Blurring Boundaries Between Scientific and Artistic Representation of Landscapes

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Abstract: This paper presents an educational experiment that merges art and science to deepen landscape architecture students' comprehension of scientific data. It explores tools and methodologies aimed at fostering more intuitive insights into data, bridging both analytical and artistic readings and expression. The study investigates techniques for representing landscapes and vegetation vitality using point clouds and vegetation indices, examining methodologies to stimulate the emergence of novel forms and morphologies in landscape architecture in artistic expressive ways. Through the analysis of airborne *LiDAR* data and utilization of near-infrared signatures, such as *NDVI*, the paper illustrates how invisible data can enhance vegetation assessment. Additionally, it evaluates the application of node-based visual programming, particularly *Geometry Nodes* in *Blender*, as an intuitive interface for handling scientific data, offering an alternative to *Grasshopper* in digital landscape architecture education.

Keywords: Point clouds, node-based programming, Blender, vegetation indices, NDVI

1 Introduction

The inspiration for this educational experiment was to explore digital methods to address two questions. Firstly, how can we artistically unveil aspects of ecology that are invisible to the human eye but detectable through digital sensing devices? Secondly, can node-based visual programming tools, specifically *Geometry Nodes* within the open-source software *Blender*, empower students to process and visualize scientific observations stored in point clouds within a short time frame and without any prior knowledge of computational workflows and methods?

Fig. 1: The Depth of the Marsh | A physical land art installation | *Making Ecologies Visible*, supervised by Kari Anne Bråthen, Eva Breitschopf, and Elisabeth Ulrika Sjødahl at Charlottenlund, Tromsø, 2022; UAV Photo: Marc Ihle

The UAV image above showcases a Land Art installation that reflects the depth of the marsh through the length of each pole's shadow. In this instance, an analogue method was employed to measure the marsh's depth using a soil sampler. The same depth measurement was represented and made visible through the length of the poles and their shadows, enabling the observer to perceive beyond the ground.

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Knowledge about ecosystems is often based on assessments of plant health, which often is indicated by the amount of photosynthetic activity conducted by each individual plant. This reflects in our human vision in the colour green but reflects even stronger outside the visible range of human vision, namely in the Near InfraRed (NIR) (Gandhi et al. 2015). Numerous examples across diverse fields demonstrate the importance of electromagnetic signatures invisible to the human eye and thus make them particularly relevant to Landscape Architecture, as related disciplines like Biology and other natural sciences, make more and more use of them to assess landscapes (Glass 2013).

As sensing technologies keep evolving and the exploration of the electromagnetic spectrum increasing in allied disciplines, especially with the purpose to understand dynamic natural processes and complex relationships beyond our human sensory apparatus, it can be key to find methods how to visualize and communicate invisible *earth evidence* (Schuppli 2019) and potentials in landscapes to decision making authorities, stakeholders or other non-scientific parties. Art tends to explore different channels of communication than the pure rational mind, here very interesting contributions between art and science have been made by various artist-researchers.

1.1 Spectral Signatures beyond Human Vision

Typically, the human eye can detect wavelengths from ~400 to ~700 nanometres within the electromagnetic spectrum (Zwinkels 2015), which when looking at the entire electromagnetic spectrum only covers a very thin slice compared to what *mechanic vision* systems are able to detect, reaching from ultra short waves used in e. g.: X-Ray devices to long-wave reflections used e. g. in space-based *Radio Detection and Ranging* (RaDAR) Systems.

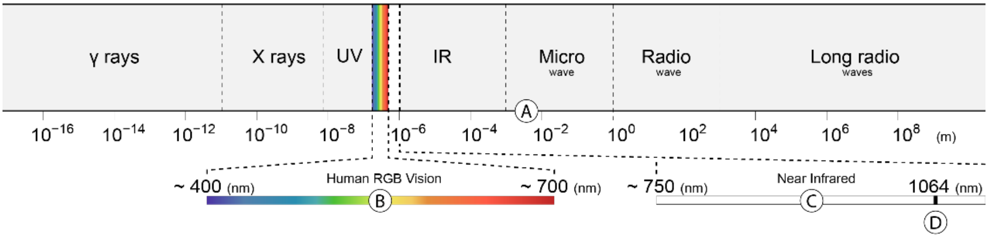


Fig. 2: (A) The electromagnetic spectrum; (B) Range visible to human vision: ~380 - ~700 nm; (C) Range used to assess vegetation vitality; (D) Wavelength of laser used to record the dataset: *Tromsø 8pkt 2019* (Kartverket 2023): 1064 nm

1.2 NDVI and LiDAR Devices that Operate in the Near Infrared

Digital sensing, in particular airborne laser scanning, is resulting in the collection of rapidly increasing volumes of data and can often easily be accessed through various online geo data portals. Here *Light Detection and Ranging* (LiDAR) data, depending on the wavelength of the emitted light pulse, can contain reflections of the electromagnetic spectrum that can be instrumental in addressing contemporary challenges (Knoebl et al. 2018), such as changing ecosystems and loss of biodiversity. An example of an attribute that can be derived using 2 reflectance values of 2 different wavelengths, one visible and one invisible, is the *Normalized Difference Vegetation Index* (NDVI), which is typically computed on imagery (raster) data sets but can also be computed directly on point clouds like outlined in the methods of this paper. Assessments using the NDVI are employed on scales ranging from the entire Arctic region to assess changes in forest and plant life (JESPERSEN et al. 2023) down to scales used in agriculture to evaluate plant health of crops (JENA et al. 2019) or in ecology to assess differences in the growth rates of various species and types, enabling informed conclusions at various scales.

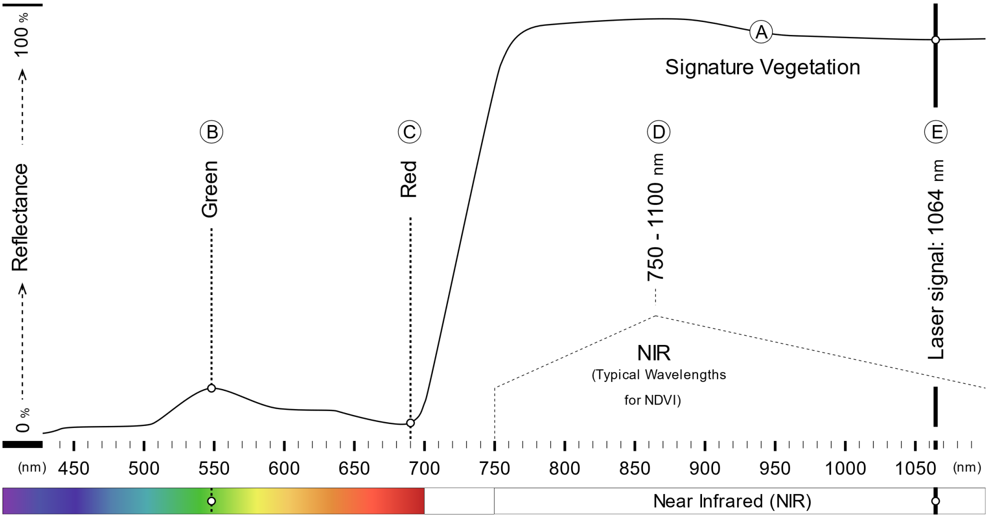


Fig. 3: (A) The signature of vegetation in the electromagnetic spectrum; (B) Green visible to human vision: ~500 - ~570 nm; (C) Red – visible to human vision: ~650 - ~700 nm; (D) Range of wavelengths in the near infrared that reflect a strong signal of vegetation; (E) Wavelength of laser signal used for data processing: 1064 nm (KARTVERKET 2023)

1.3 Node-based Visual Programming Opposed to Text-based Programming in the Education of Landscape Architecture

Coding has just in recent past been perceived as too challenging, resource-intensive, not adequately connected to practical applications, or otherwise considered secondary to the primary objective of landscape architecture programs (WESTORT 2016).

In contrast to text-based coding as referred to above, which adheres to strict syntax and offers little room for error, node-based visual programming tools offer a *Graphical User Interface* (GUI) composed of nodes and elements such as icons, flowcharts, and range-sliders. Instead of relying on written lines of code, visual programming empowers users to create complex relationships through dropping and connecting nodes on a canvas with immediate visual feedback of their actions drawn on a 3D viewport. This makes coding more intuitive and accessible to a diverse range of individuals, including those without prior coding expertise or knowledge of scripting languages (WEINTROP & WILENSKY 2017).

Opposed to *Rhino* and *Grasshopper* that have increasingly gained momentum in computational design methods in landscape architecture (BELESKY 2018), *Blender* and *Geometry*

Nodes, also a node-based visual programming interface that was released by the *Blender Foundation* in 2021, has remained more unexplored among landscape architecture.

The open-source software *Blender* was originally developed for the movie industry but has in recent years also gained momentum in the gaming industry, where interaction and timeline play an essential role and tools require a certain intuition in their interface, since many of the users come from the arts. Similar structured other node-based programming interfaces can be found and are expected to gain even more momentum in the future like *Unreal Engine* or *Unity* that also allow to walk interactively like in a video game through a 3D scene rendered in real-time.

1.4 Point Clouds Representations between Science and Art

While in landscape architecture point clouds and scientific data are mostly utilized to represent landscapes rather objectively and analytically, they are rarely explored for conveying subjective expressions or serving as a spatial framework for creative and artistic expression. However, when looking into the realm of the arts, many artists can be found that investigate the use of data and algorithms. Here artists like Refik Anadol who refers to his work also as *data paintings* or – *sculptures* making invisible aspects of the world visible, have made significant contributions along with many other artists such as listed in *the art of point clouds* (ANADOL 2015, IVSIC et al. 2021).

Another particular quality of point clouds, when it comes to the representation of landscapes is that point clouds allow depending on density, size, and the perspective to render landscapes with a certain degree of transparency allowing one to see what might ley below them, creating a new understanding of spatial relationships (ILMAR HURKXKENS 2014).

Point cloud representations also seem to not be far from the impressionistic style, seen in paintings with visible brushstrokes that offer a minimalist impression of a form, especially when assigning instances of geometries with variance in shape, direction, size, and color to these points, as they carry the possibility to inform about atmospheres or subjective impressions like in landscape paintings of romanticists such as of William Turner or Kasper David Friedrich.

2 Objectives

Main objective was to explore tools, data, and methods that where easily accessible, open-source and favoured a *Graphical User Interface* that would enable a faster learning and spark the student's interest in both computational design and digital sensing technologies (BELESKY 2018). Another objective of this teaching exploration was transcending of scientific knowledge that can be found or stored in point cloud data, and how this information could be activated not only in analytical terms to assess sites, but also in creative, experimental, and expressive terms allowing to convey subjective expressions or serving as a spatial framework for creative artistic ideas and a computational exploration of relationships.

3 Methods

There were 2 exercises during the course which were structured in 3 different phases: Scanning, Processing, and Visualization. Both exercises shared the same tools but differed in the data source and extension of site samples.

3.1 Assignment 1 | Mobile phones, RGB and Geometric Feature Attributes

The first assignment focused in the scanning phase on high participation and involvement of students during field operations. In the processing phase both RGB color information and geometric feature attributes were computed using the open-source software *Cloud Compare*, which were then assessed and graphically interpreted using the open-source Software *Blender* and *Geometry Nodes* to create digital-, as opposed to physical land art installations that might unveil aspects of ecology such as in fig.1.

Scanning with Students Using Mobile Phones Opposed to TLS

There were carried out 2 different scanning operations. One scanning exercise was to explore 3D-scanning with mobile phones using a variety of free "apps". Capturing either images or processing these directly through "apps" to point clouds. Here the focus was on scanning vegetation, in particular differences in types, patterns, clusters, and transitions of different nature types such as birch forests and marshlands. A second scanning exercise was conducted using a Leica P50 *Terrestrial Laser Scanner* (TLS) in collaboration with the Arctic University Museum of the UiT and archeologist Daniel Fallu. Although this allowed the students to get insights in the use of LiDAR equipment and recorded intensity values which became more relevant in the second assignment, the data recorded in the field was not further used due to different reasons, one simply being the file size and related need of processing power or time, that where both not available during the short time of the course and on the personal notebooks of the students.

Computation of Geometric Feature Attributes in Cloud Compare

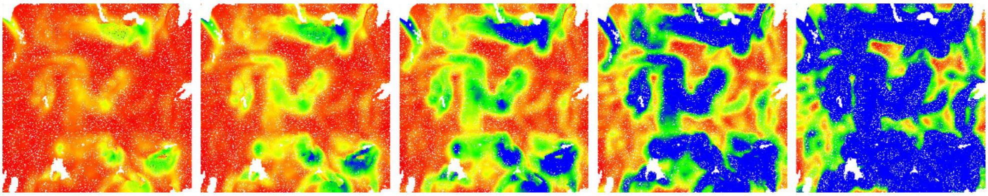


Fig. 4: 5 Iterations showing planarity computed with smaller and larger neighbourhood search radii, using *Cloud Compare* and point cloud data captured by mobile phones

In the processing phase, students learned to use the open-source point cloud processing software, *Cloud Compare*, for basic point cloud editing, including cropping, filtering, and translation. In a subsequent step, *Cloud Compare* was used to compute normal directions for each point and geometric feature attributes such as the 1st eigenvalue, 2nd eigenvalue, 3rd eigenvalue, planarity, linearity, roughness, etc. This was done in iteration by adjusting the neighborhood search radius and evaluating relationships between the search point and the neighboring points within the defined radius.

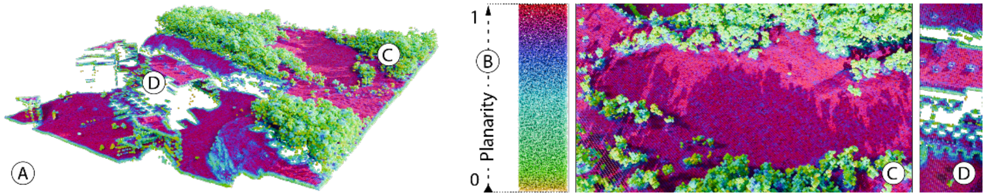


Fig. 5: (A) 150x150-meter sample data in 3D; (B) Assigned colour ramp to planarity values form 0-1 computed in *Cloud Compare* with a 1,5-meter search radius; (C) Marshland with birch forest; (D) Roofs of housing complex

During the scanning phase students paid particular attention to variances in color and topography. Through point cloud analysis in *Cloud Compare* and the computation of geometry-based attributes, students were able to extract different patches of vegetation that also in some cases showed correlation to the RGB color image, since for example flatter areas also often were areas where more water accumulated, especially within marsh landscape types.

Table 1: Vegetational indices and formulas based on RGB reflectance's of the visible electromagnetic spectrum

Index Type	**Conventional**	**Formula**
RGBVI	Red-Green-Blue Vegetation Index	[G-(B*R)] / [G*G + (B*R)]
EGI	Excess Green Index	(2*G – R – B)
GLI	Green Leaf Index	(2G – R – B) / (2G + R + B)
VARI	Visible Atmospheric Resistant Index	(G – R) / (G + R – B)
NGRDI	Normalized Green Red Difference Index	(G – R) / (G + R)

Further the collected RGB attributes were used to not only highlight existing vegetation in RGB color, but also as individual input attributes to generate false color images through representation of different vegetational indices that can be computed using only visible (RGB) bands available in the images (Tab. 1). Indices that have been developed and used for various applications, like biomass monitoring (NGRDI, TUCKER 1979); (RGBVI, BENDIG et al. 2015), to distinguish living plant material from a non-plant background (EGI, WOEBBECKE et al. 1995); (VARI, GITELSON et al. 2002) or to document grazing impacts (GLI, LOUHAICHI et al. 2001).

Blender and *Geometry Nodes* were used to convert the formulas (Tab. 1) into visual results as well as to highlight different qualities of a site based on geometric feature attributes. This was done mostly as a creative exercise and to familiarize students not only with node-based programming but also in computational thinking and establishment of co-dependencies.

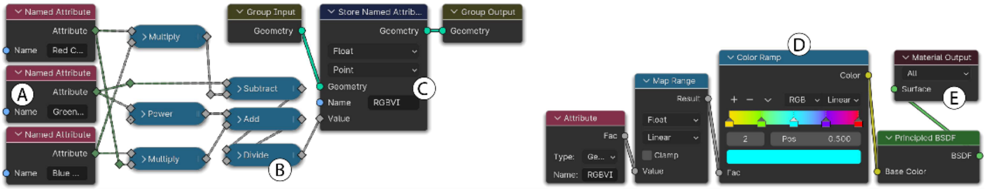


Fig. 6: Example of using the vegetational index formula: RGBVI with geometry- and shading nodes in Blender; (A) RGB input attributes; (B) Math nodes; (C) Storing attributes on point geometry; (D) Assignment of colour; (E) Material output

3.2 Assignment 2 | LiDAR, NDVI and Geometric Feature Attributes

As a second assignment, the student explored online resources and the Norwegian national geodata portal *høydedata.no* to obtain data. Here, point cloud data captured with Airborne LiDAR scanners was used, which was additionally RGB colored from orthophotos. The intensity signal of the laser, operating in the NIR (Fig. 3) where the vegetational signatures are strongest, was used to approximate NDVI values for each point.

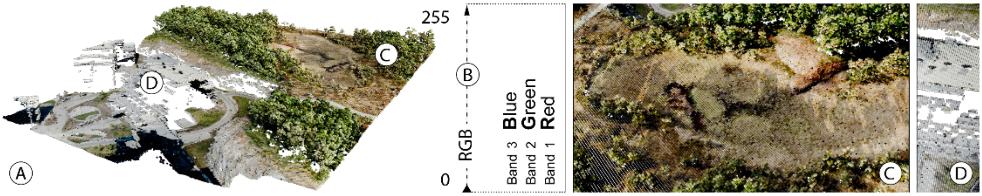


Fig. 7: (A) 150x150-meter sample data in 3D; (B) RGB bands from 0-255; (C) Marshland with birch forest; (D) Roofs of housing complex

NDVI

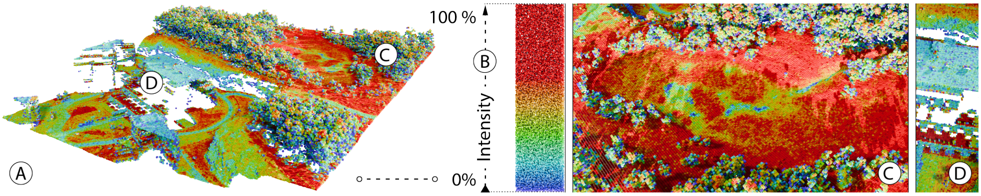


Fig. 8: (A) 150x150-meter sample data in 3D; (B) Assigned colour ramp to intensity values; (C) Marshland with birch forest; (D) Roofs of housing complex

In the processing phase, *Cloud Compare* was used like in the first assignment, but in addition as part of another workshop, the open source GIS software SAGA (CONRAD et al. 2015) was used to compute the NDVI on point clouds, which is conventionally computed using raster data formats (GANDHI et al. 2015).

The focus was on approximating NDVI attributes to quantify vegetational greenness and understand densities of different plant types and their distributions in relation to other geometric feature attributes computed in *Cloud Compare* like in the first assignment.

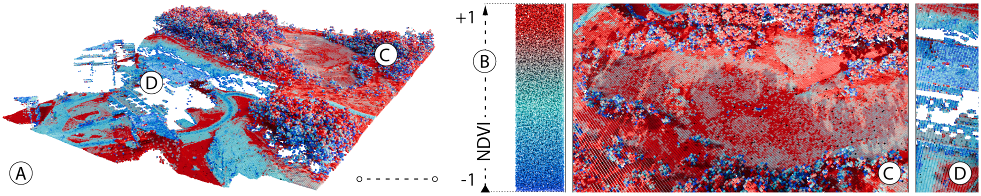


Fig. 9: (A) 150x150-meter sample data in 3D; (B) Assigned colour ramp to NDVI values; (C) Marshland with birch forest; (D) Roofs of housing complex

To obtain NDVI values without the need for expensive equipment, such as Multispectral Imaging Cameras and UAVs, online available Airborne LiDAR data was used where the intensity reflectance values are also in the NIR (Fig.3) of the electromagnetic spectrum (MÍGUEZ & FERNÁNDEZ FILGUEIRA 2023), enabling the calculation of NDVI values as a ratio between the red (R) and near-infrared (NIR) values through the formula: NDVI = (NIR - R) / (NIR + R). Here, the NIR was replaced by laser intensity, so the formula was: NDVI= (Intensity - R) / (Intensity + R).

3.3 Visualization and Node-based Programming in Blender

In the third phase of both exercises the opensource CAD software *Blender* and *Geometry Nodes* was used to visualize and manipulate the representation of point clouds.

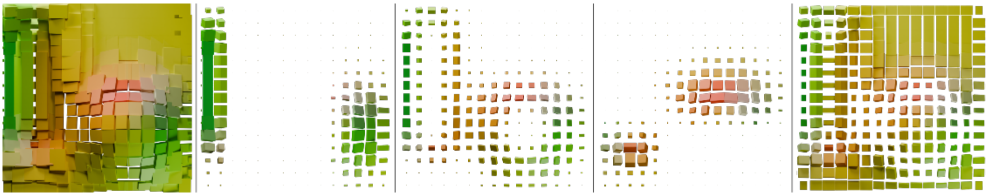


Fig. 10: Using G*eometry Nodes* in *Blender* to select ranges of values to highlight areas of a different geometric features priorly computed in *Cloud Compare*

Here the goal was to highlight potentials or differences of points, based on shared- or related properties which either reflected a scientific representation of properties at these points, or a more artistic interpretation through forming of spatial environments that communicated an expression of a thought or subjective message. To enhance a better comprehension of significance of relationships between point cloud attributes, *Blender* and its node-based visual programming interface *Geometry Nodes* were used to provide expanded opportunities to translate attributes into 3D diagrammatic models and gain more and a rather intuitive understanding of the ranges and meaning of these values.

Spatial environments and site assessments were created through colorization and through modifying size, orientation, and shape of instances of geometry rendered on the points.

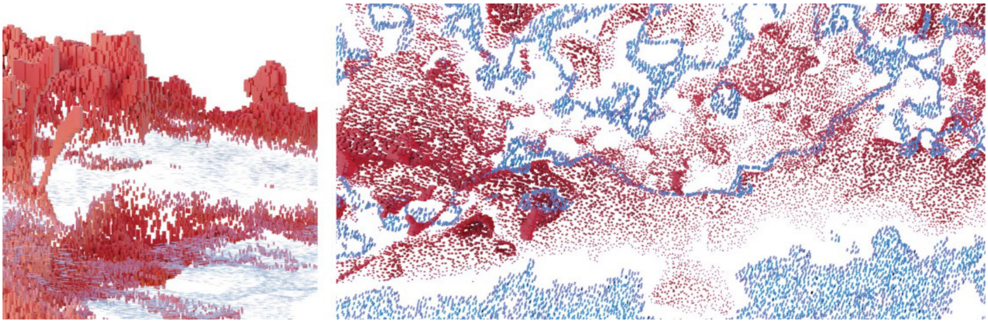


Fig. 11: Student work | *Wet and Dry*, Lola Guiguilé, 2023

This approach intended to empower students to utilize point cloud data and attributes in more creative and subjective ways, enabling them to express site conditions that may not necessarily be analyzed but are instead rooted in empirical experiences and a more intuitive access and relationship understanding to the data through a more intuitive digital tool set.

4 Results

Student work showed much variation and individuality. Below is a series of images created by the students using the methods outlined above, unfortunately the length of this paper does not allow to show more images.

Fig. 12: Student work | *The small / big landscape*, Lene Katrine Hole, 2023

Fig. 13: Student work | *Colors of the landscape*, Karoline Lindebjerg, 2023

Fig. 14: Student work | *Marsh- and woodland*, Kaja Boudewijn, 2023

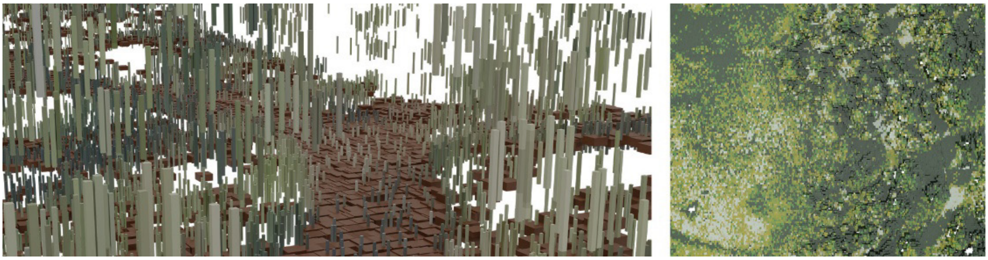


Fig. 15: Student work | *Photosynthesis*, Frida Bjerg Poulsen, 2023

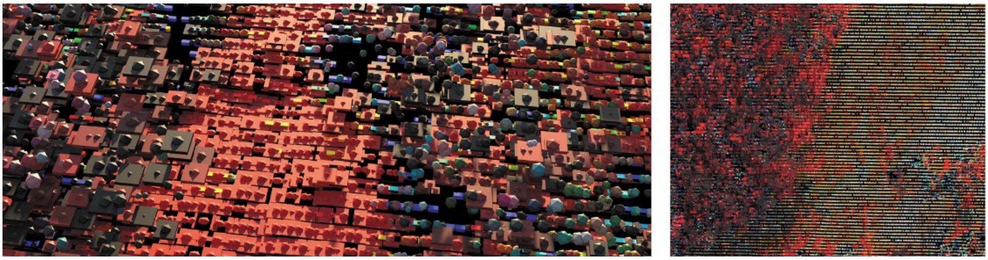


Fig. 16: Student work | *Three Attributes*, Martin Myran, 2023

Fig. 17: Student work | *CHLORO-FIELD*, Guiguilé Lola, 2023 | This image shows a convergence of different land uses: student accommodations in the upper part, farmhouses in the central area, and agriculture in the lower part that reflect a different NDVI. The green field, which also serves as agricultural ground, appears to be healthier compared to the blue field. The yellow field, on the other hand, is overgrown with spontaneous weeds.

5 Conclusion and Outlook

Teaching students' abilities to work with point clouds and attributes, can represent a method for teaching landscape architects to make use of findings from other disciplines. Here, node-based visual programming tools like *Blender* and *Geometry Nodes* can facilitate an intuitive interface to read and process data, but also offer possibilities for more artistic landscape representation and motivate students to use computational tools further in their studies.

5.1 Motivation to use Computational Tools

Although the timeframe to familiarize students with computational tools, thinking and methods was very short, even students with less technical background and initial interest in digital tools reported that using *Blender* and visual programming enabled them much easier and faster to gain insights in computational methods than they had expected. One reason was the real-time visual feedback of changes in parameters, and that they were able to easily make changes to the protocol or syntax.

Students reported higher interest in digital tools within their education, as they felt more comfortable and familiar using the tools provided and showed higher interest in a continued exploration of visual programing tools and point clouds.

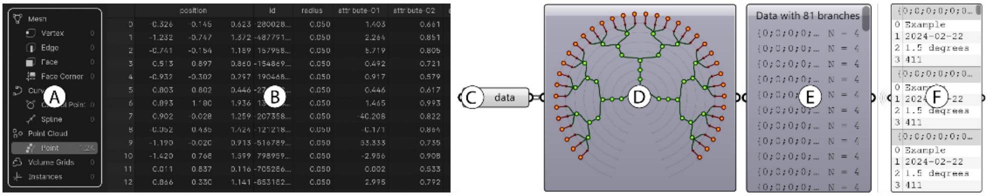
5.2 Ability to Understand Differences and Relationships more Intuitively through Computational Tools

Students showed greater ability to use simple mathematical formulas of addition, subtraction, division, etc. then using traditional interfaces such as field calculators and expression editors in GIS software. The student work reflected establishments of interesting connections and site correlations. Here, the spatial reading of data through 3D points enhanced the understanding since it also allowed to navigate in 3D space and in a more human perspective, which gave also more inspiration to the students to respond to the assignments in artistic terms.

5.3 Visual Programming as Interface to Scientific Data

Utilizing more intuitive tools for scientific data analysis demonstrated a significant improvement in comprehending the meaning within this data and effectively motivated students to delve deeper into computational tools. Node-based visual programming software, such as *Blender* and *Geometry Nodes*, provided immediate visual feedback, facilitating a better grasp of differences and relationships, through an interactive manipulation, that also encouraged a more poetic and subjective approach to the visualization of data.

5.4 Using Geometry Nodes opposed to Grasshopper



	position			id	radius	attribute-01	attribute-02
0	-0.326	-0.145	0.623	-280028...	0.050	1.403	0.661
1	-1.232	-0.747	1.372	-487791...	0.050	2.264	0.851
2	-0.741	-0.154	1.189	157958...	0.050	5.719	0.805
3	0.513	0.897	0.860	-154869...	0.050	0.492	0.721
4	-0.932	-0.302	0.297	190468...	0.050	0.917	0.579
5	0.803	0.802	0.446	-27[illegible]	0.050	0.446	0.617
6	0.893	1.180	1.936	13[illegible]	0.050	1.465	0.993
7	0.902	-0.028	1.259	-207358...	0.050	-40.208	0.822
8	-0.052	0.455	1.424	-121218...	0.050	-0.171	0.864
9	-1.190	-0.020	0.913	-516789...	0.050	53.333	0.735
10	-1.420	0.768	1.599	798959...	0.050	-2.956	0.908
11	0.011	0.837	0.116	-705286...	0.050	0.002	0.533
12	0.866	0.330	1.141	-853182...	0.050	2.995	0.792

```
Data with 81 branches
{0;0;0;0;…  N = 4
{0;0;0;0;…  N = 4
{0;0;0;0;…  N = 4
{0;0;0;0;…  N = 4
{0;0;0[illegible]  N = 4
{0;0;0;0;…  N = 4
{0;0;0;0;…  N = 4
{0;0;0;0;…  N = 4
{0;0;0;0;…  N = 4
{0;0;0;0;…  N = 4
{0;0;0;0;…  N = 4
```

```
{0;0;0;0;0;0…
0 Example
1 2024-02-22
2 1.5 degrees
3 411
{0;0;0;0;0;0…
0 Exam[illegible]
1 2024[illegible]-22
2 1.5 degrees
3 411
{0;0;0;0;0;0…
0 Example
1 2024-02-22
2 1.5 degrees
3 411
```

Fig. 18: (A) *Geometry Nodes:* different geometry types to store numerical values on; (B) *Geometry Nodes:* list of numerical values attached to the selected geometry; (C) *Grasshopper*: input data; (D, E) *Grasshopper*: example data-tree with various branches using the *param viewer*; (F) *Grasshopper*: list of numerical and alpha-numerical data.

When comparing *Rhino* and *Grasshopper* with *Blender* and *Geometry Nodes*, both tools present a fairly similar interface. However, there are notable differences that are crucial for understanding how each tool operates and unleashes its potential. One significant variance is that *Geometry Nodes* lacks data-tree structures like *Grasshopper*, which allow manipulation of data branches through operations like *grafting, flattening,* or *trimming*, enabling access to items stored in lists with varying data structures. In contrast, *Geometry Nodes* employs a single list without hierarchical organization. Another distinction is that in *Geometry Nodes*, values or data must be attached to specific geometry elements such as points, curves, or vertices and must be numerical, whereas in *Grasshopper*, data can be detached from any geometry and can also be alpha-numerical.

In contrast to previous years, where *Grasshopper* was utilized as a visual node-based programming tool to read GIS data and point clouds, student feedback and learning outcomes varied based on their prior experience with such tools. Below a few observations.

Students who were already acquainted with data-tree structures, when introduced to *Geometry Nodes*, initially felt constrained. However, through further engagement and understanding the principles of data storage on geometries, they discovered new working methods and innovative approaches to data manipulation. Some even noted how these experiences influenced their usage of *Grasshopper* or might complement that usage.

Students with no prior knowledge of data-tree structures, when tasked with using *Grasshopper*, struggled to grasp in a short time the concepts of data-trees and operations such as *grafting* or *trimming* to organize lists for further processing. These challenges posed a significant barrier for some of the students, leading partly to frustration and dampening their enthusiasm for deeper engagement into programming tools, especially through the additional time they felt necessary for them to invest to reach a higher degree of proficiency to pass these challenges.

Both groups of students with or without any prior knowledge, when instructed to use *Geometry Nodes*, encountered a rather familiar data structure of columns and rows like in Excel, or attribute tables in GIS. This familiarity facilitated a quicker adaptation to visual programming and enabled them to gain faster abilities and skills.

5.5 New Morphology in Architecture and Awareness of Vegetation Indices

The methods and tools outlined in this teaching experiment and paper can offer new opportunities to transcend knowledge in vegetation assessment while also harboring potential for exploring new forms and morphologies in landscape architecture, as well as facilitating artistic-scientific exploration in point cloud representations of site conditions and vegetation vitality.

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