translates the points by adding t_x and t_y computed so that the lower left corner of the model matches the south-west corner of the DEM. The vertical translation t_z is then similarly computed to match the lowest point of the model and the minimum height of the DEM.

DEM Processing The plugin allows users to select the method for creating the DEM from the point cloud, which can be either binning or interpolation (see Sect. 4.1). Once the DEM is created all geospatial analyses specified in a dedicated Python file are sequentially performed. Each separate analysis is represented as one function. These functions are reloaded for each new processing loop so that we can easily run different algorithms and change their parameters. This flexible system enables us to dynamically develop and test new workflows during scanning. The plugin provides a library containing often used analyses and workflows which can be readily used and combined with other GRASS GIS functionality using the GRASS GIS Python Scripting Library.

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Chapter 3
Building Physical 3D Models

Tangible Landscape works with many types of physical 3D models. When used as a continuous shape display the physical model should be built of a malleable material such as sand, clay, or wax so that users can easily deform the surface. When used for object recognition the physical model can be built of a rigid material such as a wood product, plastic, or resin. When both modes of interaction are combined the physical model should use malleable materials for the base and rigid materials for the objects. These models can be built by hand or digitally fabricated using using 3D printing or computer numerically controlled (CNC) manufacturing (Fig. 3.1).

The final model should be opaque, have a light color, and have a matte finish so that the projected image is crisp and vivid. Transparent materials like acrylic cannot be 3D scanned with a Kinect. Some 3D printing and casting materials like resin may appear opaque, but have translucent properties—this will diffuse the projection. If we desire a very crisp and vivid image on a rigid model made of wood products or resins we recommend painting the model white.

In this chapter we discuss different types of physical models and explain how to fabricate them.

3.1 Handmade Models

Rigid physical models can be handmade by hand-cutting contours and malleable physical models can be handmade by sculpting sand or clay.

Contour Models Contour models can be precise if they are finely cut, but they are inaccurate as they depict abstract, stepped landscapes that are discrete rather than continuous. They are also very legible—one can easily count the contours and read the height—but again they represent abstracted landscapes. While one can easily read the contours and then calculate slope, it is hard to intuitively visualize the slope. Furthermore this abstract, discontinuous representation may obfuscate the

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Fig. 3.1 A CNC routed model of the Sonoma Valley, California

relationship between form and process. Furthermore they are time consuming and complicated to construct especially for complex topographies. Hand cutting contour models can be dangerous as the knife may slip or jump.

Contour models can be made out of stacked boards of paperboard, cardboard, foam, or a soft wood like balsa or basswood. The thickness of the sheets should correspond to the vertical interval between contours at the desired map scale. To build a contour model by hand start by plotting a contour map at the desired map scale. Then spray the plotted paper map with a spray mount adhesive, and stick the plotted map onto a board. As an alternative to plotting and mounting, we can instead project the contour map. Cut out the lowest contour level with a precision knife such an x-acto. Glue this contour level onto the base or the level below. Repeat this process until all of the contour levels have been cut out and stacked together.

Hand Sculpted Models Hand sculpted sand and clay models are natural, intuitive, and even fun to make, but are imprecise and hard to read quantitatively (Fig. 3.2). When sculpting by hand we not only see, but also feel the three-dimensional form, using our highly developed kinaesthetic intelligence to better understand the space. While tools can help us to cut sharp edges, shape certain forms, and smooth surfaces, sculpting with our hands alone lets us feel the shape of the topography and get an intuitive understanding of its form undistorted by perspective and depth perception. Because these models are continuous they could—if sculpted well—accurately represent the topography, but as they lack discrete intervals it is challenging to quantitively judge distances and heights. Because it is so natural and easy to make, but challenging to read quantitatively freeform hand modeling is better suited to ideation than detailed design or presentation.

While hand sculpted models have traditionally been made out of sand or clay, we recommend using polymer enriched sand. Clay holds form well, but can be sticky and hard to work with. Sand while easy to move does not hold a form well—sculpt too steep a slope and it will slump, the grains avalanching down. Polymeric sand is easy to work with and holds together well without sticking to our hands. It is not only easy to sculpt, but also easy to cast into precise forms. We will discuss

Fig. 3.2 Sculpting a polymeric sand model

methods for casting sand in digitally fabricated molds in Sect. 3.3. We use the product DeltaSand, which is also marketed as Kinetic Sand. It is made by mixing sand with a low-viscosity polymer and a cross-linking agent, resulting in a sand with the plasticity, moldability, adhesiveness, and longevity required for sculpting (Modell and Thuresson 2009).

3.2 Digitally Fabricated Models

Complex physical models for Tangible Landscape can be digitally fabricated with CNC routing or 3D printing. Digitally fabricated models are rigid and precise—while they cannot easily be sculpted, they are ideal presentation models, base models for object recognition, and molds for casting malleable models. CNC machines such as laser cutters, routers, and 3D printers require digital instructions, a controller to decode the instructions, and a machining tool. Machining processes include subtraction with routers, addition with 3D printers, and deformation and molding with vacuum formers (Schodek et al. 2004, Chap. 13). In this section we will explain how to prepare GIS data for digital fabrication and discuss various methods of digital fabrication. Section 3.4 describes workflows for creating models using these methods.

3.2.1 Digital Models

Terrain and other continuous, 3D geographic data can be digitally represented as 3D points, 2.5D rasters, 3D rasters, contours, meshes, or surfaces. In GRASS GIS our workflows for landscape modeling and analysis are raster based. 3D printers and CNC routers, however, require vector data, typically meshes. After acquiring elevation data we import them into GRASS GIS and if necessary we interpolate a raster digital elevation model (DEM). This raster will later be used as the reference data for Tangible Landscape. Next, we export the raster as a point cloud and import it into a 3D modeling program to compute a surface, mesh, or solid from the point cloud. Finally, we generate a toolpath from the surface or mesh for the 3D printer or CNC router.

Digital Elevation Models The first step in modeling a landscape is to acquire data. Entire landscapes can be precisely 3D scanned as point clouds with airborne lidar. As pulses of light are emitted from the aircraft they hit and reflect back from vegetation, structures, and topography. When a pulse of light hits a tree part of the light is reflected and recorded as the first return, while the rest penetrates the outer canopy. The residual pulse, recorded as a series of returns, reflects off of leaves, branches, shrubs, and the ground. Lidar data can be used to compute very precise, high resolution models. By filtering lidar returns and classes we can extract points for the bare earth topography and interpolate a raster DEM or we can extract points with all of the structures and vegetation and interpolate a raster digital surface model (DSM). Lidar point clouds or ready to use raster DEMs are available for many locations and are well suited for building topographic models (see Appendix A.2 for links to lidar data and DEM repositories).

DEMs—raster maps of bare earth topography—and DSMs—raster maps of topography with structures and vegetation—are commonly used in GIS to represent and analyze terrain as they can easily be mathematically transformed. For example topographic parameters such as slope, aspect, and curvature can be computed from the partial derivatives of a function approximating a DEM or DSM (see Chap. 4).

Lidar, especially when filtered by classes or returns, can produce scattered, spatially heterogeneous data points that are challenging to accurately interpolate as terrain surfaces. Furthermore, other sources of elevation data such as digitized contours and surveying data can be clustered and have a highly spatially heterogeneous distribution. The regularized spline with tension (RST) interpolation function, implemented as the *v.surf.rst* module in GRASS GIS, can be used to accurately model terrain surfaces from clustered and heterogeneous data such as lidar with some experimentation and tuning (see Sect. 4.1.2).

Contour data are challenging to interpolate because the data are spatially heterogenous—they are often very dense along the contour lines with large unsampled areas in regions with flat topography. If we acquire digital contour data we can either linearly interpolate between contours with *r.surf.contour* or thin the points along contours using *v.generalize*, convert them to a point representation and then interpolate them using a function like RST with the module *v.surf.rst* (The GRASS GIS Community 2015).

Meshes Terrain can also be modeled in 3D vector representations such as polygon meshes or mathematically defined surfaces. In a mesh a vector network of polygons such as triangles or quadrilaterals forms a shape. Terrain meshes are typically triangulated irregular networks (TINs) that connect the data points from which they are computed. Triangulation was used to manually interpolate contours from surveyed spot elevations before the advent of computers. Now TINs are typically computed using the Delaunay triangulation algorithm which maximizes the smallest angle of every triangle in order to minimize the occurrence of very thin triangles. Since TINs connect the data points the input data is preserved. When meshes are low resolution, i.e. computed from small datasets, they reveal their polygonal structure with angled planes where there should be curved surfaces. When meshes are high resolution, i.e. computed from large datasets, they can be very detailed and represent highly complex forms. Even a high resolution mesh, however, is inaccurate when used to represent curved slopes as planar faces. Meshes are very useful for modeling structures and engineered topography with discontinuous slopes.

NURBS Non-uniform rational B-splines (NURBS) are parametric approximation curves and surfaces defined by a series of polynomials. The curves are basis splines defined by a knot vector, weighted control points, and the curve's order or degree (Piegl and Tiller 1995). A NURBS surface is the tensor product of two NURBS curves (Martisek and Prochazkova 2010). Since NURBS surfaces are mathematically defined they can precisely describe a continuous geometry.

Processed lidar data and rasters can be exported as point clouds from GIS and then imported into a 3D modeling program for meshing or surface generation. Toolpaths for CNC routing can be generated for a mesh or NURBS surface once it has been scaled. 3D printing, however, requires closed, solid volumes so the terrain surface should be offset or extruded to give it a thickness. Most 3D printers read the stereolithography (`.stl`) format, a mesh representation of a solid.

We typically use Rhinoceros for 3D modeling[1] with the RhinoTerrain plugin for terrain modeling[2] and the RhinoCAM plugin for CNC routing.[3] This proprietary 3D modeling program is useful for its interoperability—it can write and read a wide range of formats and can model NURBS, polygon meshes, solids, and point clouds. The RhinoTerrain plugin has modules for importing and exporting geographic data and efficiently computing large terrain meshes. While many computer aided manufacturing (CAM) programs require polygon meshes, the RhinoCAM plugin enables us to generate and simulate CNC toolpaths in Rhinoceros using NURBS, polygon meshes, or solids. The Rhino3DPRINT plugin can be used to prepare models for 3D printing.[4] Alternatives include Maya, a proprietary 3D modeling and animation program,[5] or MeshLab, an open source mesh processing program.[6]

[1] Rhinoceros: http://www.rhino3d.com/

[2] RhinoTerrain: http://www.rhinoterrain.com/

[3] RhinoCAM: http://mecsoft.com/rhinocam-software/

[4] Rhino3DPRINT: http://mecsoft.com/rhino3dprint/

[5] Maya: http://www.autodesk.com/products/maya/overview

[6] MeshLab: http://meshlab.sourceforge.net/

Fig. 3.3 A laser cut chipboard contour model with basswood buildings fabricated by David Koontz and Faustine Pastor

3.2.2 Laser Cutting

Laser cutting can be used to efficiently build precise contour models of moderate complexity (Fig. 3.3). Laser cutters are CNC machines that use a laser moving along a gantry in the x and y axes to make 2D cuts. To laser cut a contour model we separate each contour step onto different layers of a 2D vector drawing in a computer aided design (CAD) format (like `.dwg`, `.dxf`, or `.ai`). We cut each contour step out of a sheet of our material of choice and glue them together. We can also laser etch elevation values, patterns, and line work like road outlines and building footprints onto each layer. While it is easy to precisely cut complex topographies it is still challenging to construct them as we have to lay and glue each piece by hand.

The materials determine the cost. As this is a subtractive method a lot of material is wasted. Contour models cut from thick, low-cost materials like cardboard are relatively inexpensive, but have large contour steps and thus low resolution. Models cut from thin, low-cost materials like chipboard allow for small contour steps at

Fig. 3.4 A CNC routed terrain model of the Jockey's Ridge dune complex on the Outer Banks of North Carolina

moderate cost, but tend to warp with time especially if too much glue has been applied. When aesthetics and archivability are important museum board or acrylic can be cut to create presentation-quality laser cut contour models. Paper-based media such as chipboard or museum board are not suitable for casting polymeric sand as the polymer will stick and soak into them.

3.2.3 CNC Routing

CNC routing or milling is a subtractive fabrication process that can be used to precisely manufacture contour models and surface models of great complexity (Fig. 3.4). This type of digital fabrication is a precise, accurate, inexpensive, and scalable way to build terrain models. Three-axis CNC routers and milling machines move a spindle with a machining bit along the x, y, and z axes in a programmed path to carve a shape out of a block of material (Fig. 3.5). Because 3-axis routers can only carve vertically they produce 2.5D surface models on a solid base, rather than full 3D volumetric models. It is possible, however, to manufacture fully 3D volumes with 3-axis routers; after each cut one can reorient the model and then route the sides or bottom of the model (Schodek et al. 2004, Chap. 14).

To CNC route a terrain model we first prepare a solid block of our material. We can use materials such as medium to high density foam, wax, and wood

Fig. 3.5 A 3-axis CNC router carving a terrain model

Fig. 3.6 Prepare MDF for CNC routing: (**a**) pour glue onto a layer of MDF, (**b**) spread glue evenly over a layer of MDF, (**c**) stack layers of MDF, (**d**) clamp the stack of MDF, (**e**) add a weight on top of the stack of MDF, and (**f**) wait for the glue to dry

products. We typically use medium density fiberboard (MDF) or baltic birch, engineered wood products with high strength, good dimensional stability, and a fine, uniform grain with minimal voids. To prepare MDF we cut the sheet into tiles that match the desired extent of our scale model, spread wood glue evenly over each tile and stack the tiles together, and firmly clamp the stack of tiles together until the glue sets (Fig. 3.6).

In a CAD program we prepare a digital model of the geometry we wish to carve. Then we generate a toolpath for this digital model in a CAM program. To make a

Table 3.1 CNC settings: horizontal rough cut with MDF

Bit ∅	Speed	Plunge	Approach	Engage	Cut	Retract	Depart.	Step down	Stepover
0.5 in.	16,000	65	135	205	275	800	800	0.32 in.	48 %
0.25 in.	16,000	50	75	125	175	800	800	0.25 in.	40 %

Table 3.2 CNC settings: parallel finish cut with MDF

Bit ∅	Speed	Plunge	Approach	Engage	Cut	Retract	Departure	Stepover
0.5 in.	16,000	65	160	230	325	800	800	20 %
0.25 in.	16,000	50	100	150	225	800	800	20 %

contour model we use closed, 3D contour curves as our data and then carve with a contour cut. Contour cutting can also be used to carve buildings. To carve a surface model from a mesh or NURBS surface we use parallel cuts. For a surface model we typically start with a horizontal rough cut with a 0.5 in. diameter, carbide bit to remove the bulk of the excess material (Table 3.1). Then we use a parallel finish cut with a 0.25 in. diameter, carbide, ball-nose bit to carve the terrain as a continuous surface (Table 3.2). If we need a more refined presentation-quality model we then make two more parallel finish cuts in alternative cutting directions with a 0.125 in. diameter, carbide, ball-nose bit to smooth the surface and capture more detail. Finally a contour cut along the border can be used to neatly trim and remove the model from the base material. The toolpath is written as a sequence of instructions in a CNC programming language often as a `.nc` file in G-Code. The CNC machine's controller reads this code and drives the tool along the toolpath carving our model. We have a streamlined workflow using Rhinoceros with the RhinoCAM plugin for both 3D modeling and the generation, simulation, and visualization of toolpaths. We do our CAD and CAM in the same environment—Rhinoceros—so that we can easily edit our models and work with both meshes and NURBS.

Once the model has been routed we may want to finish it by sanding, priming, and painting the model. Sanding the model, a prerequisite for priming and painting, with a fine grit sandpaper produces a smoother surface. After routing and sanding we clean the model with an air hose. Applying several coats of magnetic primer to our model weakly magnetizes it so that magnetized markers stick to the slopes (Fig. 3.7). A magnetized model is useful for Tangible Landscape applications relying on object recognition rather than sculpting. Finally we may want to spray paint our model white to enhance the brightness of projected imagery (Fig. 3.8).

3.2.4 3D Printing

With 3D printing, a type of solid freeform fabrication, we can make a complex, 3D volume in a single run. While the models can be precise, accurate, and highly complex, they are also expensive and small as 3D printers have restrictively small

Fig. 3.7 A marker with a magnetic base sticking to a CNC-routed terrain model primed with magnetic paint

Fig. 3.8 Modes of interaction using markers: (**a**) rasterizing an area and (**b**) drawing a polygon

build areas and the materials are relatively expensive. 3D printing is an ideal process for fabricating small, complex models such as buildings or small, high quality presentation models for use with Tangible Landscape (Fig. 3.9a).

While CNC milling and routing are subtractive processes, 3D printing is an additive process in which a model is built up layer by layer. A digital, 3D, solid model is divided into a stack of horizontal layers or slices and a toolpath is computed for each slice. The physical model is then built slice by slice by depositing or hardening material along the toolpath. By dividing the model into cross sections, each as thin as the technology allows, a complex volume can be formed. There are a variety of different 3D printing processes including stereolithography, selective laser sintering, fused deposition modeling, and 3D ink-jet printing each with tradeoffs in build speed, quality, strength, cost, resolution, color, and material (Schodek et al. 2004, Chap. 14).

Fig. 3.9 Casting polymeric sand from 3D printed molds. (**a**) 3D prints of the terrain and canopy. (**b**) Casting sand with 3D prints. (**c**) The canopy cast in sand

3.3 Molding and Casting

To sculpt with Tangible Landscape we need a malleable model made of a soft, deformable medium. A model made of polymer enriched sand is easy to sculpt, holds its form well, and can be cast into precise forms. CNC routed and 3D printed models can be used as molds for casting polymeric sand into malleable models.

Fig. 3.10 Cast polymeric sand from CNC routed molds. (**a**) Pour polymeric sand onto the base. (**b**) Stack the inverse model on top of the sand. (**c**) Apply pressure. (**d**) Check the cast and remold if necessary. (**e**) Trim the excess sand. (**f**) Remove the inverse model

Fig. 3.11 A thermoformed polystyrene model of Lake Raleigh Woods

The mold should be the inverse of the surface that will be cast. Cast models can precisely represent complex forms that are too challenging to model by hand and can easily be recast.

To cast a terrain model either CNC route the inverse of the terrain (Fig. 3.10) or 3D print the terrain as a volume extruded with enough thickness to survive the casting process (Fig. 3.9). We press the mold into the polymeric sand to cast the form. We have to check the cast and repeat the process if necessary—sand may need to be added or removed in places to get a good cast. Clamps can be used to get strong, even pressure on a CNC routed mold when casting.

Thermoforming or vacuuming forming can be used to quickly make lightweight copies or imprints of a CNC routed terrain model in a thermoplastic. Since they are lightweight thermoformed models are very portable and are ideal for casting polymeric sand while traveling (Fig. 3.11). To thermoform a terrain model we heat a thermoplastic sheet in a vacuum former until it becomes soft. Use the vacuum to pull the hot plastic over a mold deforming the plastic into the desired shape. Once

the plastic cools into the cast shape we release the vacuum. We may need to drill small holes through our mold to make a complete vacuum (Schodek et al. 2004, Chap. 14).

3.4 Workflows

This section describes workflows for creating physical models for Tangible Landscape. Our examples use lidar point cloud data for Lake Raleigh Woods on North Carolina State University's (NCSU) Centennial Campus acquired during a 2013 lidar survey by Wake County. The data are provided as a single tile in the standard LAS format (`tile_0793_015_spm.las`). We processed this data within a GRASS GIS data set `nc_spm_tl`. All examples in the following subsections assume running GRASS GIS with this data set; see Appendix A.3 for information on how to download the data, start GRASS GIS with this location data set, and perform basic display and other operations (Fig. 3.12).

3.4.1 Selecting a 3D Model Scale

The scale of the physical 3D model depends on the extent of the data, the desired model size, and the desired scale. The scale may also depend on the material of the model, the scanning technology, and the resolution of the data. Here we assume that we know the spatial extent of our data and want our model to be approximately half a meter long on each side. If we do not already know the extent of our data we can determine the values once the data has been imported into GRASS GIS for example using *v.info* or *r.info*.

We can perform this computation in the Python interactive console. First, we enter the spatial extent of the data and approximate the size of the model (in meters):

Fig. 3.12 3D renderings of terrain models derived from lidar tile 0793_015 using (**a**) GRASS GIS and (**b**) Rhinoceros with the RhinoTerrain plugin (see Sect. 3.4.4)

```
n = 224028.45
s = 223266.45
e = 639319.28
w = 638557.28
desired_model_x = 0.50
```

Then we compute the scale using the equation:

$$s = \frac{d_m}{d_r} \tag{3.1}$$

where s is the scale of the model, d_m is the distance measured on the model, and d_r is the real-world distance. For convenience we can also compute the scale number using the equation:

$$s_n = \frac{1}{s} \tag{3.2}$$

where s_n is the scale number of the model and s is the scale of the model.

We then type the following in the Python console:

```
scale = desired_model_x / (n - s)
scale_number = 1. / scale
```

The scale is now 1:1524 and the scale number is 1524. Since we want the scale to be a round number and do not want to add or remove data we need to modify the scale and reverse the computation in the previous step so that we can compute the new size of the model at the selected scale. We select a scale of 1:1500 (a round value close to the previously computed scale). In Python we then write:

```
scale_number = 1500
scale = 1. / scale_number
model_x = (n - s) * scale
```

The resulting model size is 50.8 cm.

So far we have only used the spatial extent along the north-south direction. We skipped the east-west direction because the extent of both the data and the model were squares. In a region with an elongated rectangular shape we might need to determine a suitable scale for each of the horizontal directions and then decide on a compromise.

Next we determine the vertical size of the model and its vertical exaggeration. First, we enter the minimum and maximum elevation in the dataset (called top and bottom in GRASS GIS) and we also include the desired height of the model (in meters). In our example we set the desired height of the model to 0.04 m:

```
t = 109.33
b = 76.54
desired_model_h = 0.04
```

Then we compute the model height without vertical exaggeration and the exaggeration based on the desired model height using the equation:

$$e = \frac{h_e}{h} \tag{3.3}$$

where e is the exaggeration, h_e is the exaggerated height (in our case the desired height of the model) and h is the height of the model according to the scale in case the model would not be exaggerated.

Since we already know the scale of the model from the previous computations we can now compute the exaggeration and model height without vertical exaggeration:

```
model_h = scale * (t - b)
exaggeration = desired_model_h / model_h
```

With the given the inputs the exaggeration is now approximately 1.8. Since we want a round number we set the vertical exaggeration to 2 and compute the actual height of the model using Eq. (3.3):

```
exaggeration = 2
actual_model_h = exaggeration * model_h
```

With the exaggeration set to 2 the model height (or more precisely the maximum height difference of the top surface of the model) will be approximately 4.4 cm. The base of the model will increase the actual model height. Depending on how it is constructed the base may or may not be an integral part of the model. If we set the exaggeration to 1.5 the model height difference would be approximately 3.3 cm, which might be too shallow. At a different scale, however, an exaggeration of 1.5 might be the right choice.

We have used the same scale in both the x and y horizontal directions (1:1500). However, in the vertical direction (z) we exaggerated the scale by a factor of 2. As a result the vertical scale (1:750) is different than horizontal scale (1:1500). Depending on the audience it may be advantageous to note either the horizontal and vertical scales or the scale and exaggeration. When the scale and exaggeration are known the vertical scale can be computed using the equation:

$$s_v = se \tag{3.4}$$

where s_v is the vertical scale, s is the horizontal scale and e is the exaggeration. Once we have computed the size of our model we can build the model using any of the methods described in the following sections.

3.4.2 Sculpting a Malleable Model from Data

A simple way to create a malleable 3D model is to sculpt the landscape in polymer-enriched sand using projected contours derived from DEM as a guide.

In this workflow we used a point cloud of elevation data in the LAS format (`tile_0793_015_spm.las`) and worked in the GRASS GIS location `nc_spm_tl`. To sculpt a malleable model from lidar data perform the following steps:

Import the lidar points classified as ground (standard class 2) into GRASS GIS using the module *v.in.lidar*:

```
v.in.lidar -t input=tile_0793_015_spm.las output=ground \
    class_filter=2
```

Set the region to the spatial extent of the imported tile and resolution to 1 m. Then interpolate the DEM from the processed lidar data:

```
g.region vector=ground res=1
v.surf.rst -t input=ground elevation=dem tension=100 npmin=250 \
    dmin=2
```

Check the results, adjust the parameters, and rerun with the overwrite flag if necessary. Then compute the 1 m interval contours from the DEM:

```
r.contour input=dem output=contours_1m step=1
```

We can now sculpt the terrain in polymer-enriched sand using the projected DEM and contours as a guide (Fig. 3.2). Once we have made at least a rough approximation of the form, we can use DEM differencing to critique and refine the modeled form (see Sect. 4.2.2).

3.4.3 CNC Routing a Topographic Model from Contour Data

Import the contours provided in the file `contours.dxf` into Rhinoceros:

```
_Import contours.dxf _Enter
```

Zoom to the extent of all viewports:

```
Zoom All Extents
```

Select the contours and interpolate a terrain mesh:

```
_RtMeshTerrainCreate _Accept _Enter
```

Scale the model uniformly in the x, y, z direction to our chosen map scale by selecting the mesh, setting the origin to 0,0,0 and setting the scale factor:

```
_Scale 0,0,0 1/450 _Enter
```

Optionally scale the model in the z-direction to exaggerate the relief by selecting the mesh, setting the origin to 0,0,0, setting the scale factor to 2, and setting the scale direction by drawing a line in the z-axis with ortho mode, using the gumball, or entering the coordinates 0,0,0 and 0,0,1:

```
_Scale1D 0,0,0 2 0,0,0 0,0,1 _Enter
```

Use RhinoCAM to generate the toolpath. Then CNC route the model.

3.4.4 CNC Routing Topographic and Surface Models from Lidar Data

Import the lidar data classified as ground (standard class 2) into GRASS GIS:

```
v.in.lidar -t input=tile_0793_015_spm.las output=ground \
    class_filter=2
```

Import the first return lidar data into GRASS GIS filtering unnecessary points:

```
v.in.lidar -t input=tile_0793_015_spm.las output=surface \
    return_filter=first class_filter=1,2,3,4,5,6,9
```

Set the region and resolution and interpolate the DEM from the ground points:

```
g.region vector=ground res=1
v.surf.rst -t input=ground elevation=dem tension=100 npmin=250 \
    dmin=2
```

Check the results, adjust the parameters, and rerun with the overwrite flag if necessary. With the region already set in the previous step, interpolate the DSM from the surface points:

```
v.surf.rst -t input=surface elevation=dsm tension=200 \
    smooth=0.5 npmin=120 dmin=2
```

Check the results, adjust the parameters, and rerun with the overwrite flag if necessary. Export the DEM to a space delimited text file with x, y, and z values:

```
r.out.xyz input=dem output=dem.xyz separator=space
```

Export the DSM to a space delimited text file with x, y, and z values:

```
r.out.xyz input=dsm output=dsm.xyz separator=space
```

Import the DEM text file into Rhinoceros as a point cloud. In the import options, set delimiter to ‘space’ and check ‘create point cloud’:

```
_Import dem.xyz
```

Import the DSM text file as a point cloud. In the import options, set delimiter to ‘space’ and check ‘create point cloud’:

```
_Import dsm.xyz
```

Zoom to the extent of all viewports:

```
Zoom All Extents
```

Select the DEM point cloud, interpolate a terrain mesh, and delete or hide the point cloud:

```
_RtMeshTerrainCreate _Accept _Enter
```

Select the DSM point cloud and interpolate a terrain mesh. Delete or hide the point cloud:

```
_RtMeshTerrainCreate _Accept _Enter
```

Scale both the DEM and DSM meshes uniformly in the x, y, z direction to our chosen map scale by selecting the meshes, setting the origin to 0,0,0 and setting the scale factor:

```
_Scale 0,0,0 1/1500 _Enter
```

Optionally scale both the DEM and DSM meshes in the z-direction to exaggerate the relief by selecting the meshes, setting the origin to 0,0,0, setting the scale factor to 2, and setting the scale direction by drawing a line in the z-axis with ortho mode, using the gumball, or entering the coordinates 0,0,0 and 0,0,1:

```
_Scale1D 0,0,0 2 0,0,0 0,0,1 _Enter
```

Optionally, create a vector curve delineating the border of the DEM or DSM:

```
_RtMeshFindBorder _Enter
```

Use RhinoCAM to generate the toolpaths. CNC route the models.

3.4.5 3D Printing Topographic and Surface Models from Lidar Data

Import the lidar data classified as ground (standard class 2) into GRASS GIS:

```
v.in.lidar -t input=tile_0793_015_spm.las output=ground \
    class_filter=2
```

Set the region to the given tile and set a relatively low resolution of 10 m. Interpolate the DEM from the ground points:

```
g.region vector=ground res=10
v.surf.rst -t input=ground elevation=dem tension=100 npmin=250
```

Export the DEM to a space delimited text file with x, y, z values:

```
r.out.xyz input=dem output=dem.xyz separator=space
```

Import the DEM text file into Rhinoceros as a point cloud. In the import options, set delimiter to ‘space’ and check ‘create point cloud’:

```
_Import dem.xyz _Enter
```

Zoom to the extent of all viewports:

```
Zoom All Extents _Enter
```

Select the DEM point cloud and interpolate a terrain mesh. Delete or hide the point cloud:

```
_RtMeshTerrainCreate _Accept _Enter
```

Scale the mesh uniformly in the x, y, z direction to our chosen map scale by selecting the mesh, setting the origin to 0,0,0 and setting the scale factor:

```
_Scale 0,0,0 1/3000 _Enter
```

Optionally scale the mesh in the z-direction to exaggerate the relief by selecting the mesh, setting the origin to 0,0,0, setting the scale factor to 2, and setting the scale direction by drawing a line in the z-axis with ortho mode, using the gumball, or entering the coordinates 0,0,0 and 0,0,1:

```
_Scale1D 0,0,0 2 0,0,0 0,0,1 _Enter
```

Create a vector curve delineating the border of the DEM:

```
_RtMeshFindBorder _Enter
```

Prepare the mesh for 3D printing. Select the border curve as the boundary and the DEM mesh as the mesh. Set offset to relative or absolute. Set a base height:

```
_RtMesh3dPrintPrepare
```

Export the selected mesh as a stereolithography file (`.stl`) and send it to the 3D printer:

```
_SaveAs
```

3.4.6 Casting a Malleable Topographic Model with a CNC Routed Mold Derived from Lidar Data

Import the lidar data classified as ground (standard class 2) into GRASS GIS:

```
v.in.lidar -t input=tile_0793_015_spm.las output=ground \
    class_filter=2
```

Set the region and resolution, then interpolate the DEM from the ground points:

```
g.region vector=ground res=1
v.surf.rst -t input=ground elevation=dem tension=100 npmin=250 \
    dmin=2
```

Check the results, adjust the parameters, and rerun with the overwrite flag if necessary. Export the DEM to a space delimited text file with x, y, z values:

```
r.out.xyz input=dem output=dem.xyz separator=space
```

Import the DEM text file into Rhinoceros as a point cloud. In the import options, set delimiter to 'space' and check 'create point cloud':

```
_Import dem.xyz _Enter
```

Zoom to the extent of all viewports:

```
Zoom All Extents _Enter
```

Select the DEM point cloud and interpolate a terrain mesh. Delete or hide the point cloud:

```
_RtMeshTerrainCreate _Accept _Enter
```

Optionally, create a vector curve delineating the border of the DEM:

```
_RtMeshFindBorder _Enter
```

Invert the DEM by rotating it 180° on the z axis. Set the 'first reference point' by drawing a vertical line with ortho mode on and then set the 'second reference point' to '180' or by or entering the coordinates 0,0,0 and 0,0,1 and then 180 in the command line:

```
_Rotate 0,0,0 0,0,1 180 _Enter
```

Scale the mesh uniformly in the x, y, z direction to our chosen map scale by selecting the mesh, setting the origin to 0,0,0 and setting the scale factor:

```
_Scale 0,0,0 1/1500 _Enter
```

Optionally scale the mesh in the z-direction to exaggerate the relief by selecting the mesh, setting the origin to 0,0,0, setting the scale factor to 2, and setting the scale direction by drawing a line in the z-axis with ortho mode, using the gumball, or entering the coordinates 0,0,0 and 0,0,1:

```
_Scale1D 0,0,0 2 0,0,0 0,0,1 _Enter
```

Optionally, create a vector curve delineating the border of the DEM or DSM:

```
_RtMeshFindBorder _Enter
```

Use RhinoCAM to generate the toolpath, CNC route the inverted terrain model, and use this routed model as a mold to cast polymeric sand into a solid, malleable model of the topography.

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Chapter 4
Basic Landscape Analysis

Tangible Landscape allows us to explore the spatial patterns of topographic parameters and their relation to basic surface geometry. We can easily sculpt a physical model of a landscape with our hands changing its topography. With Tangible Landscape we can analyze the topography of a landscape model and how it changes by continually 3D scanning the model and computing DEMs from the scanned point clouds using binning or interpolation. By computing basic topographic parameters, morphometric units, and DEM differencing we can map changes in elevation, slope, and landform as the model is modified. These maps are then projected over the physical model of the landscape so that we have near real-time feedback and can understand the impact of the changes we are making as we make them.

4.1 Processing and Analyzing the Scanned DEM

To start working with Tangible Landscape, the setup is first calibrated using a flat surface, typically a table, to minimize the scanning distortion (see Sect. 2.2.4). After successful calibration the model can be scanned continuously. With each scan the edges of the model are detected and georeferenced and the point cloud is converted into a DEM via binning or interpolation. Standard GRASS GIS modules are then used to compute maps of topographic parameters or landforms that are then projected over the model. This chapter explains how the DEM is derived and demonstrates the results in a case study.

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4.1.1 Creating DEM from Point Cloud

There are two ways to derive a raster DEM from a set of points in Tangible Landscape:

Binning A cell value is assigned based on the univariate statistics of the points that fall inside the particular cell. When constructing a DEM the mean of the z coordinates is typically used. Binning is fast, but creates a rough surface so it is only useful for certain types of analyses.

Interpolation Cell values are estimated from available point data using a selected mathematical or statistical interpolation technique.

4.1.2 Interpolation with the RST Function

The point clouds produced by the scanning process are usually noisy. The regularized spline with tension (RST) function, implemented as the *v.surf.rst* module in GRASS GIS, can be used to interpolate smooth DEMs from noisy point data and simultaneously compute topographic parameters such as slope and curvature. RST approximates a surface from data points by minimizing a smoothness seminorm and the deviations between the given points and the resulting surface (Mitasova et al. 2005). The RST smoothness seminorm includes derivatives of all orders with their weights decreasing with the increasing derivative order leading to the function:

$$z(\mathbf{r}) = a_1 + \sum_{j=1}^{N} \lambda_j R(\varrho_j) \tag{4.1}$$

$$R(\varrho_j) = -[E_1(\varrho_j) + \ln(\varrho_j) + C_E] \tag{4.2}$$

where $z(\mathbf{r})$ is the elevation at a point $\mathbf{r} = (x, y)$, a_1 is a trend, λ_j are coefficients, N is a number of given points, $R(\varrho_j)$ is a radial basis function, $\varrho_j = (\varphi r_j/2)^2$, φ is a generalized tension parameter, $r_j = |\mathbf{r} - \mathbf{r}_j|$ is a distance, $C_E = 0.577215$ is the Euler constant, and $E_1(\varrho_j)$ is the exponential integral function (Abramowitz and Stegun 1965; Mitasova and Mitas 1993). The coefficients a_1, $\{\lambda_j\}$ are obtained by solving the system of linear equations:

$$\sum_{j=1}^{N} \lambda_j = 0 \tag{4.3}$$

$$a_1 + \sum_{j=1}^{N} \lambda_j \left[R(\varrho_j) + \delta \frac{w_0}{w_j} \right] = z(\mathbf{r}_i), \qquad i = 1, \ldots, N \tag{4.4}$$

where w_0/w_j are positive weighting factors representing a smoothing parameter at each given point $\mathbf{r_j} = (x_j, y_j)$.

Tension influences the detail of the surface and smoothing influences the deviations between the given points and the resulting surface. A higher smoothing value can be used to reduce the noise in the data. Because this is a global operation acting on the entire dataset it can be processing intensive for large datasets so the *v.surf.rst* implementation uses a quadtree segmentation algorithm with smooth overlaps to separately process overlapping neighborhoods of points. A quadtree is a tree data structure that recursively partitions processing regions into smaller processing regions by dividing them into quadrants. Depending on the distribution of the input points in relation to the surface complexity, interpolation with *v.surf.rst* may require experimental, iterative tuning of the parameters. By adjusting the parameters which control the RST function properties and distribution of points used for interpolation, this function can be used to accurately model smooth or rough topography (Mitasova and Mitas 1993; Mitasova et al. 2005).

4.1.3 Analyzing the DEM

The geometry of an elevation surface at any point can be described by topographic parameters—slope, aspect, and several types of curvatures (Mitasova et al. 2005; Olaya 2009). Elevation surface can be partitioned into units with specific geometric properties; one approach to defining these units is geomorphons.

Basic Topographic Parameters The steepest slope angle β in degrees or percent and the aspect angle α in degrees are the most commonly used topographic parameters topographic parameters (Fig. 4.2). They represent the magnitude and direction of the surface gradient vector $\nabla z = (f_x, f_y)$ (its direction is upslope) and are computed as follows:

$$\beta = \arctan\sqrt{f_x^2 + f_y^2} \qquad \beta[\%] = 100\sqrt{f_x^2 + f_y^2} \tag{4.5}$$

$$\alpha = \arctan -\frac{f_y}{f_x} \tag{4.6}$$

where $f_x = \partial z/\partial x$ and $f_y = \partial z/\partial y$ are the first order partial derivatives of elevation surface function $z = f(x, y)$. The slope values range from 0° to 90° and the aspect values range from 0° to 360°. Therefore, computing the correct angle for aspect requires the evaluation of all possible combinations of negative, positive and zero values of f_x, f_y in relation to the selected direction of 0° (usually east or north).

For applications in geosciences the curvature in the gradient direction (profile curvature) is important because it reflects the change in the slope angle and thus controls the change of the velocity of mass flowing downwards along the slope curve. The equation for the profile curvature is

$$\kappa_s = \frac{f_{xx}f_x^2 + 2f_{xy}f_xf_y + f_{yy}f_y^2}{p\sqrt{q^3}} \tag{4.7}$$

where κ_s is the profile curvature in m^{-1} and f_{xx}, f_{xy}, f_{yy} are the second order partial derivatives of the elevation surface function $z = f(x, y)$, $p = f_x^2 + f_y^2$ and $q = p + 1$. The curvature in a direction perpendicular to the gradient (tangential curvature) reflects the change in the aspect angle and influences the divergence/convergence of water flow. The equation for tangential curvature at a given point is

$$\kappa_t = \frac{f_{xx}f_y^2 - 2f_{xy}f_xf_y + f_{yy}f_x^2}{p\sqrt{q}} \tag{4.8}$$

where κ_t is the tangential curvature in m^{-1}. Partial derivatives can be computed from a suitable approximation function $z = f(x, y)$ such as local second order polynomial or certain types of splines.

Partial Derivatives from a Raster DEM We can use a second order polynomial approximation of a surface defined by a given grid point and its 3×3 neighborhood to estimate the topographic parameters (Horn 1981):

$$z(x, y) = a_0 + a_1x + a_2y + a_3xy + a_4x^2 + a_5y^2 \tag{4.9}$$

By fitting this polynomial to the nine grid points (the given point $z_{i,j}$ and its 3×3 neighborhood as shown below in Fig. 4.1) using weighted least squares we can derive the coefficients of this polynomial as well as its partial derivatives ($f_x = a_1, f_y = a_2, f_{xx} = 2a_4, f_{yy} = 2a_5, f_{xy} = a_3$):

$$f_x = \frac{(z_{i-1,j-1} - z_{i+1,j-1}) + 2(z_{i-1,j} - z_{i+1,j}) + (z_{i-1,j+1} - z_{i+1,j+1})}{8\Delta x} \tag{4.10}$$

$z_{i-1,j+1}$	$z_{i,j+1}$	$z_{i+1,j+1}$
$z_{i-1,j}$	$z_{i,j}$	$z_{i+1,j}$
$z_{i-1,j-1}$	$z_{i,j-1}$	$z_{i+1,j-1}$

Fig. 4.1 The elevation values of a grid cell and its 3×3 neighborhood

$$f_y = \frac{(z_{i-1,j-1} - z_{i-1,j+1}) + 2(z_{i,j-1} - z_{i,j+1}) + (z_{i+1,j-1} - z_{i+1,j+1})}{8\Delta y} \tag{4.11}$$

where Δx and Δy is the resolution (grid spacing) in the east-west and north-south directions respectively. To compute the second order partial derivatives we first denote $D(i,\delta) = z_{i,j+1} + z_{i,j-1} - 2z_{i,j}$ and $D(\delta,j) = z_{i+1,j} + z_{i-1,j} - 2z_{i,j}$. Then we can write:

$$f_{xx} = \frac{D(\delta,j+1) + (4z_{i-1,j} + 4z_{i+1,j} - 8z_{i,j}) + D(\delta,j-1)}{6(\Delta x)^2} \tag{4.12}$$

$$f_{yy} = \frac{D(i-1,\delta) + 4(z_{i,j+1} + z_{i,j-1} - 2z_{i,j}) + D(i+1,\delta)}{6(\Delta y)^2} \tag{4.13}$$

$$f_{xy} = \frac{(z_{i-1,j-1} - z_{i+1,j-1}) - (z_{i-1,j+1} - z_{i+1,j+1})}{4\Delta x\Delta y} \tag{4.14}$$

where $z_{i,j}$ is the elevation value at row j and column i, Δx is the east-west grid spacing, and Δy is the north-south grid spacing (resolution).

Landforms Landforms can be identified automatically by fitting a quadratic function to the elevation values in a given neighborhood or 'moving window' using least squares. This method for identifying landforms using differential geometry is implemented in GRASS GIS as a module *r.param.scale* (Fig. 4.3). While real-world landforms are scale-dependent and may be nested, this method can only identify landforms at a single scale based on the size of the moving window.

Fig. 4.2 Slope (**a**) and aspect (**b**) maps in degrees draped over a DEM

Fig. 4.3 Profile (**a**) and tangential (**b**) curvature maps draped over a DEM

Fig. 4.4 Landforms identified by geomorphons (see *r.geomorphon* manual page for explanation of landform types)

Fig. 4.5 Geomorphons: local ternary patterns and line-of-sights concepts applied to landform identification. The relationship between a cell and its neighbors in terms of relative elevation (higher than, equal to, or lower than) is expressed as a ternary pattern (**a**). Ternary patterns are derived using the line-of-sight method and comparing the zenith angle Φ and nadir angle Ψ (**b**)

Geomorphons—geomorphologic phonotypes—is a novel method for identifying landforms using pattern recognition developed by Jasiewicz and Stepinski (2013) and implemented in GRASS GIS as the add-on module *r.geomorphon* (Fig. 4.4). A geomorphon is an abstract unit of terrain described by the local ternary pattern rather than by relief. The relationship between a cell and its neighborhood is described using an 8-tuple pattern of lower (−), equal (0), higher (+) elevation values (Fig. 4.5a). Neighborhoods are based on visibility rather than the predefined dimensions of a moving window. Geomorphons uses the line-of-sight principle to dynamically determine the optimal size of the search radius for a neighborhood based on openness of the terrain (see Fig. 4.5b). Thus, unlike methods based on differential geometry, the geomorphons approach is able to efficiently classify landforms across a range of spatial scales (Jasiewicz and Stepinski 2013).

4.2 Case Study: Topographic Analysis of Graded Landscape

In this section we demonstrate how changes in elevation impact topographic parameters and landforms in a small study area on NCSU's Centennial Campus.

4.2.1 Site Description and Model

Our 56 ha case study area is located on NCSU's Centennial Campus on the southwest side of Lake Raleigh (Fig. 4.6). The topography is largely natural, but there are some anthropogenic features, such as informal trails and the Chancellor's house with its access road, parking, and retention pond. There is rapid development on the campus; several new buildings are currently under construction. At the same time there is a desire to preserve part of the campus as a park and a natural teaching area. In this case study we developed part of the natural area as student housing and constructed an access road. Since significant grading would be required to develop the site given the steep slopes we extensively modified the topography and mapped the change in elevation (cut and fill), slope, aspect, curvature, and landform.

We CNC routed the base and mold for the model from MDF based on a DEM derived from a 2013 lidar survey. We used the base and the mold to cast a sculptable sand model. Each side of the 1:1500 scale model is 50 cm and represents 750 m. The model is two times vertically exaggerated and has 44 mm of relief which represent 33 m of elevation change.

Fig. 4.6 Lake Raleigh Woods with our study site highlighted

We sculpted the sand model to grade a road and building sites. With Tangible Landscape we were able to analyze these modifications and understand how we had changed the slope, aspect, shape, and volume of the landscape.

4.2.2 Basic Workflow with DEM Differencing

To explore the impact of the new development we graded building sites and a road for the future neighborhood. We start with the original molded sand model, scan it and save the scan under different name so that it is not overwritten by the next scan. Then we compute and display 1 m countours:

```
g.rename raster=scan,scan_before
g.region raster=scan_before
r.contours input=scan_before output=contours_1m step=1
```

Figure 4.7a shows the terrain conditions before grading. While sculpting the model, we can pause the continuous scanning or keep it running to get ongoing feedback on our design as we progress.

We can visualize the magnitude and extent of our changes by differencing the scanned elevation before and after the change and then assigning a diverging color scheme to helps us distinguish between cut and fill (Fig. 4.7d):

Fig. 4.7 Basic workflow: (**a**) the scanned elevation with contours, a *red curve* indicates the planned road; (**b**) modifying the terrain; (**c**) the finished design; (**d**) and the difference in meters between the elevation before and after grading, *red* representing soil removal (cut) and *blue* representing soil deposition (fill)

```
g.rename raster=scan,scan_after
r.mapcalc "diff = scan_after - scan_before"
r.colors -n map=diff color=differences
```

Because the scans are noisy, they do not align precisely in vertical direction. When computing difference between scans, any vertical shift is undesirable and should be minimized. The following workflow uses linear regression to match one scan to the other on the assumption that there has only been a moderate change in elevation. The linear regression of the form $y = a + bx$ estimates the vertical shift a and scale coefficient b (which should be close to 1) for adjusting the scan. Here we define a function in Python for adjusting the scan to match the other; we will refer to this function throughout the book:

```
def adjust_scan(scan_before, scan_after, scan_adjusted):
   coeff = gscript.parse_command('r.regression.line',
       mapx=scan_after, mapy=scan_before, flags='g')
   gscript.mapcalc("{scan_adjusted} = {a} + {b} *
       {scan_after}".format(scan_adjusted=scan_adjusted,
       a=coeff['a'], b=coeff['b'], scan_after=scan_after))
```

Here we use the function for adjusting scans to compute the difference:

```
adjust_scan('scan_before', 'scan_after', 'scan_adjusted')
gscript.mapcalc("diff = scan_adjusted - scan_before")
gscript.run_command('r.colors', flags='n', map='diff',
    color='differences')
```

4.2.3 The Impact of Model Changes on Topographic Parameters

In our case study the new neighborhood is planned on an east-facing hillside with a gentle slope of about 5° (Fig. 4.8). The slope values are steep on two sides of the hillside where it changes into parallel valleys; the profile curvature increases at the edge of the valleys (Fig. 4.9). The profile curvature on the hillside varies between positive and negative values denoting convex (ridges) and concave shapes (valleys).

We computed the slope and aspect using the *r.slope.aspect* module based on the standard polynomial approximation using 3×3 window, see Eqs. (4.9)–(4.14). When computing curvature, we use a more flexible method with a larger window (21×21 grid cells) to capture the larger scale morphology associated with the main valleys and ridges at our study site. This method is implemented in the module *r.param.scale* and we used this module to compute profile and tangential curvature. To visualize the variability in the curvature values we used a dedicated color ramp with divergent scheme:

Fig. 4.8 Slope (**a**, **b**) and aspect (**c**, **d**) in degrees computed from the scanned model before (**a**, **c**) and after (**b**, **d**) modification

Fig. 4.9 Profile (**a**, **b**) and tangential (**c**, **d**) curvature computed from the scanned model before (**a**, **c**) and after (**b**, **d**) modification

```
r.slope.aspect elevation=scan aspect=scan_aspect \
    slope=scan_slope
r.param.scale input=scan output=scan_pcurv size=21 method=longc
r.param.scale input=scan output=scan_tcurv size=21 method=crosc
r.colors map=scan_pcurv color=curvature
r.colors map=scan_tcurv color=curvature
```

To build a new road with gentle slopes we constructed a series of switchbacks with low areas raised on embankments. As a result there are steep slopes beside the road on the faces of the embankments (Fig. 4.8). We also flattened parts of the hillside as building sites. When we analyzed the curvature of the modified landscape the flat roads were mapped as concave areas with high curvature due to the larger neighborhood size used in the analysis (Fig. 4.9).

4.2.4 Changing Landforms

The new development would change the landforms creating new ridges and valleys. We explored these changes by running the *r.geomorphon* add-on module which can be installed using *g.extension*. We can tune the results with parameters such as *search* and *skip* that determine the appropriate scale of analysis. By increasing these parameters we can skip small terrain variations in order to capture larger landforms:

```
g.extension r.geomorphon
r.geomorphon dem=elevation forms=landforms search=16 skip=6
```

In the resulting landform classification the new road has formed a major ridge (Fig. 4.10).

Fig. 4.10 Landform classification: (**a**) before development, (**b**) after development with the new elevated road classified as a ridge, (**c**) legend and (**d**) a detailed view of the modification done in Fig. 4.7

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Chapter 5
Surface Water Flow and Soil Erosion Modeling

The topography of the Earth's surface controls the flow of water and mass over the landscape. Modifications to the surface geometry of the land redirect water and mass flows influencing ecosystems, crop growth, the built environment, and many other phenomena dependent on water and soil. We used Tangible Landscape to explore the relationship between overland flow patterns and landscape topography by manually changing the landscape model while getting near real-time feedback about changing flow patterns. We coupled Tangible Landscape with a sophisticated dam break model to investigate flood scenarios after a dam breach.

5.1 Foundations in Flow Modeling

Water flow over complex terrain can be described by a bivariate form of the shallow water continuity equation. The continuity equation can be coupled with momentum (Navier-Stokes) equations to simulate flooding due to dam failure.

5.1.1 Overland Flow

For shallow water flow the spatial variation in velocity with respect to depth can be neglected and the overland water flow during a rainfall event can be approximated by the following bivariate continuity equation (Julien et al. 1995):

$$\frac{\partial h}{\partial t} + \nabla \cdot (h\,\mathbf{v}) = i_e \tag{5.1}$$

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where:

h is the depth of overland flow in m
t is the time in s
$\mathbf{v}$ is the flow velocity vector $\mathbf{v} = (v_x, v_y)$ in m/s
i_e is the rainfall excess (rainfall − infiltration − vegetation intercept) in m/s.

If we assume that the dynamic friction slope of the water surface can be approximated by the static bare ground slope the flow velocity can be estimated by the Manning's equation:

$$\mathbf{v} = \frac{1}{n} h^{2/3} |\mathbf{s}|^{1/2} \mathbf{s_0} \tag{5.2}$$

where:

n is the Manning's coefficient expressed here with units $\mathrm{m}^{-\frac{1}{3}}\,\mathrm{s}$
$\mathbf{s}$ is the negative elevation gradient $-\nabla z = -(f_x, f_y)$ of the bare ground surface
$|\mathbf{s}|$ is the magnitude of elevation gradient (slope, see Sect. 4.1.3)
$\mathbf{s_0}$ is the unit vector in the flow direction (the negative elevation gradient direction).

For steady state water flow and a steady rainfall excess rate the continuity equation has the following form:

$$\partial h/\partial t = 0 \quad \longrightarrow \quad \nabla \cdot (h\,\mathbf{v}) = i_e \tag{5.3}$$

We introduce a diffusion-like term proportional to $\nabla^2[h^{5/3}]$ to incorporate the diffusive wave effects in at least an approximate way. The spatially distributed, steady overland water flow is then expressed as follows:

$$-\frac{\varepsilon}{2}\nabla^2[h^{5/3})] + \nabla \cdot (h\,\mathbf{v}) = i_e \tag{5.4}$$

where ε is a spatially variable diffusion coefficient. The diffusion term, which depends on $h^{5/3}$ instead of h, makes the equation [Eq. (5.4)] linear in the function $h^{5/3}$ which enables us to solve it by the Green's function method using a stochastic technique referred to as path sampling method (Mitasova et al. 2004).

The path sampling method is based on the duality between the particle and field representation of spatially distributed phenomena. In this concept the density of particles in a space defines a field and vice versa, i.e. a field is represented by particles with a corresponding spatial distribution. Using this duality, processes can be modeled as the evolution of fields or the evolution of spatially distributed particles (Mitasova et al. 2004).

The flow evolution (accumulation process) can be also interpreted as an approximation of a dynamical solution for shallow water flow, in which velocity is mostly controlled by terrain slope and surface roughness rather than water depth and friction slope. Therefore the change of velocity over time at a given location

is negligible. The robustness of the path sampling method enables us to simulate complex, spatially variable conditions and efficiently explore flow patterns for a wide range of landscape configurations. This method is implemented in GRASS GIS as the module *r.sim.water*.

5.1.2 Dam Break Modeling

Surface water flow and flooding due to a dam breaking are also represented by the shallow water flow equation, but in this application we assume that there is no rainfall and the only source is water from the reservoir. In order to ensure a realistic representation given a large mass of moving water the shallow water continuity equation:

$$\frac{\partial h}{\partial t} + \nabla \cdot (h\,\mathbf{v}) = 0 \tag{5.5}$$

is coupled with the momentum (Navier-Stokes) equation of fluid motion (Cannata and Marzocchi 2012):

$$\frac{\partial h v_x}{\partial t} + \frac{\partial h v_x^2}{\partial x} + \frac{\partial h v_x v_y}{\partial y} = S_x \tag{5.6}$$

$$\frac{\partial h v_y}{\partial t} + \frac{\partial h v_y v_x}{\partial x} + \frac{\partial h v_y^2}{\partial y} = S_y \tag{5.7}$$

where $\mathbf{S} = (S_x, S_y)$ is the source vector (water flowing from the lake):

$$S_x = -gh\left(\frac{\partial z_w}{\partial x} + \frac{n^2 v_x |\mathbf{v}|}{h^{4/3}}\right) \qquad S_y = -gh\left(\frac{\partial z_w}{\partial y} + \frac{n^2 v_y |\mathbf{v}|}{h^{4/3}}\right) \tag{5.8}$$

and

g is the gravitational acceleration in $\mathrm{m\,s^{-2}}$
z_w is the water level expressed as elevation above sea level in m
n is the Manning's roughness coefficient expressed here with units $\mathrm{m^{-\frac{1}{3}}\,s}$
$|\mathbf{v}|$ is the flow velocity magnitude $|\mathbf{v}| = (v_x^2 + v_y^2)^{1/2}$ in m/s.

The resulting partial differential equations are hyperbolic and non-linear and therefore must be solved numerically. The finite volume method with an upwind conservative scheme proposed by Ying et al. (2004) is used to solve the equations on a regular grid which makes the model suitable to GIS-based implementation. Green's theorem is used to obtain the discrete equations. The numerical method explicitly solves the governing equations in two separate steps. First, the continuity equation (5.5) is evaluated deriving the water depth at time $t + \Delta t$ and later

on these values are used in the source term [Eq. (5.8)] to solve the momentum equations (5.6), (5.7) and evaluate the flow velocities at time $t + \Delta t$. More details about the numerical solution can be found in Cannata and Marzocchi (2012). The model is implemented in GRASS GIS as an add-on module *r.damflood*.

5.1.3 Sediment Transport, Erosion, and Deposition

The *Simplified Erosion/Deposition model* (*SED*) model estimates sediment transport across a complex landscape and the resulting pattern of erosion and deposition using the idea originally proposed by Moore and Burch (1986). The model assumes that the sediment flow can be approximated by sediment transport capacity and the net erosion and deposition is transport capacity limited. It combines the Universal Soil Loss Equation parameters and upslope contributing area per unit width A to estimate the sediment flow T:

$$T \approx RKCPA^m (\sin \beta)^n \tag{5.9}$$

where:

T is the sediment flow rate in $\mathrm{kg\,m^{-1}\,s^{-1}}$
R is the rainfall factor in $\mathrm{MJ\,mm\,(ha\,h\,year)^{-1}}$
K is the soil erodibility factor in $\mathrm{ton\,ha\,h\,(ha\,MJ\,mm)^{-1}}$
A is the upslope contributing area per unit width in m
β is the steepest slope angle
C is the dimensionless land-cover factor
P is the dimensionless prevention-measures factor.

The net erosion/deposition D in $\mathrm{kg\,m^{-2}s^{-1}}$ is then computed as a divergence of sediment flow:

$$D = \nabla \cdot (T\mathbf{s_0}) = \frac{\partial (T \cos \alpha)}{\partial x} + \frac{\partial (T \sin \alpha)}{\partial y} \tag{5.10}$$

where $\mathbf{s_0} = (\cos \alpha, \sin \alpha)$ is the unit vector of the steepest slope (flow) direction (direction of the negative gradient $-\nabla z$) given by the aspect angle α (see Sect. 4.1.3). The exponents m, n control the relative influence of the water and slope terms and reflect the impact of different types of flow. The typical range of values is $m = 1.0$–1.6, $n = 1.0$–1.3 with the higher values reflecting the pattern for prevailing rill erosion with more turbulent flow when erosion sharply increases with the amount of water. Lower exponent values close to $m = n = 1$ better reflect the pattern of the compounded, long term impact of both rill and sheet erosion and averaging over a long term sequence of large and small events.

5.2 Case Study: The Hydrological Impact of Development

The development on North Carolina State University's Centennial Campus raises concerns about the impact of stormwater runoff and erosion during construction. We used Tangible Landscape to explore changes in overland flow and erosion patterns caused by potential construction site grading and to provide feedback for the design of stormwater and erosion control measures.

In this case study we worked with the same area and physical model used in Sect. 4.2.1. To familiarize ourselves with the basic hydrologic conditions of this site we computed flow accumulation and delineated watershed boundaries. First, we set the computational region to match our study area and the resolution to 1 m and then we ran the least cost path flow tracing implemented in the module *r.watershed* to derive the flow accumulation raster and watersheds. We set the threshold for the approximate size of the watershed areas to 1000 grid cells and we converted the areas to a vector representation so that we could display the watershed boundaries:

```
g.region n=223765 s=223015 e=638450 w=637700 res=1
r.watershed elevation=dem accumulation=flow_accum \
    basin=watersheds threshold=1000
r.to.vect input=watersheds output=watersheds type=area
```

The resulting map that combines the flow accumulation raster with the vector representation of watershed boundaries and contours was then projected over the model in Fig. 5.1a.

5.2.1 The Impact of Development on Surface Water Flow

To explore the potential impact of new development we graded sites for new apartment buildings with flat slopes and constructed an access road (see Fig. 4.7d). We carved a narrow culvert to allow water to flow under the road. By calculating flow accumulation and watersheds for the modified topography (Fig. 5.1b) we could immediately see that the watershed boundaries in the developed area changed significantly due primarily to the new road acting as an artificial watershed boundary.

Flow accumulation derived by the module *r.watershed* is based on the least cost path algorithm and is not designed to represent water depth and pooling of water in depressions. Therefore, we used the shallow water flow model implemented in the module *r.sim.water* to simulate the overland flow depth during a storm event for the current conditions and after the grading. We first derived the components of elevation surface gradient $\nabla z = (f_x, f_x)$ (parameters dx, dy in the module *r.slope.aspect*) and then ran the water flow simulation with the rainfall excess value of 150 mm/h:

```
r.slope.aspect elevation=scan dx=scan_dx dy=scan_dy
r.sim.water elevation=scan dx=scan_dx dy=scan_dy \
    rain_value=150 depth=depth
```

Fig. 5.1 Flow accumulation and watershed boundaries computed with *r.watershed* before and after the terrain modifications shown in Fig. 4.7

The resulting water depth maps were projected over the model with the initial terrain conditions and then in near real time as the terrain was modified with the final water depth pattern shown in Fig. 5.2b. Note that we have used an extremely high value of rainfall excess to provide rapid maps of water depth as the model was modified. Once we have the final design we can run the simulation with a selected storm and obtain realistic water depth estimates.

We can also run the module *r.sim.water* in a dynamic mode (*-t* flag) and project the evolution of water depth during the storm event as an animation using the GRASS GIS animation tool.

Fig. 5.2 Water depth computed with *r.sim.water* (**a**) before and (**b**) after the terrain modifications shown in Fig. 4.7. A detailed view of the modified water flow is shown in (**c**)

5.2.2 The Impact of Grading on Erosion and Deposition Pattern

We also explored the impact of grading on sediment transport and erosion/deposition patterns using the SED model. We assumed a uniform rainfall factor $R = 270$ in (hundreds of ft-tonf.in)/(acre.h.year) as well as uniform soils and land cover with the soil erodibility factor $K = 0.2$ and the land cover factor $C = 0.01$ (grass, no trees). The topographic factor exponents were set to $m = n = 1$ to represent prevailing sheet flow. Since we used uniform values for the R-, K- and C-factors, the pattern of erosion and deposition depends solely upon the slope of the terrain and the upslope contributing area. In the following workflow we first computed the slope and aspect maps of the scanned model. Then we computed flow accumulation and combined it with the slope using map algebra to estimate the topographic factor and sediment transport capacity [see Eq. (5.9)].[1] Finally, we computed the divergence of the sediment flow vector field with the add-on module *r.divergence* to generate the erosion-deposition map:

[1] For a general case when m, n and resolution are not set to 1 see the erosion modeling tutorial: http://ncsu-osgeorel.github.io/erosion-modeling-tutorial/grassgis.html

Fig. 5.3 Soil erosion and deposition maps draped over the model (**a**) before and (**b**) after grading shown in Fig. 4.7. Detailed view of the erosion-deposition pattern is in (**c**)

```
r.slope.aspect elevation=scan aspect=scan_aspect \
    slope=scan_slope
r.flow elevation=scan flowaccumulation=scan_flowacc
r.mapcalc "scan_sedflow = 270. * 0.2 * 0.01 * scan_flowacc * \
    sin(scan_slope)"
r.divergence magnitude=scan_sedflow direction=scan_aspect \
    output=scan_usped
r.colors map=scan_usped rules=color_erdep.txt
```

The resulting erosion-deposition map is projected over the model in Fig. 5.3.

5.3 Case Study: Dam Breach

The Lake Raleigh dam located within our Centennial Campus study area broke in September of 1996 after Hurricane Fran. In this case study we simulated how flood water would spread across the current landscape if the dam was breached again. We also modified the terrain to explore how different morphologies would influence the spread of flooding. We used the add-on *r.damflood*, which was designed specifically to simulate dam breaks and analyze the subsequent flooding.

Fig. 5.4 An overview of Lake Raleigh's surroundings with the dam highlighted in *red*. The digital elevation model on which the orthophoto is draped was created by fusing the latest 2014 data with the lake bathymetry data from 2001

Fig. 5.5 (**a**) The current conditions with a stream and a greenway below the dam; (**b**) a scenario in which the road has been removed

5.3.1 Site Description and Input Data Processing

Figure 5.4 shows the terrain and the most recent orthophotograph of our Lake Raleigh study area including the dam. The stream flowing out from the lake merges with the stream coming from the south in the area just below the dam, which is actively used for recreation providing space for disc golf, running, and cycling (Fig. 5.5a).

The dam break simulation requires several input layers including the elevation raster that describes the lake bathymetry and the surrounding topography, the depth of the lake water, the Manning's roughness coefficient, and the geometry of the dam break. The elevation raster was created by fusing the latest DEM based on the 2014 lidar survey with a DEM from the 2001 survey which we used as a proxy for the lake bathymetry. The 2001 survey captured the topography while the lake was drained after the dam failure in 1996 and we considered the 2001 DEM in the lake area a suitable approximation of the current lake bathymetry.

The lake depth raster was computed with the module *r.lake* using the fused DEM as an input. This module fills an area with water for a designated elevation level starting from a given seed point and outputs a map of the water depth for the flooded area. We determined that the current water level elevation for the Lake Raleigh was 85 m by querying the DEM along the outline of the lake. We selected an arbitrary point inside the lake area as a seed point. While *r.lake* assigns null values to the cells outside of the filled area, *r.damflood* requires zero values outside of the lake, so we converted null values to zeros with the *r.null* module and limited the flooded area to the lake mask:

```
g.region n=224026 s=223007 e=639480 w=637798 res=3
r.lake elevation=lake_bottom_dem water_level=85 \
    lake=lake_depth_tmp coordinates=638792,223659
r.null map=lake_depth_tmp null=0
r.mapcalc "lake_depth = if(lake_mask, lake_depth_tmp, 0)
```

The Manning's roughness coefficient influences the speed of water. It depends on landcover and varies between 0 and 1 with higher values resulting in slower flows. To derive Manning's coefficients we could for example reclassify a landcover map. In our example for simplicity's sake we created a raster map with a uniform Manning's value:

```
r.mapcalc "manning = 0.01"
```

Finally, the module *r.damflood* requires a dam breach raster which represents the height of the breach from the top of the dam. To obtain this raster we scanned the model with the dam. Then we carved a breach into the dam and rescanned the model. We computed the difference using the function defined in code snippet 4.2.2. We used a vertical limit of 1 m to avoid detecting differences due to noise from scanning:

```
adjust_scan('scan_before', 'scan_after', 'scan_adjusted')
gscript.mapcalc("breach = if(scan_before - scan_adjusted > 1,
    scan_before - scan_adjusted, 0)")
```

5.3.2 The Impact of the Road on Flooding

For our first flood simulation we used the current conditions. A major road with a culvert crosses the stream below the dam. We carved a culvert into the sand model by removing a narrow channel of sand from the road and scanned this model to provide input for our simulation.

Since our sand model does not incorporate the lake bathymetry we had to combine the fused DEM that includes the bathymetry with the scan. We then ran the *r.damflood* module with the input map layers and set the simulation parameters such as the length of the simulation, the time step for creating output maps, and the

Fig. 5.6 The flood simulation with current conditions

Fig. 5.7 The flood simulation after the road has been removed

computational time step. Since the simulation is computationally intensive it may take several minutes to compute depending on the settings and resolution.

```
r.mapcalc "scan_combined = if(lake_mask > 0, lake_bottom_dem, \
    scan_adjusted)"
r.damflood elev=scan_combined lake=lake_depth dambreak=breach \
    manning=manning h=flood timestep=0.1 tstop=1000 deltat=10
```

The series of output raster maps generated by the simulation can be registered in the GRASS GIS Temporal Framework and then visualized using module *g.gui.animation*. The results for the current conditions are shown in Fig. 5.6. Clearly, the road creates a significant obstacle for the spread of water and causes pooling below the dam. Contained by the road the water floods upstream areas to the west.

In the next simulation we were interested in the conditions before the road was built in 2004. We simply removed the road (Fig. 5.5b) and then rescanned and recomputed the simulation (Fig. 5.7). Removing the road changes the flow pattern and as a result water spreads freely at lower depth thus impacting a larger area, but potentially reducing risk.

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Chapter 6
Viewshed Analysis

Viewshed (visibility) analysis is used in many different fields for both practical and aesthetic applications. It can play an important role when planning new buildings or roads especially in urban settings where obstructed views may raise safety concerns. In recreation areas views of beautiful landscapes are highly valued and protected with great passion. Visibility analysis is also crucial when planning location of monitoring cameras or communication towers in order to maximize coverage. With the increasing availability of high-resolution DEMs and DSMs derived from lidar visibility analysis is becoming more accurate, broading the range of its applications. We used Tangible Landscape to analyze viewsheds on North Carolina State University's (NCSU) Centennial Campus from different observer positions and explored how future development would affect the viewsheds. We introduced object recognition to collaboratively designate observer positions.

6.1 Line of Sight Analysis

Line-of-sight analysis is used to map visible areas. If the line of sight between point A and point B does not intersect the terrain then these points are mutually visible. More precisely, with the slope of the line between A and B defined as $(z_B - z_A)/d_{AB}$ where z is the height and d is the horizontal distance, points A and B are considered visible to each other if the line does not cross any location C such that the slope of AC is larger than the slope of AB (Fig. 6.1). The viewshed of A on a raster DEM is the set of all cells of the DEM that are visible from A. The height of the observer A above terrain has significant influence on the viewshed extent. The observer height can be changed to model the view of a standing person, the view from a multi-story building, or the view from the top of a cell tower. The resulting viewshed can be represented for example as a binary raster (containing only 0 and 1s) or a raster with the values of vertical angles with regard to the viewpoint.

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Fig. 6.1 Line of sight analysis: point B is not visible from point A because the line of sight between A and B has a smaller slope $\tan \alpha_{AB}$ than the line of sight between A and C

Viewsheds from multiple locations can be computed and combined as the sum of binary viewsheds into a cumulative viewshed (Wheatley 1995) that allows us to assess the overall visibility of a place from selected locations. The concepts of visibility analysis have been applied to diverse geospatial applications. For example landform identification using geomorphons combines visibility analysis with computer vision (Jasiewicz and Stepinski 2013) (see Sect. 4.1.3). Several terrain relief visualization techniques take advantage of visibility analysis to highlight subtle terrain features. For example sky-view factor—the visible part of the sky unobscured by relief—can be used to render topographic relief as if it was diffusely illuminated in order to clearly visualize the relative height of features. Sky-view factor uses openness as a proxy for uniform diffuse illumination (Zakšek et al. 2011). It is implemented in GRASS GIS as the add-on module *r.skyview*. Haverkort et al. (2009) describe an efficient method implemented in the module *r.viewshed* for computing viewsheds on a raster DEM using a technique called line sweeping (Fig. 6.1).

6.2 Case Study: Viewsheds Around Lake Raleigh

We used object recognition with Tangible Landscape to explore different viewsheds on NCSU's Centennial Campus by placing markers representing observer positions on a physical model of the landscape. We also evaluated how changes to the topography, the forest canopy, and the buildings would impact these viewsheds.

6.2.1 Site Description and Model

Our study area shown in Fig. 6.2 is the Lake Raleigh landscape on NCSU's Centennial Campus. Key features of the landscape include Lake Raleigh Woods in the southwest, the Chancellor's house and State Club in the south, and the Hunt Library in the northwest.

Fig. 6.2 Lake Raleigh study site: a lidar-based DSM with an orthophoto draped over the surface

We CNC routed a base model and a mold of the landscape surface from MDF based on a lidar-derived DEM and DSM. Both models are approximately 1:2400 scale without vertical exaggeration. We used the base and the mold to cast a malleable layer of polymer enriched sand representing the forest canopy and buildings on top of the terrain model.

6.2.2 Identifying View Points

We modeled the views from different locations by placing markers on the model for Tangible Landscape to detect and recognize. The position of each marker was registered as a vector point and its coordinates were then used as an input for automated computation of viewshed from this location.

Given the complex 3D form and steep slopes of some terrains it may be hard to place markers on a rigid model such as a 3D printed or CNC routed terrain. If the model is coated with magnetic paint then a magnetized marker will hold to the slopes, normal to the surface (see Fig. 3.7). If the model has been sculpted or cast in polymeric sand then markers can simply be stuck vertically into the sand.

There are multiple ways to detect markers. The most reliable approach is to detect the markers based on the difference between a base scan of the terrain model without the markers and the scan with the markers placed on the model. We computed the difference using the function defined in the code snippet in Sect. 4.2.2. A threshold value for the difference in elevation must be set in order to distinguish markers from noise. The threshold can be specified in millimeters and since we know the horizontal scale and vertical exaggeration during the processing it can be automatically converted into the real world elevation difference required in the following code snippet. Areas with difference values above the threshold are vectorized as points for viewshed analysis as follows. We first convert the areas from

raster to vector areas (polygons) using the module *r.to.vect* and then extract the area centroids as vector points using the module *v.to.points*.

```
adjust_scan('scan_before', 'scan_after', 'scan_adjusted')
gscript.mapcalc("change = if(scan_adjusted - scan_before >
    threshold, 1, null())")
gscript.run_command('r.to.vect', flags='st', input='change',
    output='change_vector', type='area')
gscript.run_command('v.to.points', flags='t',
    input='change_vector', type='centroid', output='markers')
```

6.2.3 Visibility Analysis on DSM Using Markers

We explored viewsheds from different points of interests such as the Chancellor's house, the North Shore neighborhood, the Hunt Library's observation deck, the lakeside pier, and the middle of the lake. The viewsheds were computed on the lidar-derived DSM. To identify the markers we first scanned the model and saved the scanned raster. We continued scanning while placing the markers at the locations of interest (Fig. 6.3). The markers were then identified and stored as vector points. We used the following workflow to compute the viewsheds and set the desired color scheme. In this case visible areas are highlighted in yellow.

```
coordinates = gscript.read_command('v.out.ascii',
    input='change_vector', separator=',').strip().splitlines()
for i, line in coordinates:
   output = 'viewshed_%s' % i
   coordinate = [float(c) for c in line.split(',')[0:2]]
   gscript.run_command('r.viewshed', flags='b',
       input='elevation', output=output,
       observer_elevation=1.75, coordinates=coordinate)
   gscript.run_command('r.null', map=output, setnull=0)
   gscript.write_command('r.colors', map=output, rules='-',
       stdin='1 yellow')
```

Fig. 6.3 Placing a marker to identify a viewpoint

Fig. 6.4 Viewsheds computed on lidar-based DSM from viewpoints at (**a**) the North Shore neighborhood, (**b**) Hunt Library's observation deck, (**c**) a lakeside pier, (**d**) and a canoe on the lake

The viewsheds computed from different marker positions are shown in Fig. 6.4. The best views of the lake are from the Hunt Library's observation deck and the lakeside pier.

6.2.4 Modeling Viewsheds from a New Building

In the previous section we computed viewsheds on the lidar-derived DSM. In this section we used the scanned surface to model viewsheds on a modified landscape. We explored a scenario in which we built a hotel on the southeastern side of the lake and assessed the viewshed from the new hotel (Fig. 6.5a).

We began by sculpting the new building in sand. Then we scanned the modified sand surface and saved the scan. We placed a marker that was automatically detected and digitized as a viewpoint. We computed the viewshed using the base scan rather than the newer scan with the marker because the marker would act as an obstacle blocking the observer's view. Fig. 6.5c shows the viewshed from the southwest side of the new hotel. The hotel is oriented so that it has nice views of the lake. Since the hotel is a tall building it is visible from many places around the lake such as Hunt Library (Fig. 6.5d).

Fig. 6.5 Modeling viewsheds from a new building: (**a**) building a new hotel, (**b**) digitizing a viewpoint, and evaluating viewsheds from (**c**) the hotel and (**d**) the library

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Chapter 7
Trail Planning

The design of a walking or hiking trail is based on fine scale topographic conditions and varied criteria specific to the particular context such as aesthetics, views, construction cost, and environmental sensitivity. As a result trail planning is typically a product of expert knowledge, field surveys, and creative design decisions—often made on site. However, when high resolution data is available geospatial modeling can be used to identify routes optimized for travel time and suitability. To design trails with Tangible Landscape we can hand place waypoints on a physical model and then the optimal network connecting the waypoints is computed in near real-time. This approach—hand placing tangible waypoints and computationally networking the waypoints—combines creative, collaborative decision making with mathematical optimization. In this chapter we explain the theory and methodology for designing trails with Tangible Landscape and then discuss a case study, the design of hiking trail scenarios for Lake Raleigh Woods, North Carolina.

7.1 Trail Design Methodology

Our approach for designing trail networks with Tangible Landscape combines the creative identification and siting of key waypoints like trailheads and scenic spots with computationally optimized routing between these points. With Tangible Landscape we can place tangible markers by hand to automatically digitize waypoints. This allows us to work intuitively, feel the slopes and curvature with our hands, and easily collaborate.

To find the optimal routes we compute the least cost path between pairs of waypoints over the terrain and a cost surface as a function of walking energetics. First we create a cost surface that represents friction—the additional time required to cross a cell. Next we designate waypoints, points through which we want the trail to pass. For each unique pair of waypoints we use the *r.walk* module to

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compute the anisotropic cumulative cost of walking between these points across the terrain and the friction surface based on Naismith's rule for hiking times. Then we compute the least cost path between those points across this cumulative cost surface. All of the least cost paths are combined into a network of potential routes. Finally we solve the traveling salesman problem to identify the best route across this network.

7.1.1 Least Cost Path Analysis

With least cost path analysis we can determine the most cost-effective route between a source and destinations on a cost surface. The cost surface is a raster representing cost for traversing a cell and can be derived as a function of distance, slope, land cover or other relevant criteria. To find the least cost path between locations we need to compute a cumulative cost surface where each cell contains the lowest cumulative cost of traversing the space between each cell and the specified location. We also need to generate a movement direction raster tracing the movements that created the cumulative cost surface.

First we compute the walking cost raster using Naismith's rule for walking times (Naismith 1892) with further adjustments (Aitken 1977; Langmuir 1984) of the cost for specific slope intervals. Considering only the elevation surface the cost to walk across a grid cell, expressed as time T in seconds is computed as follows:

$$T = a \cdot \Delta S + b \cdot \Delta H_u + c \cdot \Delta H_{md} + d \cdot \Delta H_{sd} \tag{7.1}$$

where:

- ΔS is the horizontal distance in m
- ΔH is the height difference in m
- a is the time in seconds it takes to walk for 1 m on flat surface
- b is the additional walking time in seconds, per meter of elevation gain ΔH_u on uphill slopes
- c is the additional walking time in seconds, per meter of elevation loss ΔH_{md} on moderate downhill slopes
- d is the additional walking time in seconds, per meter of elevation loss ΔH_{sd} on steep downhill slopes

Up to a specific slope value threshold, walking downhill is faster; after that it becomes more difficult and adds to the time needed to cross the cell. The slope value threshold (slope factor) derived from experiments is -0.2125 corresponding to $12°$ downslope ($\tan 12° = 0.2125$).

Taking into account land cover conditions the total cost T_{total} in seconds is estimated as a linear combination of movement and friction costs using the dimensionless weight λ:

$$T_{\text{total}} = T + \lambda \cdot F \cdot \Delta S \tag{7.2}$$

where F is the friction in s/m. It represents the additional time in seconds that it takes to walk 1 m within a given cell due to its land cover conditions. The friction map may simply be a landcover map that has been recoded as time costs. If landcover data is not available at an appropriate resolution or if there are other important factors that need to be considered, the friction map can be created through map overlay analysis. Parameters such as soils, hydrology, roads, and existing trails can then be incorporated into the cost surface using the friction map.

We used the total cost surface given by Eq. (7.2) to compute a cumulative cost surface where each cell contains the lowest cumulative cost of traversing the space between each cell in the region and the target location. The movement direction raster is also generated tracing the movements that created the cumulative cost surface. We can then compute least cost path between any point in the study area and the target location based on the cumulative cost raster and movement directions raster.

7.1.2 Network Analysis

Using least cost path analysis it is possible to create many combinations of routes between the given waypoints. This can result in a large number of connections and potential trails. We can use network analysis to find a trail loop that goes through all given waypoints in an optimal order, avoiding connections with high costs (Fig. 7.1). The solution for this well-known optimization problem—the traveling salesman problem (TSP)[1]—is implemented in the module *v.net.salesman*, which uses a heuristic algorithm yielding a good solution in a reasonable amount of time.

7.1.3 Trail Slope Extraction

When planning trails we are typically interested in the average and maximum slope of a trail. However, the extracted values are the slope values in the direction of steepest slope rather than in the direction of the trail. To compute that, we need to know the direction of the trail, which can be derived from its vector representation. The slope along the trail β_t can then be computed as the steepest slope β [see Eq. (4.5)] multiplied by the cosine of the angle between the direction of the trail α_t and the steepest slope direction α [i.e. aspect, see Eq. (4.6)]:

$$\tan \beta_t = \tan \beta \cos(\alpha - \alpha_t) \tag{7.3}$$

[1] See: https://en.wikipedia.org/wiki/Travelling_salesman_problem

Fig. 7.1 The TSP applied to a network of potential trails. *Black lines* represent potential routes. The *red line* is the most cost-effective combination of routes that connects all of the waypoints

Fig. 7.2 The difference between the trail slope extracted (**a**) in the direction of the steepest slope and (**b**) in the direction of the trail (in degrees)

The difference is visible in Fig. 7.2 where part of a trail along a contour line has very low slope values along the trail, but has higher slope values in the direction of the steepest slope. Both types of slope computation can be useful depending upon our objectives. When building and maintaining a trail we may be interested in the steepness of the terrain in that area, while a hiker may be more interested in the directional slope of a trail.

7.2 Case Study: Designing a Recreational Trail

We used Tangible Landscape to design alternative trail scenarios for Lake Raleigh Woods on North Carolina State University's Centennial Campus. This old growth woodland on the south shore of Lake Raleigh is rich in biodiversity with approximately 200 species of vascular plants and regionally important stands of mesic mixed hardwood and dry-mesic oak-hickory forest (Blank et al. 2010). Informal hiking and mountain biking trails have caused significant disturbance in the woods and erosion along the lakefront. A formal trail system could concentrate people on low-impact routes and thus conserve the landscape while enhancing opportunities for recreation.

7.2.1 Input Data Processing

We derived a bare earth DEM and DSM with buildings and vegetation from a lidar survey acquired in 2013. Then we CNC routed 1:1500 scale models of the DEM, the DSM, and their inverses (see Sect. 3.4.4). We used the inverse models as molds for casting polymeric sand models.

We created the friction map—a required input for computing the cost surface—by computing the average friction cost for each cell from a set of friction maps based on the recoded rasterized maps of buildings, hydrology, floodplains, roads, soils, and trails with *r.series* using the average function.

First we converted all of the necessary vector maps to raster. Before converting linear features we set the resolution to 3 m in order to give these features reasonable widths.

```
g.region n=224134 s=223005 w=637732 e=639085 res=1

v.to.rast input=lake_raleigh output=lake_raleigh use=val
v.to.rast input=chancellors output=chancellors use=val
v.to.rast input=buildings output=buildings use=val
v.to.rast input=floodplain output=floodplain use=val
v.to.rast input=hydrology_areas output=hydrology_areas use=val
v.to.rast input=trail_areas output=trails use=val
v.to.rast input=roads output=roads use=val

g.region res=3
v.to.rast input=greenways output=greenways use=val
v.to.rast input=streets output=streets use=val
v.to.rast input=hydrology output=hydrology use=val
g.region res=1
```

In order to limit processing to publicly accessible areas we made a composite map of inaccessible areas by combining maps of private land, buildings, and the lake using *r.mapcalc*[2] and then created an inverted mask from this map.

```
r.mapcalc "masking = if((buildings ||| chancellors ||| \
    lake_raleigh), 1, null())"
r.mask -i raster=masking
```

Next, we recoded all maps as friction (time penalties—additional time it takes to walk 1 m), and then overlaid the maps using *r.mapcalc* and *r.series*.

```
r.mapcalc "hydro = if(isnull(hydrology_areas ||| hydrology), \
    1, 10)"
r.mapcalc "flood = if(isnull(floodplain), 1, 10)"
r.mapcalc "paths = if(isnull(trails ||| greenways), 10, 1)"
r.mapcalc "transit = if(isnull(streets ||| roads), 1, 10)"

r.series input=flood,hydro,paths,transit,soils output=friction \
    method=average
r.colors -n map=friction color=ryg
r.mask -r
```

The resulting friction map is shown in Fig. 7.3.

7.2.2 Computing the Trail Using the Least Cost Path

In our case study we computed least cost paths between waypoints to create a trail network. Least cost paths were computed for each combination of two points. The following code snippet shows how such a network can be generated. For each waypoint we called the function `trail` defined below, which computes a raster representing the cumulative cost (time) from this waypoint and then multiple least cost paths from the remaining waypoints.

```
def trail(elevation, friction, walk_coeff, lambda_,
    slope_factor, point_from, points_to, vect_paths):
   """Computes least cost path to multiple locations based on
       walking time"""
   gscript.run_command('r.walk', flags='k',
       elevation=elevation, friction=friction, lambda_=lambda_,
       walk_coeff=walk_coeff, slope_factor=slope_factor,
       start_coordinates=point_from,
       stop_coordinates=points_to, output='tmp_walk',
       outdir='tmp_walk_dir')

   for i in range(len(points_to)):
```

[2]Note that ||| is a symbol for logical OR which ignores NULL values and treats them as logical false.

Fig. 7.3 The friction map in seconds per meter created by combining layers of buildings, hydrology, floodplains, roads, and trails

```
      gscript.run_command('r.drain', flags='d',
          input='tmp_walk', direction='tmp_walk_dir',
          output='tmp_drain', drain=vect_paths[i],
      start_coordinates=points_to[i], overwrite=True)

   # remove temporary maps
   gscript.run_command('g.remove', type=['raster', 'vector'],
       name=['tmp_walk', 'tmp_walk_dir', 'tmp_drain'],
       flags='f')
```

This is repeated for all waypoints except the last.

```
def trails_combinations(elevation, friction, walk_coeff,
    lambda_, slope_factor, points, vector_routes):
   import itertools

   coordinates = gscript.read_command('v.out.ascii',
       input=points, format='point', separator=',').strip()
   coords_list = []
   for coords in coordinates.split():
      coords_list.append(coords.split(',')[:2])

   combinations = itertools.combinations(coords_list, 2)
   combinations = [list(group) for k, group in
       itertools.groupby(combinations, key=lambda x: x[0])]
```

```
    i = k = 0
    vector_routes_list = []
    for points in combinations:
       i += 1
       point_from = ',',.join(points[0][0])
       points_to = [',',.join(pair[1]) for pair in points]
       vector_routes_list_drain = []
       for each in points_to:
          vector_routes_list_drain.append('route_path_' +
              str(k))
          k += 1
       vector_routes_list.extend(vector_routes_list_drain)

       trail(elevation, friction, walk_coeff, lambda_,
           slope_factor, point_from, points_to,
           vector_routes_list_drain)

    gscript.run_command('v.patch', input=vector_routes_list,
        output=vector_routes)
```

The path, however, is only computed for combinations that were not covered in previous steps in order to reduce computation time. This means that the least cost path is only computed in one direction. The direction matters because the speed of walking uphill and downhill differs. Therefore, the walking coefficients and slope factor of *r.walk* should be adjusted to affect uphill and downhill speed equally. This can be achieved by setting the slope factor to zero and using the same absolute number for coefficients b and d.

7.2.3 Finding the Optimal Trail

Using least cost path analysis we created all of the combinations of routes between waypoints. This can result in a large number of connections and potential trails. Therefore we used network analysis to find a trail loop that goes through all our waypoints in an optimal order avoiding connections with high costs. The solution for this well-known optimization problem—the traveling salesman problem (TSP)—is implemented in the module *v.net.salesman*.

All GRASS GIS network analysis modules require a network vector map containing connected lines (arcs) and points (nodes). This vector map can be prepared using the module *v.net* which topologically connects the given points (our waypoints) and lines (our trail combinations). Since we wanted to route the trail through all our waypoints we found the categories of all waypoints in the network and then passed them to module *v.net.salesman*:

```
def trails_salesman(trails, points, output):
   gscript.run_command('v.net', input=trails, points=points,
       output='tmp_net', operation='connect', threshold=10)
```

Fig. 7.4 A trail around Lake Raleigh

```
    cats = gscript.read_command('v.category', input='tmp_net',
        layer=2, option='print').strip().split()
    gscript.run_command('v.net.salesman', input='tmp_net',
        output=output, center_cats=','.join(cats), arc_layer=1,
        node_layer=2)
    # remove temporary map
    gscript.run_command('g.remove', type='vector',
        name='tmp_net', flags='f')
```

The final computation combines above defined functions and takes the scanned DEM and the detected points as input:

```
trails_combinations('scan', friction='friction',
    walk_coeff=[0.72, 6, 0, 6], lambda_=0.5, slope_factor=0,
    points='markers', vector_routes='route_net')
trails_salesman(trails='route_net', points='markers',
    output='route_salesman')
```

Examples of final output are shown in Figs. 7.1 and 7.4.

7.2.4 Mapping Trail Slopes

The simplest way to map the slope of a trail is to rasterize the trail using *v.to.rast* and then use *r.mapcalc* to extract the slope values from a slope raster computed with the module *r.slope.aspect*:

```
r.slope.aspect elevation=dem slope=slope
v.to.rast input=trail output=raster_trail type=line use=cat
r.mapcalc "trail_slope = if(raster_trail, slope)"
```

This extracts the slope values in the direction of the steepest slope. To compute the slope in the direction of the trail we first need to rasterize its vector representation by deriving raster values from the vector direction. The slope along the trail can then be computed as the slope multiplied by the cosine of the angle between the direction of the trail and the steepest slope (i.e. aspect):

```
r.slope.aspect elevation=dem slope=slope aspect=aspect
v.to.rast input=trail output=raster_trail_dir type=line use=dir
r.mapcalc "trails_slope_dir = abs(atan(tan(slope) * cos(aspect \
    - raster_trail_dir)))"
```

7.2.5 Alternative Trail Scenarios

We designed the initial trail scenario for Lake Raleigh Woods by placing markers at key points of interest—potential trailheads and scenic viewpoints (for more information about marker detection see Sect. 6.2.2). The siting of trailheads was informed by a previous 1:2500 scale study of potential routes around the entire lake (Fig. 7.4). We used realtime viewshed analysis to evaluate potential viewpoints (Fig. 7.5a). To test the viewsheds we cast the DSM in polymeric sand, carved clearings in the woodland canopy for viewpoints, placed markers to designate the viewpoints, and computed the viewsheds. We also computed the slope along the trail so that we could critique the routes (Fig. 7.5b).

Our trail needed to cross three large gullies with steep slopes. In the initial trail scenario the route follows the contours and ridge lines to avoid the gullies with their challenging slopes. This route formed two loops that intersected at the mouth of the central gully near the lakefront with moderately steep slopes (Fig. 7.6a). We, however, wanted to experiment and see what a route with a single loop would look like so we built bridges across the gullies (Fig. 7.6b). The trail rerouted across the bridges to form a single, shorter loop with a lower average slope (Fig. 7.6c).

Fig. 7.5 Trail analytics: (**a**) the viewshed from a waypoint with areas visible represented in orange and (**b**) the slope of the trail

Fig. 7.6 Iteratively designing trail scenarios for Lake Raleigh Woods. (**a**) The initial route for a trail in Lake Raleigh Woods. (**b**) Building bridges to reroute the trail across gullies with steep slopes. (**c**) The updated route for the trail across the new bridges

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Chapter 8
Solar Radiation Dynamics

Solar radiation (insolation) is the primary driving force for Earth's atmospheric, biophysical, and hydrologic processes. Knowing the amount of radiation at different geographic locations at different times is therefore necessary in many fields including energy production, agriculture, meteorology, ecology, and urban planning. We modeled direct solar radiation and cast shadows in an urban setting to show how different spatial configurations of buildings change the amount of sunlight available throughout the day and the year.

8.1 Solar Radiation Modeling

Solar radiation modeling is critical for the optimal site selection of solar power plants (Carrion et al. 2008; Janke 2010) and for placing photovoltaic systems in often complex urban environments (Freitas et al. 2015; Hofierka and Kaňuk 2009; Jakubiec and Reinhart 2013). In urban design dynamic solar radiation simulations are used to study the effect of urban geometry and building configurations on solar access and shading conditions in order to get insight into the "urban canyon" phenomenon (Arnfield 1990; Lobaccaro and Frontini 2014).

On a global scale solar radiation depends spatially and temporally on the orientation of the Earth relative to the Sun. At a local scale solar radiation is influenced by topography (i.e. an elevation surface's inclination, orientation, and shadows), atmospheric conditions, and surface properties such as land cover. We can analyze the spatial distribution and dynamics of solar radiation and cast shadows using the equations that relate the sun position to the geometry of the terrain surface (Hofierka and Suri 2002). The clear-sky solar radiation model applied in this chapter is based on work undertaken for the development of the European Solar Radiation Atlas (Page et al. 2001; Rigollier et al. 2000; Scharmer and Greif 2000). We include here only the equations for direct solar radiation—beam irradiance—which

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is influenced by the local topography. For a complete set of equations see Hofierka and Suri (2002). The diffuse and reflected components as well as atmospheric parameters can be also found in Rigollier et al. (2000).

First we compute position of the Sun in the sky as a function of time and location on Earth. The Sun declination angle depends on the day number (1–365 or 366):

$$\delta = \arcsin(0.3978 \sin(j' - 1.4 + 0.0355 \sin(j' - 0.0489))) \tag{8.1}$$

where δ is the Sun declination angle in radians and j' is expressed as day angle in radians:

$$j' = 360^\circ \cdot j/365.25, \quad j = 1, 2, \ldots, 365\,(366) \tag{8.2}$$

The position of the Sun in respect to a horizontal plane is defined by the solar altitude and solar azimuth. The solar altitude angle γ_s is a function of the solar hour angle ω, the solar declination angle δ and the latitude φ of the given location:

$$\sin \gamma_s = \cos \varphi \cos \delta \cos \omega + \sin \varphi \sin \delta \tag{8.3}$$

Given that the solar hour angle ω changes at 15° per hour and equals zero at noon it can be computed from local solar time t in decimal hours on the 24 h clock:

$$\omega = 15^\circ \cdot (t - 12) \tag{8.4}$$

The solar azimuth angle α_s (a horizontal angle between the sun and meridian measured from east) can be expressed as a function of the solar altitude angle γ_s, the solar declination angle δ, and the latitude φ of the given location:

$$\cos \alpha_s = (\sin \varphi \sin \gamma_s - \sin \delta)/\cos \varphi \cos \gamma_s \tag{8.5}$$

$$\sin \alpha_s = \cos \delta \sin \omega / \cos \gamma_s \tag{8.6}$$

The position of the Sun in respect to an inclined plane with slope β and aspect α (e.g., a hillslope or a building roof) is described by a solar incidence angle ν:

$$\cos \nu = \cos \gamma_s \sin \beta \cos(\alpha_s - \alpha) + \sin \gamma_s \cos \beta \tag{8.7}$$

To estimate the duration of solar radiation we compute the sunrise and sunset angle $\omega_{r,s}$ over a horizontal plane:

$$\cos \omega_{r,s} = -\tan \varphi \tan \delta \tag{8.8}$$

and the corresponding time of sunrise T_{sr} and sunset T_{ss} in hours is then:

$$T_{sr} = 12 - \omega_{r,s}/15^\circ \qquad T_{ss} = 12 + \omega_{r,s}/15^\circ \tag{8.9}$$

The sunrise/sunset angle over a south-facing inclined plane (for a location in the northern hemisphere) is computed as follows:

$$\cos \omega'_{r,s} = -\tan(\varphi - \beta) \tan \delta, \qquad \omega''_{r,s} = \min(\omega_{r,s}, \omega'_{r,s}) \tag{8.10}$$

where $\omega''_{r,s}$ is the sunrise and sunset angle over the inclined plane. More general equations can be found in Hofierka and Suri (2002).

Solar irradiation analysis has been implemented in GRASS GIS by Hofierka and Suri (2002) in the module *r.sun*. In addition to the direct solar irradiation described above the module incorporates diffuse and reflected irradiation and cast shadows. The module *r.sun* works in two modes. In the first mode it computes the solar incident angle in degrees and solar irradiance values in $\mathrm{W\,m^{-2}}$ for a specific instance in time. In the second mode it computes the daily sum of solar irradiation in $\mathrm{Wh\,m^{-2}\,day^{-1}}$ and the duration of the direct irradiation. To compute a series of direct irradiance maps for a given day with a selected time interval we use the add-on *r.sun.hourly*, which calls *r.sun* in a convenient loop. Similarly we use the add-on *r.sun.daily* to compute daily sums of direct irradiation for the entire year.

8.2 Case Study: Solar Irradiation in Urban Environment

In this case study we studied how different spatial configuration of buildings changed direct solar radiation and cast shadows dynamics throughout the day. We placed wooden blocks of different shapes and sizes representing hypothetical buildings on a flat surface with an approximate scale of 1:300. We located this abstract site in Raleigh, North Carolina at latitude 36°. We examined two building configurations—one with four medium-sized houses with gabled roofs and the other with three medium-sized houses with gabled roofs and one tall building with a flat roof (Fig. 8.1a, b).

Fig. 8.1 Two configurations of buildings at approximately 1:300 scale viewed from the south. (**c**) Shows the DSM and contours derived from a scan and projected over buildings

8.2.1 The Impact of Building Configuration on Cast Shadows

We compared the shadows cast by the buildings in both configurations during summer and winter solstice. After scanning the scenes we used the add-on *r.sun.hourly* to derive binary raster time series of cast shadows from 6:00 to 22:00 (local solar time) with a 30-minute time step. We had to specify the selected date as a day of year number. For example if we pick the summer solstice in 2015 we can easily compute the day of year using the Python *datetime* module:

```
import datetime
datetime.datetime(2015, 6, 21).timetuple().tm_yday
```

which gives us the number 172.

Running the following commands results in a time series of binary rasters with zeros representing cast shadow based on the direct (beam) radiation. The time series is registered in a spatio-temporal dataset and can be easily rendered as an animation and projected over the physical model.

```
r.slope.aspect elevation=scan aspect=aspect slope=slope
r.sun.hourly -t -b elevation=scan aspect=aspect slope=slope \
    start_time=6 end_time=22 time_step=0.5 day=172 year=2015 \
    beam_rad_basename=shadows_summer
g.gui.animation strds=shadows_summer
```

By changing the day parameter to 356 we obtained the time series of cast shadows for the winter solstice. Figure 8.2 compares the cast shadows at 16:30 and 19:00 (local solar time) during the summer and winter solstice for the two different building configurations.

There is a clear difference in the length of cast shadows during winter and summer. The orientation of the cast shadows at the time close to sunset changes during the year as shown in Fig. 8.2a, c. During the summer the Sun sets below the horizon later (after 19:00) far to the northwest, while it sets earlier (after 16:30) and far to the southwest during winter. As a result the house in the southeast corner only has a view of the sunset during part of the year as the summer view is blocked by another building.

By adding a tall building to the scene we cast more shadow in the space between the houses and on houses in the east. Depending upon the season one of the houses on the east side becomes shadowed by the high building sooner than the other.

8.2.2 The Impact of Building Configuration on Direct Solar Irradiation

Cast shadows give us information about the availability of direct solar radiation at a particular time on particular days. However, we are often interested in the cumulative solar irradiation, which tells us the amount of solar energy received on

Fig. 8.2 A comparison of cast shadows viewed from south. The *first and second rows* show two different building configurations. The *first and second columns* show cast shadows at 16:30 local solar time during the winter (**a**), (**d**) and summer solstice (**b**), (**e**), respectively. The *third column* shows cast shadows at 19:00 local solar time during the summer solstice. A figure for winter solstice at 19:00 is not shown as it would be after sunset

a given surface during a given time interval. Such information can then be used to assess the suitability of a location for solar energy applications.

To compute direct solar irradiation for individual days we called the add-on *r.sun.daily* with parameters similar to those we used for *r.sun.hourly*. We specified the first and last day of the year resulting in 365 daily irradiation maps. Additionally by specifying the `beam_rad` parameter we computed the sum of all of the daily maps. Again we can animate the time series projected over the scene to get more insight into the spatial patterns of solar radiation over the course of a year.

```
r.slope.aspect elevation=scan aspect=aspect slope=slope
r.sun.daily -t elevation=scan aspect=aspect slope=slope \
    start_day=1 end_day=365 day_step=1 \
    beam_rad=radiation_year_sum \
    beam_rad_basename=radiation_day_sum
g.gui.animation strds=radiation_day_sum
```

Figure 8.3 shows direct solar irradiation in $\mathrm{Wh\,m^{-2}\,day^{-1}}$ during the winter solstice, spring equinox, and summer solstice with a common color ramp. The color ramp was specified in a plain text file `solar_color.txt` as:

```
100% red
70% yellow
0% gray
```

and then this color ramp was set for the entire time series:

```
t.rast.colors input=radiation_day_sum rules=solar_color.txt
```

Fig. 8.3 Direct solar irradiation in Wh m^{-2} day^{-1} during the winter solstice, spring equinox, and summer solstice

Fig. 8.4 Solar irradiation patterns in March for different building configurations

Figure 8.4a shows the solar irradiation on a particular day in March in order to compare the cumulative solar irradiation for the two building configurations. In the first scenario there is variable irradiation in the space between the buildings as a result of the interaction between the spatial configuration of the buildings and the dynamic solar geometry. In the second scenario the pattern is even more pronounced because the street gets less direct sunlight. The slope of the buildings' roofs affects the amount of irradiation as a visual comparison of the color of the flat and tilted roofs clearly demonstrates. Furthermore, the shadow cast by the tall building has lowered the irradiation values on part of the roof of the southeastern house.

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Chapter 9
Wildfire Spread Simulation

Forest fires, whether naturally occurring or prescribed, are potential risks for ecosystems and human settlements. These risks can be managed by monitoring the weather, prescribing fires to limit available fuel, and creating firebreaks. With computer simulations we can predict and explore how fires may spread. We can explore scenarios and test different fire management strategies under different weather conditions. Using Tangible Landscape and the GRASS GIS wildfire toolset we simulated several wildfire scenarios. We tested different configurations of firebreaks on the physical model and evaluated their effectiveness.

9.1 Fire Spread Modeling Methods

Fire spread across landscapes is a complex, highly dynamic process influenced by weather, topography, and fuel. The fire spread models predict the rate of fire spread and fire perimeter growth using a combination of physical principles such as energy conservation and empirical parameters derived from observations and experimental data. For reviews of physical and empirical models of fire spread and methods of implementing fire simulation please refer to Sullivan (2009a,b,c).

9.1.1 Input Data

The fuel model is one of the most important input variables for fire simulation. Albini (1976) and Anderson (1982) describe 13 classes of fuel (Table 9.1), which differ in fuel loads and the distribution of fuel particle size classes. The size of individual pieces of fuel influences the fire; heat is absorbed faster by small twigs

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Table 9.1 The fuel model by Anderson (1982) describes 13 classes of fuel

Fuel class	Description
Grass and grass-dominated	
1	Short grass (1 foot)
2	Timber (grass and understory)
3	Tall grass (2.5 feet)
Chaparral and shrub fields	
4	Chaparral (6 feet)
5	Brush (2 feet)
6	Dormant brush, hardwood slash
7	Southern rough
Timber litter	
8	Closed timber litter
9	Hardwood litter
10	Timber (litter and understory)
Slash	
11	Light logging slash
12	Medium logging slash
13	Heavy logging slash

due to their large surface to volume ratio. The moisture content of the fuel affects the amount of heat needed to ignite the fuel. The smaller the fuel size, the faster the fuel dries out and becomes more combustible.

The slope of the terrain and the speed and direction of the wind control the rate of spread and direction of the fire. Steeper slopes cause faster ignition in the upslope direction. This rule has been observed and quantified in several laboratory experiments (Silvani et al. 2012; Viegas 2004; Weise and Biging 1996).

Wind is specified by speed and direction at a given height. Unlike the slope of the terrain, wind is difficult to characterize due to its variability in space and time and spatially and temporally averaged values are used in the models. Sparks and embers can be carried great distances by strong winds; this process known as spotting allows fire to spread beyond firebreaks (Albini 1983).

9.1.2 Fire Spread Algorithm

In our simulation we used the GRASS GIS modules *r.ros* and *r.spread*, implemented by Xu (1994), to compute the rate of spread and simulate the spread of fire.

The rate of spread computation is based on the BEHAVE model (Andrews 1986). The inputs are the fuel model, fuel moisture, wind speed and direction and terrain slope and aspect. The rate of spread is computed using the following equation:

$$R = \frac{I_R \xi (1 + \Phi_W + \Phi_S)}{\rho_b \varepsilon Q_{ig}} \tag{9.1}$$

where:

R	is the rate of spread in m/s
I_R	is the reaction intensity in kW/m
ξ	is the propagating flux ratio
Φ_W	is the wind coefficient
Φ_S	is the slope factor
ρ_b	is the oven-dry fuel per cubic meter of fuel bed in kg/m^3
ε	is the effective heating number
Q_{ig}	is the heat of preignition in kJ/kg.

For a detailed description of the underlying mathematical model and an explanation of the input data refer to Rothermel (1972).

The module *r.spread* uses Huygens' principle to simulate elliptically anisotropic spread where each cell center is a potential origin of spread and the local spread is ellipsoidal (Anderson et al. 1982). The sizes and orientations of the ellipses vary by cell. Local wind and slope directions determine the orientation of ellipses. The module *r.spread* uses a specific implementation of the shortest path algorithm.

We used the GRASS GIS add-on module *r.fire.spread* to call the modules *r.ros* and *r.spread* streamlining the fire spread computation and visualization. With this add-on we can use temporally variable input conditions and export the fire spread for each time step so that we can animate the simulation with the module *g.gui.animation*.

9.2 Case Study: Controlling Fire with Firebreaks

With Tangible Landscape we can intuitively create new fire management scenarios, rapidly testing how different sizes, shapes, and placements of firebreaks affect the spread of fire. To test different management strategies we simulated how a fire might spread across NCSU's Centennial Campus and tried to contain it by creating firebreaks of different sizes and alignments. In this case study we modeled a phenomenon—fire spread—that started outside the extent of the physical model, but spread towards the model (Fig. 9.1). Once the fire spread onto the model we could interact with it by creating firebreaks. Geospatial models and simulations need not be constrained to the boundary of the physical model, i.e. the extent of the tangible user interface. The processing extent can extend beyond the interactive area allowing us to work across scales.

We built a malleable physical model of the tree canopy by casting polymeric sand. To build the molds for casting we interpolated a DEM and a DSM from 2013 lidar data and then CNC routed the DEM and the inverse of the DSM. Then we cast a

Fig. 9.1 The study area on Centennial Campus: (**a**) an orthophotograph and (**b**) available fuel map projected over the table with the tangible 3D model

layer of sand representing the tree canopy between the two molds. Since this layer of sand represents tree canopy and thus fuel availability we could model clearcutting simply by removing sand. Thus we were able to intuitively design firebreaks by carving into the sand layer and reducing the fuel load. Please refer to Sect. 6.2.1 for a more detailed description of the site and model.

9.2.1 Data Preparation

To simulate fire spread we prepared several input raster layers for the module *r.ros* including the data about terrain, wind, fuel, and moisture conditions. We also specified the coordinates of location where the fire started.

Terrain Terrain slope influences the speed of spread and aspect influences the spread direction. After we set the region to our study area we derived the slope and aspect raster maps from the provided DEM:

```
g.region n=224134 s=222501 e=639326 w=637211 res=3
r.slope.aspect elevation=dem slope=slope aspect=aspect
```

The DEM is also used as input for computing the maximum spotting distance.

Wind Wind has two components—midflame velocity and direction—and both can be spatially variable. In this case we used the prevailing wind speed and direction obtained from the nearest weather station through the State Climate Office of North Carolina.[1] The module *r.ros* requires velocity in feet per minute so the wind velocity data acquired from the State Climate Office of North Carolina must be converted from meters per second to feet per minute (to convert multiply by a factor of approximately 197). Wind direction is typically reported by the direction *from* which

[1] State Climate Office of North Carolina: www.nc-climate.ncsu.edu/

it originates, clockwise from the north. The module *r.ros*, however, requires the "to" direction (also clockwise from north). To simulate spatial variability we applied a random effect, for example, using the module *r.surf.gauss* to produce a raster map of Gaussian deviates with a specified mean and standard deviation:

```
r.surf.gauss output=wind_speed_avg mean=542 sigma=30
r.surf.gauss output=wind_dir mean=75 sigma=20
```

Fuel The module *r.ros* uses Anderson's 13 standard fire behavior fuel models. Fuel data layers at 30 m resolution for the USA are publicly accessible via the LANDFIRE website.[2] Most of our study site falls into fuel classes 8 and 9, i.e. timber litter (Fig. 9.1b).

Moisture Since fuel moisture data were not readily available for our site we generated the required, spatially variable raster maps of 1-h fuel moisture and live fuel moisture percentage for dry conditions:

```
r.surf.gauss output=moisture_1h mean=10 sigma=5
r.surf.gauss output=moisture_live mean=20 sigma=5
```

Starting Location The starting sources of the fire are represented as raster cells and can be created by digitizing points or importing coordinates from a file and converting them to a raster. We provided the fire starting location in a text file with the point coordinates (for example `638097,222934`) and converted them to a raster with the module *v.to.rast*:

```
v.in.ascii input=source.txt output=source separator=comma
v.to.rast input=source output=source type=point use=cat
```

9.2.2 Scenario with Multiple Firebreaks

In our first scenario the fire started near Trailwood Drive and was drawn to the northeast by a southwesterly wind. The fire jumped over the road and quickly spread towards the Chancellor's House (Fig. 9.2).

Using the following workflow we simulated and then animated the spread of the fire. The output raster maps generated by this workflow represent the relative time of ignition in minutes. To better visually represent the spread of the fire we used a red-yellow-gray color ramp. The steepness of the color gradient shows the relative rate of spread. The steeper the color gradient, the slower the spread. To prepare the suggested color ramp we saved the color rules in a plain text file `fire_colors.txt`:

[2]LANDFIRE: http://www.landfire.gov/

Fig. 9.2 The spread of the fire without intervention

```
0% 50:50:50
60% yellow
100% red
```

To run the simulation we called the module *r.ros* once and then *r.spread* with the desired time lag parameter specifying the length of the simulation. To see the intermediate states we can run the module *r.spread* multiple times and assign our color ramp to the resulting spread raster map:

```
r.ros model=fuel moisture_1h=moisture_1h \
    moisture_live=moisture_live velocity=wind_speed_avg \
    direction=wind_dir slope=slope aspect=aspect \
    elevation=elevation base_ros=out_base_ros \
    max_ros=out_max_ros direction_ros=out_dir_ros \
    spotting_distance=out_spotting

r.spread -s base_ros=out_dir_ros max_ros=out_max_ros \
    direction_ros=out_dir_ros start=source \
    spotting_distance=out_spotting wind_speed=wind_speed_avg \
    fuel_moisture=moisture_1h output=spread_1 lag=20
r.spread -s -i base_ros=out_dir_ros max_ros=out_max_ros \
    direction_ros=out_dir_ros start=spread_1 \
    spotting_distance=out_spotting wind_speed=wind_speed_avg \
    fuel_moisture=moisture_1h output=spread_2 lag=20
r.spread ...
```

Fig. 9.3 Creating a firebreak by (**a**) manually removing sand and then (**b**) scanning and detecting the change

```
r.null map=spread_1 setnull=0
r.colors map=spread_1 rules=fire_colors.txt
```

Alternatively we can use the add-on module *r.fire.spread*, which conveniently wraps the previous sequence of commands into a single command:

```
r.fire.spread -s start=source times=0 end_time=1600 \
    time_step=20 output=spread model=fuel \
    moisture_1h=moisture_1h moisture_live=moisture_live \
    direction=wind_dir slope=slope aspect=aspect \
    elevation=elevation speed=wind_speed_avg
```

After simulating the initial spread of the fire we attempted to prevent fire from spreading towards Chancellor's House by creating firebreaks. First we scanned the model to save the unmodified state. Next we manually removed sand (representing canopy) from the location where we want to have a firebreak (see Fig. 9.3a). We scanned the modified model and vertically matched the new scan to the unmodified scan using the function defined in code snippet 4.2.2. We derived the new fuel raster layer based on the difference between the two scans introducing no data values into the copy of the original fuel model using a simple raster algebra expression:

```
adjust_scan('scan_before', 'scan_after', 'scan_adjusted')
gscript.mapcalc("changed_fuel = if(scan_before - scan_adjusted
    > 0, null(), fuel)")
```

We repeated our simulation using the new fuel raster layer. The resulting fire spread in Fig. 9.4 shows that our attempt was only a partial success. While we significantly slowed the spread of the fire, potentially giving firefighters more time to act, the fire jumped over the firebreak and started to spread towards Chancellor's House suggesting that a wider firebreak would be needed. With more precise data about fire behavior we could control and limit the spotting effect in the simulation.

Fig. 9.4 The spread of the fire after creating a firebreak

Fig. 9.5 The simulation with additional firebreak: (**a**) the creation of a new firebreak by removing sand and (**b**) the result of the new simulation

In our second scenario we added another firebreak to protect the neighborhood north of Lake Raleigh. The lake creates a natural barrier that constrains the spread of the fire. To protect the community to the north we extended this barrier by creating an additional firebreak starting on western shore of the lake (Fig. 9.5a). After we rescanned the model and reran the simulation, we found that the additional firebreak was only locally effective—while the fire was significantly slowed, it would have eventually reached the neighborhood.

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Chapter 10
Coastal Modeling

In this chapter we discuss how to simulate inundation and flooding in coastal landscapes, explain workflows for developing storm surge and sea level rise scenarios, and present two case studies. The first case study is a series of storm surge and dune breach scenarios for a populated barrier island. The second is a design—informed by flood and erosion modeling—for resilient, sustainable guest housing at a coastal research institute.

10.1 Modeling Potential Inundation

Inundation and flooding in coastal landscapes is caused by storm surge and sea level rise. It is very complex and depends upon topography and bathymetry, tides, sea level surge and waves, and wind and rainfall. The spatial extent of flooding can be approximated by "spreading" the observed or predicted water level throughout the landscape (Clinch et al. 2012).

To approximate inundation and flooding we can spread the given water level from a predefined seed located in the ocean using the module *r.lake*. This approach respects the obstacles, so if a foredune protects a low lying area, this area will not be flooded even if the water level exceeds its elevation. We describe the algorithm as follows: an increase in water level approximates the dynamics of inundation, but we assume that the water spreads at an infinite speed and thus floods everything that it can reach instantly. Therefore this method is best used to map the maximum possible extent assuming that there are no changes in topography during the process.

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10.2 Case Study: Simulating Flood Risks for Barrier Island Communities

We explored the impact of topography on inundation and flooding at the Jockey's Ridge sand dune complex in Nags Head on the Outer Banks barrier islands of North Carolina (Fig. 10.1) with a series of a storm surge scenarios. We carved breaches into the foredune of our sand model to identify which homes were most vulnerable to storms.

For this study we selected a study area including the beach, foredune, homes, road, dune complex, maritime forest, and soundside shore. We derived a bare earth DEM and a DSM with buildings and vegetation for our study from a 2009 lidar survey. Then we cast a polymeric sand model of the DEM from a CNC routed mold. We projected an orthophotograph, elevation data, the shoreline, and building footprints as context. Based on the building footprints we added massing models of the buildings to our sand model.

To study the potential impacts of a hurricane we simulated storm surge at increasing levels from 1 to 4 m using the add-on module *r.lake.series*. Then we breached the foredune at a point where it has been compromised by the construction of boardwalk for beach access and compared the extent of flooding at different surge levels (Fig. 10.2).

```
r.lake.series elevation=elev_2009_1m output=flood \
    start_water_level=1 end_water_level=4 water_level_step=0.1 \
    coordinates=913525,249507
g.gui.animation strds=flood
```

Fig. 10.1 The Jockey's Ridge dune complex in Nags Head, North Carolina

Fig. 10.2 Inundation extent simulations for Jockey's Ridge area for (**a**) 1 m and (**b**) 2 m of storm surge

10.3 Case Study: Designing Resilient Coastal Architecture

Two architecture students—David Koontz and Faustine Pastor—used Tangible Landscape to site a series of residential pavilions (Fig. 10.3) for visitors staying at the UNC Coastal Studies Institute on Roanoke Island, North Carolina as part of an joint architecture-engineering studio. They used storm surge and water flow simulations to inform the selection of building sites. Then they spaced pilings for the buildings and adaptively graded a biofiltration swale based on near real-time feedback about water flow, sediment flux, and erosion-deposition.[1]

The UNC Coastal Studies Institute—the site for the studio—is a research institute on Roanoke Island in the Outer Banks of North Carolina. Students in this North Carolina State University studio course led by Professors Joe DeCarolis, David Hill, and Ranji Ranjithan were tasked with designing sustainable housing for guests and researchers visiting the institute.[2] The site is at risk of inundation from sea level rise and storm surge and is in a sensitive back-barrier salt marsh.

Given the risk of flooding David and Faustine used Tangible Landscape to visualize different levels of inundation and test the vulnerability of potential building sites. They placed basswood massing models of buildings on a cast sand model of the landscape and then used the module *r.lake* to simulate 4 m storm surge and check if their buildings would stay dry (Fig. 10.4). In their design the buildings would be raised on piers and connected by boardwalks over a bioswale. They simulated water flow to find the right spacing for the piers over swale. Then they adaptively graded the swale using feedback from water flow, erosion-deposition, and sediment flux simulations, sculpting the channel so that water and sediment flowed towards a bioretention pond (Fig. 10.5).

[1] Watch the video on Youtube: https://youtu.be/PbbzWymGvLo

[2] Read more about the studio on the Coastal Dynamics Design Lab website: http://design.ncsu.edu/coastal-dynamics-design-lab/

Fig. 10.3 The students' design for a series of pavilions for the UNC Coastal Studies Institute on Roanoke Island, NC. Images by David Koontz and Faustine Pastor. (**a**) A rendering of the proposed design for a residential pavilion. (**b**) A masterplan of the UNC Coastal Studies Institute with the proposed residential pavilions

Fig. 10.4 Students using water flow and flood simulations to adaptively inform the placement of a series of pavilions for the Coastal Studies Institute on Roanoke Island, NC: (**a**) siting buildings by hand on an artificial ridge, (**b**) studying the flow of water around the buildings and (**c**) testing whether the buildings stay dry with 4 m storm surge

Fig. 10.5 Students using (**a**) water flow, (**b**) erosion-deposition, and (**c**) sediment flux simulations to space structural piers and adaptively grade a biofiltration swale for the Coastal Studies Institute on Roanoke Island, NC

Reference

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Appendix A

A.1 Applications of Tangible Landscape

In this section we briefly describe additional applications of Tangible Landscape that we, our students, and our colleagues have developed. For each project we explain the aim, used methods and studied processes.

Modeling Avalanches in High Tatras

Eva Stopkova modeled snow avalanches in the High Tatras mountain range in Slovakia (Stopková 2007, 2008). Avalanche potential is closely related to landscape topography so Stopkova built a physical model of her study area in High Tatras in order to visualize the spatial pattern of topographic parameters and landforms (Fig. A.1). She was able to project the results of avalanche danger assessment over the model, but she was not able usefully compute the assessment using the modified and scanned physical model. The scanned models were not accurate enough for practical applications due to their small scale and the steepness of their slopes. Modeling avalanches with Tangible Landscape would require a larger physical model at a larger map scale. CNC routing can be used to precisely and efficiently fabricate the size of model needed for such an application.

Visualizing the Evolution of Oregon Inlet

Liliana Velasquez Montoya created a projection augmented sand model of Oregon Inlet where she was modeling how storms drive the morphological evolution of barrier islands. To visualize and present the results of her research Montoya

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Fig. A.1 A sand model of High Tatras in Slovakia augmented with a projection of the landforms computed by the module *r.geomorphon*; a legend and a diagram of the landform types are projected on the table beside the model

Fig. A.2 A sand model of Oregon Inlet with a projected video showing its formation and evolution along with a graph of wave height changing over time

projected a video depicting the evolution of the inlet in response to storm events onto a sand model. She built the sand model to physically represent the present 3D form of the inlet. Since the sand model was not dynamic it only matched the end of animation. This was a useful mode of representation as the model acted as a datum that helped us compare the present and past morphology of the inlet. Since the small sand model was only large enough to show the most active part of the inlet she also projected the surrounding coastal landscape (Fig. A.2).

Designing Disaster Relief Housing for Rodanthe

Logan Free designed disaster relief shelters for an emergency ferry terminal at Rodanthe on the Outer Banks of North Carolina. The ferry terminal is used for evacuation and relief when there are disasters like hurricanes or bridge failures. Free was tasked with designing temporary housing structures and a community service

Fig. A.3 Simulating storm surge at the Rodanthe emergency ferry terminal on the Outer Banks of North Carolina: (**a**) the mean high water level on the sound side of the island and (**b**) the approximate water level during high storm surge

Fig. A.4 Landscape change modeling for a watershed in Charlotte, North Carolina: (**a**) a sand model of the terrain at the Charlotte study area augmented with a projected hillshade to enhance perception of relief; (**b**) using a mouse and the digitizer tool to draw a polygon to designate a development area

center for disaster recovery at the ferry terminal. To identify vulnerable hotspots and select safe sites for the shelters he built a sand model of the site and used Tangible Landscape with the module *r.lake* to simulate the potential extent of storm surge flooding (Fig. A.3).

Simulating Landscape Change in Charlotte

Douglas A. Shoemaker created a model of a small watershed in Charlotte, North Carolina to test how the FUTure Urban-Regional Environment Simulation (FUTURES) framework could be integrated with Tangible Landscape. FUTURES uses a stochastic patch growing algorithm to simulate urban growth and land use change (Meentemeyer et al. 2013). It has been integrated with GRASS GIS as the add-on module *r.futures* (Petrasova et al. 2015). Shoemaker used the raster digitizer tool in the GRASS GIS GUI to designate a site for development and change the land cover. He also sculpted the sand to grade the topography for the new development. Then he ran FUTURES to explore how the new development would influence longterm landscape change in the watershed-scale study area (Fig. A.4).

Fig. A.5 Reconstructing a paleolake and a terrain model used for cell tower planning. (**a**) A reconstruction of a paleolake in the Galuut Valley, Mongolia showing the landforms computed by *r.geomorphon*. (**b**) A physical model used to site cell towers in Athens county, Ohio

Reconstructing a Paleolake in Mongolia

Gantulga Bayasgalan used a sand model to reconstruct a paleolake in the Galuut Valley in central southwest Mongolia. He modeled alternative reconstructions of the landscape in sand and used Tangible Landscape to compute the flow accumulation pattern, geomorphological features, and several other characteristics for each landscape configuration (Fig. A.5a).

Cell Tower Planning in Athens County

Jesse Boyd used Tangible Landscape to site cell towers in Athens county, Ohio. To find good sites for cell towers, Boyd tested different spatial configurations by placing markers representing cell towers on a physical model of the landscape (Fig. A.5b). Since topography blocks cellular signals he used viewshed analysis to estimate cellular coverage. He experimented with different cell tower heights by changing the observer elevation parameter of the module *r.viewshed*.

Monitoring Coastal Erosion

Tristan Dyer used terrestrial lidar data to monitor coastal erosion on a beach near the US Army Corps of Engineers' Field Research Facility in Duck on the Outer Banks of North Carolina. Coastal erosion can be visually and tactilely explored by building a sand model for each lidar survey. Dyer scanned a transect of the beach with a terrestrial lidar system, interpolated the lidar point cloud as a DEM, and then built a sand model with the aid of Tangible Landscape to quickly prototype and visualize the landform (Fig. A.6a). A sequence of these models would show the morphological evolution of the beach.

Fig. A.6 Sand models used to study beaches and streams. (**a**) A sand model of a beach in Duck, North Carolina used to study beach erosion. (**b**) A sand model of a valley in North Carolina Piedmont used to study how beaver dams influence stream flow and morphology

Exploring Impacts of a Beaver Dam

Karl W. Wegmann and his students used Tangible Landscape to study how beaver dams affect streams in North Carolina. They used Tangible Landscape to model the morphology and flow of a stream with and without beaver dams. First they built a sand model of a segment of the existing stream with beaver dams and studied its topographical parameters and hydrological processes. Then they sculpted the sand model and computed different water flow scenarios to study how the stream could have been without beaver dams (Fig. A.6b).

In this application we merged the scanned elevation model with a DEM of the surrounding landscape to put the modeled area into its broader context and account for water flowing from the entire contributing watershed. The water flow simulation was then run over the entire area so that the water from the contributing watersheds would fill the stream.

Modeling the Potential Impacts of a Coal Ash Pond Spill

Matthew Horvath (2014) studied the potential impacts of spills from the Cape Fear Plant coal ash ponds near Moncure, North Carolina. Horvath built a sand model for a study area near the Cape Fear river and used Tangible Landscape with the add-on module *r.damflood* to simulate a breach in a coal ash pond (Fig. A.7). Artificial landforms kept the simulated spread of contaminated surface water from reaching the nearby Cape Fear river.

Fig. A.7 Making a breach in a coal ash pond (**a**) and simulating the spread of contaminated water (**b**)

Fig. A.8 Iteratively sculpting a landform in sand to generate time-series data: (**a**) the initial state followed by (**b**) changing the position and shape of the landform

Testing a Landform Migration Algorithm

Petras et al. (2015) used Tangible Landscape to test the behavior of a newly developed algorithm for describing landform migration. The algorithm maps the horizontal migration of complex landforms as gradient fields based on the analysis of contour evolution. The gradient field is a vector field representing the movement and deformation of contours. It can be used to quantify the rate and direction of landform migration at any point in space and time. Data for testing algorithms is usually computer generated. In this case, however we wanted to create simplified, yet realistic abstractions of landforms that would allow us to clearly model and visualize landform migration. It was easier to make these abstract landforms by hand than on the computer. To create test data in a controlled environment we built sand models by hand to represent a moving landform. Using Tangible Landscape we sculpted and scanned a model of the initial terrain and then sculpted and scanned a model of the terrain after it had migrated to create an elevation time-series (Fig. A.8).

Fig. A.9 Using object recognition to digitize polygons and pixels representing treatment areas in order to computationally steer (**a**) Sudden Oak Death in Sonoma Valley, California, and (**b**) termites spread simulation in Fort Lauderdale, Florida

Managing the Spread of Sudden Oak Death in Sonoma Valley

In collaboration with Francesco Tonini and Douglas A. Shoemaker we used Tangible Landscape to test the effectiveness of different treatment scenarios for controlling the spread of Sudden Oak Death in Sonoma Valley, California. We used a stochastic model to simulate the spread of Sudden Oak Death and Tangible Landscape to visualize the spread and designate new treatment areas. We CNC routed a large (1 m × 1 m) MDF model of the terrain and coated it with magnetic paint. To make markers that would hold in place on the complex topography we attached adhesive magnetic strips to the base of basswood markers. We used the markers to collaboratively draw polygons representing treatment areas with Tangible Landscape (Fig. A.9a). The polygons reduced the host species of the disease on aligned pixels thus influencing the next run of the simulation. Each treatment area was automatically assigned a label with its area. The sum of all of the treatment areas was dynamically displayed on a simple dashboard. The disease spread simulation was written in the R (R Core Team 2013) statistical programing language and environment.

Managing the Spread of Termites in Fort Lauderdale

In collaboration with Francesco Tonini we used Tangible Landscape as a spatial decision support tool for collaboratively managing the spread of termites in Dania Beach, Fort Lauderdale, Florida. We used pixel-based object recognition to interact with a stochastic simulation of the spread of termites. Placing a marker on a flat surface with a projected grid changed a value on the corresponding pixel in the simulation input—a raster index of termite habitat (Fig. A.9b).

Fig. A.10 Exploring subsurface moisture by removing sand and projecting the cross-section of a scanned surface with the 3D raster of moisture

Tangible Exploration of Subsurface Data

Using Tangible Landscape we explored the 3D distribution of the percentage of subsurface moisture (Petrasova et al. 2014) measured in Kinston, North Carolina and represented as a GRASS GIS 3D raster (GRASS Development Team 2015). By digging into the sand model with our hands we could explore underground as if we were at an excavation site. As we dug into the sand the cross-section of the scanned surface with the 3D raster representing soil properties was projected in real-time (Fig. A.10). We also projected additional GIS layers (such as an orthoimagery, elevation contours, and flow accumulation) over the model to provide spatial context and gain further insights into soil moisture distribution and its relation to the landscape.

Additionally, in combination with marker detection from Sect. 6.2.2 we can create and visualize vertical profiles or soil core samples. This method is an intuitive and natural way of exploring subsurface data and it represents an alternative to more abstract 3D computer visualization tools.

A.2 Data Sources

Throughout the book we use various data sources. Here is a list of the most useful data sources for the study areas presented in the book.

Sample Data for This Book

NCSU OSGeo Research and Education Laboratory

http://geospatial.ncsu.edu/osgeorel/data.html

US Lidar Data

United States Interagency Elevation Inventory

http://coast.noaa.gov/inventory/

Earth Explorer

http://earthexplorer.usgs.gov/

Digital Coast

http://coast.noaa.gov/dataviewer/

Open Topography

http://www.opentopography.org/

US Digital Elevation Models

National Elevation Dataset on the National Map Viewer

http://viewer.nationalmap.gov/viewer/

US Orthoimagery

USGS EROS Orthoimagery web mapping service

http://raster.nationalmap.gov/arcgis/services/Orthoimagery/USGS_EROS_Ortho_1Foot/ImageServer/WMSServer?

US Soil Surveys

USDA Web Soil Survey

http://websoilsurvey.sc.egov.usda.gov

US Fire Modeling Data

LANDFIRE

http://www.landfire.gov/

Global Datasets

GRASS GIS community list of global datasets
http://grasswiki.osgeo.org/wiki/Global_datasets

NC Climate Data

State Climate Office of North Carolina
http://www.nc-climate.ncsu.edu/

A.3 Starting with GRASS GIS

To run examples from this book we provide a dataset which can be downloaded from the NCSU OSGeo Research and Education Laboratory website.[1] Once the downloaded dataset is unzipped we create a directory `grassdata` in our home directory and place the dataset there. Then we start GRASS GIS and a start up dialog in Fig. A.11 appears on screen. In the upper text field we specify the path to our `grassdata` directory. Then we should be able to see Location `nc_spm_tl` containing several Mapsets. We select mapset `practice1` and press the Start button.

After opening the Layer Manager and Map Display windows we display the raster map `elevation` as shown in Fig. A.12. To execute commands from this book presented in boxes with green background we paste the commands into the *Command console* tab as shown in Fig. A.13a and press Enter. The Python code in boxes with blue background can be executed in the *Python shell* tab (Fig. A.13b) or in any Python shell running in a GRASS GIS session.

More instructions how to use GRASS GIS GUI are available on the official GRASS GIS introduction page[2] and in the GRASS GIS GUI manual.[3]

[1] http://geospatial.ncsu.edu/osgeorel/data.html

[2] http://grass.osgeo.org/grass70/manuals/helptext.html

[3] http://grass.osgeo.org/grass70/manuals/wxGUI.html

Fig. A.11 Starting GRASS GIS

Fig. A.12 Display raster map elevation: click on *Add raster map layer* button in toolbar, select `elevation` from drop-down list, and press OK

Fig. A.13 GRASS GIS modules can be run from (**a**) the *Command console* tab or (**b**) Python shell using Python syntax

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