sustainability

MDPI

Article

A Geospatial Thinking Multiyear Study

Carlos Carbonell-Carrera [1,*], Jose Luis Saorin [2] and Stephany Hess-Medler [3]

1 Area of Cartographic, Geodetic and Photogrammetry Engineering, Department of Techniques and Projects in Engineering and Architecture, Universidad de La Laguna, 38204 La Laguna, Spain
2 Area of Engineering Graphics, Department of Techniques and Projects in Engineering and Architecture, Universidad de La Laguna, 38204 La Laguna, Spain; jlsaorin@ull.edu.es
3 Department of Clinical Psychology, Universidad de La Laguna. Psychobiology and Methodology, Area of Methodology of Behavioral Sciences, 38204 La Laguna, Spain; sthess@ull.es
* Correspondence: ccarbone@ull.edu.es

Received: 19 May 2020; Accepted: 2 June 2020; Published: 4 June 2020

Abstract: In the field of environmental sustainability and landscape management, geospatial thinking is necessary. A good level of geospatial thinking is related to academic success in engineering degrees. It is relevant, therefore, to detect the possible deficiencies that university students may have in tasks related to geospatial thinking. This research presents the results of a 2014-2019 multiyear study with agricultural engineering students, in which seven geospatial tasks were analyzed. The statistical analysis shows that geospatial tasks related to slope, stream/water flow, visibility, and relief interpretation are the best at predicting the final course mark. The present research provides quantitative data on the efficiency that four technologies have to reinforce geospatial thinking focused on each task. Augmented Reality is an appropriate 3D technology for geospatial tasks related to route search, stream/water flow, and elevation points. SketchUp Make 2017 and Autodesk 123D Make showed their potential to solve tasks related to terrain slope and visibility analysis. Spatial Data Infrastructure has given the best results in geospatial tasks related to the photointerpretation of the relief and with topographic profiles of the terrain. Our findings will help teachers to select the most appropriate geospatial tasks to include in their courses.

Keywords: geospatial thinking; geospatial tasks; sustainability education; 3D technologies; spatial data infrastructure

1. Introduction

Since the middle of the last century, many researchers have announced that the increasing demands for resource consumption and population growth, among other factors, are unsustainable on an Earth with limited capacity [1–3]. Sustainability is defined as "meeting fundamental human needs while preserving the life-support systems of planet Earth" [4] (p. 641). In this context, geospatial technologies are an efficient resource for the analysis and planning of sustainable development [5]. Geospatial disciplines related to the representation of the Earth's surface are increasingly focusing on aspects related to sustainability [6]. Authors such as Scott and Rajabifard [7] (p. 66) affirm that "global policy and intergovernmental mechanisms [are] now recognizing and calling for the need to integrate geospatial information into sustainable development processes."

Geospatial technologies are relevant for landscape planning from a sustainability approach. Geography and geospatial disciplines, from its specificity and scope, constitute a favorable environment for sustainability education and research [6,8]. In the field of Higher Education, educational contents and careers related to sustainability are increasingly implemented [9]. The increasing numbers of geospatial applications, as well as 3D technologies for the topographic representation of the Earth's surface, also form a solid baseline tool for an education in sustainable development.

In the field of environmental sustainability and landscape management, different disciplines such as geography, engineering, and architecture, among others, make decisions based on maps, plans, and geospatial information, for which spatial thinking is necessary. Spatial thinking is defined as the ability to visualize and solve problems spatially [10], and geospatial thinking is a subset of spatial thinking in the field of the Earth's surface and its representations [11]. That is, as stated by Ishikawa [12] (p. 93), geospatial thinking "involves geographical, beyond purely spatial, components and accordingly points to the importance of geographical knowledge (hence the term *geospatial* thinking)." This author, among others such as Carbonell and Medler [13], emphasizes the importance of geospatial thinking for the use, reading, and understanding of maps, placing it as a central component of the geographical sciences. In this field of cartographic interpretation, Kainz [14] stated that it is necessary to promote research on new strategies and technologies that facilitate these tasks, as is carried out in this article. Authors such as Ishikawa, Bednarz and Bednarz, and Lobben and Lawrence [12,15,16] consider the relevance of geospatial thinking in teaching in the field of Earth science. This is in line with Zwartjes et al. [17], who stated that geospatial thinking needs to be integrated into educational settings. The report of the National Research Council (NRC), "Learning to think spatially," highlights the leading role of geospatial thinking in geographical areas [12,18]. A concept similar to geospatial thinking is so-called geospatial intelligence, which "includes the perception, cognition, computation, control, reaction, and understanding of physical features and geographically referenced" [19] (p. 151).

In the geographical environment in which the present research has been carried out, the European Higher Education Area, there are many competencies and learning outcomes related to map reading and cartographic interpretation [20]. This has motivated research carried out in university education destined for the development of geospatial thinking, in which different geospatial technologies have been used, such as, for example, GIS applications [21–23] and spatial data infrastructures (SDI) [7,13]. Also, in K-12 education, geospatial technologies have been used for the development of geospatial thinking [24,25]. Three-dimensional technologies have also been used for this purpose, such as augmented reality and CAD applications [13,26]. Geospatial thinking plays a relevant role in sustainability studies. Detecting what geospatial technologies and what 3D rendering technologies can develop geospatial thinking is necessary for an educational proposal based on sustainable development.

In the same way, it is important to detect the possible deficiencies that university students may have in tasks related to geospatial thinking [27]. These university students, specifically in disciplines related to sustainability, will make future decisions about sustainable development. Understanding geospatial concepts such as scale, altitude, slope, water flow/interaction, topographical position, visibility, profile processing, and landforms interpretation, among others, often presents difficulties for students. In this sense, authors such as Hwang [5] (p. 286) affirm that "geographic concepts are conducive to advancing an understanding of sustainability challenges, and these can be incorporated into the sustainability curriculum." Map reading and the use of geospatial technologies are complex tasks that involve a large number of these geospatial concepts in various combinations, depending on the type of task. Knowledge of 3D spatial perception from maps and 2D representations can help diagnose the nature of student error in these tasks [27,28]. Therefore, it is necessary to know the students' understanding of these geospatial concepts at the beginning of the academic course, in order to detect possible deficiencies that could limit their future learning in sustainable development.

For this purpose, the research group for the development of spatial skills (http://dehaes.webs.ull.es), as well as the consolidated group of educational innovation Techno-Digital Terrain Modell of the University of La Laguna has been developing since 2014 a geospatial thinking multiyear study. This multiyear study aims to detect possible deficiencies in the geospatial thinking of engineering students at the beginning of each academic year. Could these possible deficiencies be predictors of poor academic performance? Institutions like the National Research Council (NRC) [18] have correlated a good level of spatial skills with academic success in STEM (Science, Technology, Engineering and Mathematics) degrees. The detection of possible deficiencies at the beginning of the course could allow for the adoption of strategies to correct them throughout the academic year. In this way, the academic performance of students could be improved, while improving their geospatial thinking.

The educational model of the European Higher Education Area, the geographical environment in which this research was carried out, is based not only on the acquisition of knowledge, but also on the development of skills (in the context of the present research: geospatial thinking skills). The motivation for this research stems from the need to check whether geospatial task-based strategies are effective for the development of geospatial thinking. In this sense, it is also relevant to check which technologies may be appropriate for performing geospatial tasks related to landscape analysis for infrastructure planning in a sustainable environment.

The multiyear study presented in the present research has been carried out over four academic years (2014-15, 2015-16, 2016-7, and 2018-19) with 106 agricultural engineering students. The collective of agricultural engineers plays an important role in decision-making in the field of sustainability [29]. The students who participated in the study all took the course "Topography, Cartography and Geospatial Technologies." This is a subject within the Agronomic Engineering degree of the University of La Laguna that develops contents related to geospatial thinking.

The geospatial tasks analyzed in this research were: path, stream/water flow, slope, visibility, elevation points, photointerpretation relief, and profile. For the measurement of these tasks, the Topographic Map Assessment tool [30] has been used, which is described in Section 3. Task-based teaching is an effective strategy for students' learning [31]. In landscape analysis for infrastructure planning in a sustainable environment, geospatial tasks such as those studied in the present research need to be performed. For instance, in the field of sustainability education, Hwang [5] worked with concepts related to recognizing components and patterns of water systems, water flows, recognition of a watershed, identifying locations of spatial entities, recognizing how entities are connected among places/regions, and connections between places. Other tasks such as intervisibility between points are necessary in studies and simulations of landscape and visual impact assessment [32].

The present research, in addition to offering quantitative data on the deficiencies detected in tasks related to the geospatial thinking (geospatial tasks), also provides strategies, 3D tools, and geospatial technologies that have been shown to be effective in improving geospatial thinking, based on previous studies. Therefore, the strategy used in previous research that is most effective in solving the deficiencies in each geospatial task studied in the present research is provided.

2. Previous Studies on Geospatial Thinking Development

Different 3D technologies as well as geospatial technologies have been studied for the improvement of geospatial thinking. In these studies, four workshops were carried out in which undergraduate engineering students of La Laguna University participated in pre/post test experiments. The research group for the development of spatial skills at the University of La Laguna performed the studies.

Regarding the technological tools used to carry out these workshops, we focused on terrain representation. Among many technologies available, we selected those that were simple to implement without the need for extensive training, since the purpose was to develop geospatial thinking rather than learn to use programs. Augmented Reality is a powerful three-dimensional visualization and representation tool. CAD environments are widely used in engineering. For three-dimensional modeling, Sandboxes offer an easy-to-use environment with great teaching possibilities. Finally, GIScience environments such as Spatial Data Infrastructures are a powerful visualization and query tool for geospatial information. The geoportal structure makes the program, very comfortable to use.

With this in mind, four technologies used were: 3D technologies such as Augmented Reality, Autodesk 123D Make (Mill Valley, California, USA) and SketchUp (Trimble, Sunnyvale, California, USA), and a Spatial Data Infrastructure geospatial technology [13,26]. In these studies, the same measurement tool has been used as in the present research: a Topographic Map Assessment (TMA) [30]. Students participating in these workshops did not have previous exposure to the TMA. Before and after each workshop, participants took the Topographic Map Assessment in order to measure the possible improvement in geospatial thinking (pre-test, post-test).

The question is: which technology is best for each task? The data from previous studies [13,26] have shown different significant gains for each of the geospatial tasks of the TMA. Table 1 shows with which technology the greatest significant gains were obtained in each of the tasks performed in the Topographic Map Assessment. The gains in Table 1 are expressed as a percentage of the highest possible score of the TMA. Since there were no cases in which more than two technologies offered statistically significant improvements, the ranking is two positions.

Table 1. Ranking of significant gains by technology.

Task	1st Technology (Gain %, SD, *p*)	2nd Technology (Gain %, SD, *p*)
I Path	Augmented Reality (AR) (17%, SD = 0.42, p = 0.003)	No significant gains with SketchUp 123, Autodesk 123D or SDI
II Stream/Water flow	Augmented Reality (AR) (37.5%, SD = 2.12, p = 0.000)	SketchUp Make 123 (12.5%, SD = 1.22, p = 0.001)
III Slope	SketchUp Make 123 (19.33%, SD = 0.88, p = 0.006)	Autodesk 123D Make (14.00%, SD = 1.06, p = 0.001)
IV Visibility	SketchUp Make 123 (11.29%, SD = 1.02, p = 0.002)	Autodesk 123D Make (10.71%, SD = 1.29, p = 0.000)
V Elevation Points	Augmented Reality (AR) (20.87%, SD = 0.61, p = 0.000)	Autodesk 123D Make (9.67%, SD = 0.69, p = 0.002)
VI Photo-interpretation relief	Spatial Data Infrastructure (SDI) (14.25%, SD = 1.29, p = 0.002)	Autodesk 123D Make (9.50%, SD = 1.10, p = 0.022)
VII Profile	Spatial Data Infrastructure (SDI) (36.00%, SD = 1.03, p = 0.000)	SketchUp Make 123 (31.5%, SD = 0.71, p = 0.000)

For the present research, we have carried out an analysis of the data from those works, but focused on each of the geospatial tasks. Each of the technologies employed in these workshops is described below, as well as the full results on the development of geospatial thinking.

2.1. Augmented Reality

Augmented reality technology offers great possibilities in the context of sustainability. For example, in the field of sustainable architectural design, Ayer et al. [33] developed a simulation called ecoCampus for Sustainable Design Education using augmented reality and simulation 3D game technology. Others like Barrado-Timón and Hidalgo-Giralt [34] used Augmented Reality combined with Virtual Reality in the context of urban heritage tourism from the perspective of sustainability. This combination of Augmented Reality and Virtual Reality technologies is changing the way we perceive our environments [35]. It has also been used in teaching-learning processes in the field of long-term sustainability of industrial enterprises: authors such as Gabajová et al. and Nakamae, Qin and Tamadura [36,37] worked with AR in environmental assessment and landscape visualization. Augmented reality has also been used in research with university students on the geomorphological interpretation of the terrain [38].

Focused on geospatial thinking development, there is research in which Augmented Reality (AR) was used in the field of 3D landscape visualization and relief interpretation, using Digital Terrain Models (DTM) performed with AR technology [26]. The AR technology was used as a 3D tool to interpret cartographic relief representations. In the so-called "AR relief" workshop, 63 engineering students participated. They belonged to the 2014–2015 academic course. Participants used iPads for the 3D visualization. The TMA was used to measure the improvement of geospatial thinking in a pre/post experiment. Results showed a positive impact on the geospatial thinking development of the students, with a significant ($p < 0.001$) improvement of 19.32% (percentage of the highest possible score of the TMA). Analyzing the results for each geospatial task of which the TMA consists, the results were:

Task I, Path (Gain = 17%, SD = 0.42, p = 0.003), Task II Stream/water flow (Gain = 37.50%, SD = 2.12, p = 0.000), Task III Slope (Gain = 8%, SD = 0.64, p = 0.046), Task IV Visibility (Gain = 8.86%, SD = 1.08, p = 0.002), Task V Elevation points (Gain = 20.67%, SD = 0.81, p = 0.000), Task VI Photointerpretation relief (Gain = 9.25%, SD = 1.18, p = 0.020) and Task VII Profile (Gain = 19%, SD = 0.68, p = 0.001). The data expressed as a percentage indicate the percentage of the gain acquired based on the maximum gain to be acquired in each task.

2.2. Autodesk 123D Make

Autodesk products develop solutions, in the field of sustainable design, among others, providing a powerful tool that engineers, urban planners, and architects use for landscape analysis and landscape design. It also provides solutions for sustainable design education, which serve as a tool for planning educational strategies. This is the case of the workshop carried out in the 2016-17 course, with 24 engineering students [13]. In this workshop, students worked with topographical contour lines and LiDAR Digital Elevation Models. They generated seven landforms (plains, elevations, depressions, ridges, valleys, hills, and cols, also called mountain passes or saddle points), using the Autodesk 123D Make application. On the date the workshop was held (in 2016), the application was named Autodesk 123D Make, although it is currently (2020) called Autodesk Slicer for Fusion360. The results showed a positive impact on students, with a significant (p = 0.000) gain in geospatial thinking of 10.70%. Analyzing the results for each geospatial task of which the TMA consists, the results were: Task I, Path (there was no statistically significant gain), Task II Stream/water flow (Gain = 7.88%, SD = 2.20, p = 0.003), Task III Slope (Gain = 14%, SD = 1.06, p = 0.001), Task IV Visibility (Gain = 10.71%, SD = 1.29, p = 0.000), Task V Elevation points (Gain = 9.67%, SD = 0.69, p = 0.002), Task VI Photointerpretation relief (Gain = 9.50%, SD = 1.10, p = 0.022) and Task VII Profile (Gain = 10.71%, SD = 3.46, p = 0.000).

2.3. SketchUp Make 2017 with Sandbox Tools Plugin

The SketchUp Sandbox is a utility for creating 3D terrain modeling. It is an easy-to-use tool that offers great possibilities for geospatial training in the educational field. The surfaces created with this tool are called a triangulated irregular network (TIN). In the workshop, held in the 2017-18 academic year, 24 participants modeled seven landforms (plains, elevations, depressions, ridges, valleys, hills, and cols) using SketchUp Make 2017 with the Sandbox Tools plugin [13]. Digital 3D terrain models are used to represent landforms, and it is an active field of research [27,39]. Participants modeled the landforms starting from a flat rectangular TIN, and also starting with a model with contour lines through the "Sandbox From Contours" tool. Results showed a positive impact on the students, with a significant (p = 0.000) gain in geospatial thinking of 12.60%. Analyzing the results for each geospatial task of which the TMA consists, the results were: Task I, Path (there was no statistically significant gain), Task II Stream/water flow (Gain = 12.50%, SD = 1.22, p = 0.001), Task III Slope (Gain = 19.33%, SD = 0.88, p = 0.006), Task IV Visibility (Gain = 11.29%, SD = 1.02, p = 0.002), Task V Elevation points (Gain = 9.67%, SD = 0.55, p = 0.003), Task VI Photointerpretation relief (Gain = 5.25%, SD = 0.51, p = 0.068) and Task VII Profile (Gain = 31.50%, SD = 0.71, p = 0.000).

2.4. Spatial Data Infrastructure Geospatial Technology

A Spatial Data Infrastructure geoportal is a geospatial technology that facilitates the access and management of digital geospatial information. The functionality of SDIs' geoportals makes them a tool that has been used for spatial skills and geospatial thinking training [40,41]. In their research, Otero and De Lazaro highlighted the possibilities of SDIs in the geography educational field for the development of geospatial thinking [42]. Also, SDIs are powerful geospatial information platforms represented in 2D and 3D that offer the ability to respond to the challenges of sustainable development [7]. In the 2018-19 academic year, 46 engineering students performed a workshop using the Canary Spatial Data Infrastructure geoportal [30]. Participants worked with six different modes of digital terrain representation: digital surface model (DSM) generated from LiDAR, topographic map, the HillShade

DTM, digital elevation model (DEM; Hypsometric), the high-resolution orthophoto, and slope model. They performed an exploratory geovisualization activity working with different landforms, using the geovisualization tools and the command line of the SDI.

The significant gain ($p < 0.001$) in geospatial thinking was 13.89%. Analyzing the results for each geospatial task of which the TMA consists, the results were: Task I, Path (there was no statistically significant gain), Task II Stream/water flow (Gain = 25.50%, SD = 2.52, $p = 0.000$), Task III Slope (there was no statistically significant gain), Task IV Visibility (there was no statistically significant gain), Task V Elevation points (there was no statistically significant gain), Task VI Photointerpretation relief (Gain = 14.25%, SD = 1.29, $p = 0.002$) and Task VII Profile (Gain = 36.00%, SD = 1.03, $p = 0.000$).

3. Materials and Methods

3.1. Materials

The Topographic Map Assessment [30] is made up of seven geospatial tasks, throughout which 18 exercises are carried out, in which different terrain forms are represented through contour lines, perspectives, views, 2D-printed 3D representations, and photos. For each terrain representation, questions are asked related to the topographic and geomorphological interpretation, such as, route choice with the least effort, intervisibility between points located in geographical features, interpretation of perspectives, route choice with the least effort, water flow, and transversal and longitudinal profile interpretation.

Table 2 shows the TMA exercises, associating them with the task performed in each one. The maximum score of the TMA is 28 points: item 3 is worth five points; items 9, 10, 12, and 17 are worth two points; item 11 is worth three points; and the rest of the items are worth one point.

Table 2. Topographic map assessment tasks description.

	Task	Description	Item Number
I	Path	Easy route between two points	1
II	Stream/water flow	Water flow between two points in different geographical settings	2, 10, 11, 12
III	Slope	Steeper slope between two points	5, 9
IV	Visibility	Questions about visibility between points	3, 17
V	Elevation points	Questions about elevation points in a contour interval scenario	4, 6, 7
VI	Photo interpretation relief	From a photograph/image of a land and a contour lines topographic map, different questions are asked	8, 15, 16, 18
VII	Profile	Questions about topographic profiles from a contour lines topographic map	13, 14

Therefore, the percentage score over the total TMA score for each Task is: Task I 3.57%, Task II 28.57%, Task III 10.71%, Task IV 25%, Task V 10.71%, Task VI 14.29% and, finally, Task VII 7.14%.

In addition to the previous work listed in point 3, the TMA has been used in other works in the field of geospatial thinking research [43–45]. The study carried out by Newcombe et al. [44] on the characteristics of the TMA showed a high reliability and a wide range of performance, which makes it a useful tool to measure the geospatial thinking of students. In addition, the TMA exercise typology includes geospatial tasks related to landscape analysis for infrastructure planning in a sustainable environment, which is suitable for the study carried out in this research.

The Topographic Map Assessment and the Topographic Map Assessment key are freely available at https://www.silc.northwestern.edu/topographic-map-assessment-tma/.

Regarding the participants, 106 second-year agricultural engineering students (75 female, 31 male) over four academic years (2014–15, 2015–16, 2016–17 and 2018–19), enrolled in the "Topography, Cartography and Geospatial Technologies" course, participated in the study. Each year the class had between 21 and 29 students. Ages were between 19 and 33 years (M = 21.27; SD = 2.63), and the gender distribution was 70.8% males and 29.2% females. All groups were equivalent in age ($F_{3,102} = 0.381$; $p = 0.767$) and gender distribution ($\chi^2{}_3 = 4.904$; $p = 0.179$).

3.2. Methodology

The students carried out, at the beginning of each academic year, a Topographic Map Assessment (TMA) [30], a battery of exercises based on different tasks related to the geospatial thinking in which they worked with geospatial concepts. Before carrying out the TMA, the students received a 2-h basic training seminar related to the forms of representation of the relief, contour lines, geospatial concepts (altitude, scale, slope, water flow interaction, etc.) and interpretation of landforms. Students participating in the multiyear study did not have previous exposure to the Topographic Map Assessment. They voluntarily participated in the multiyear study.

In accordance with the TMA instructions, the assessment was not timed. The average delivery time of the TMA was 25 min, which is consistent with previous experiments [13,26].

The results of the TMA were compared with the final grades that the students obtained in the course "Topography, Cartography and Geospatial Technologies," in order to check if the results obtained in the TMA could serve as a predictor of the academic performance of the participants. Many studies have correlated a high level in spatial thinking with students' success in Science, Technology, Engineering and Mathematics (STEM) degrees [18,46–48].

3.3. Data Analysis

The obtained data were subjected to a descriptive analysis and Pearson's correlations to map the univariate relations between tasks and mark. A multiple linear regression will allow for establishing a conjoint relation between tasks and mark. To analyze if year, gender, or age has an influence on task performance and if performance along the tasks is different, a multivariate analysis of covariance (MANCOVA) 4x2x7 (year, gender, tasks) with age as covariate was carried out, which allows us to detect poor performance. We included the covariate because it was seen in other studies [49] that age can affect spatial abilities. In all tests, the level of significance was set to 0.05. All statistical analyses were performed using SPSS, v.21.0. [50]. Finally, correlations between tasks will show if they are independent each other. The steps followed in the research (see Figure 1).

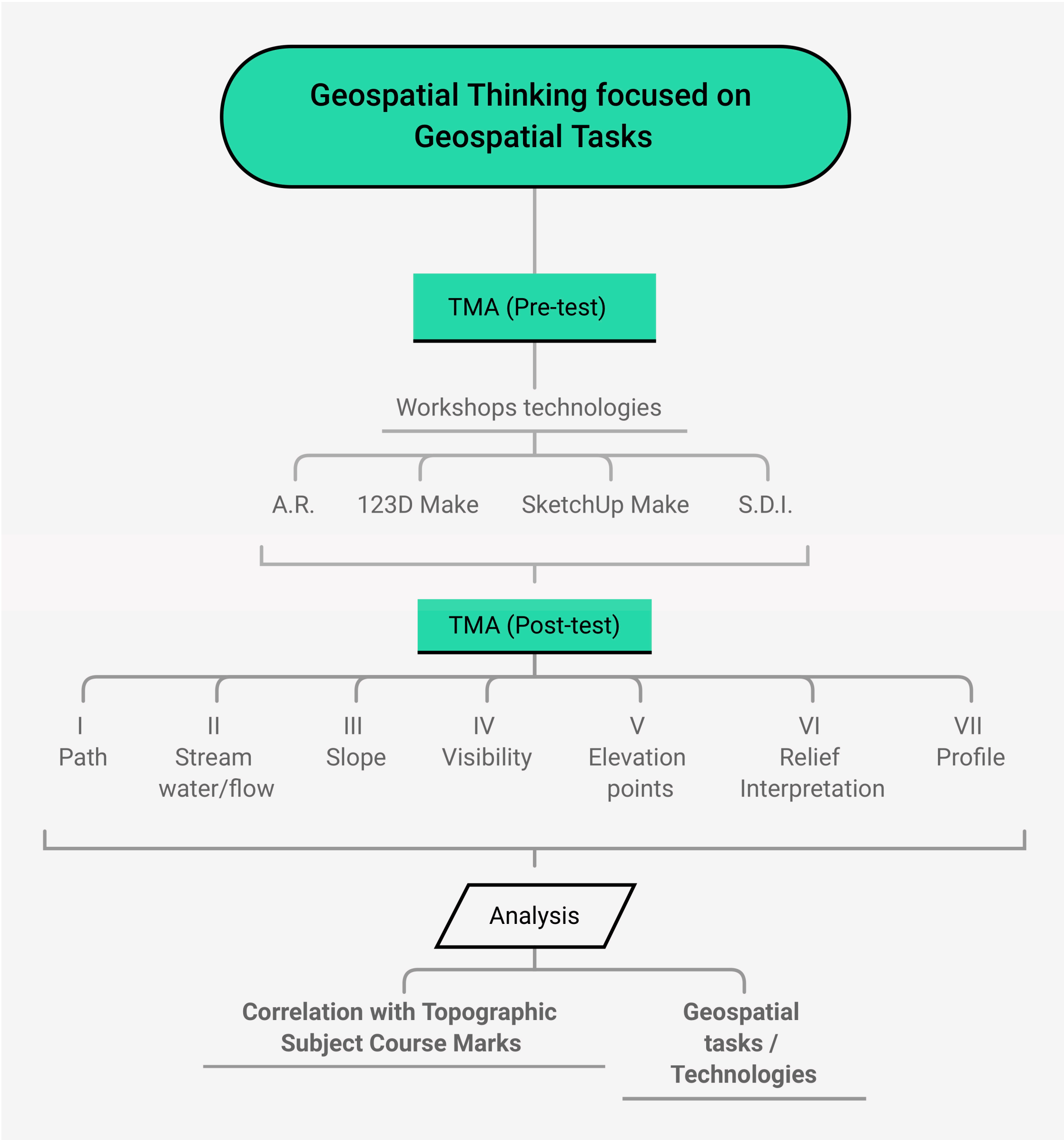

Figure 1. Methodology flow chart. TMA: Topographic Map Assessment Test. A.R.: Augmented Reality. S.D.I.: Spatial Data Infrastructure.

4. Results

Pearson's correlations show how the tasks are related to the final grade in the course "Topography, Cartography, and Geospatial Technologies." Table 3 shows that the course mark shares most variance (in terms of the coefficient of determination, r^2) (25%; $r = 0.50$; $p < 0.01$) with the TMA total score. Among the tasks, Tasks II (10.2%, $r = 0.32$; $p < 0.01$) and IV (14.7%; $r = 0.38$; $p < 0.01$) are most closely related to the mark. The rest present correlations below 0.3—that is, they share less than 9% of their variance.

In order to establish a regression model to predict the course mark based on task performance, a stepwise multiple linear regression analysis was conducted. A model including Tasks II, III, IV, and VI accounts for 27.4% of course mark variance ($R^2 = 0.302$; R^2adj = 0.274; F4, 101 = 10.91, $p < 0.001$). That is, these tasks explain 27.4% of why some students get better marks than others. Table 4 shows the corresponding nonstandardized and standardized coefficients.

Table 3. Correlations between final course mark, tasks and TMA total score.

n = 106		Task I	Task II	Task III	Task IV	Task V	Task VI	Task VII	TMA Total Score
Course Mark	r	−0.01	0.32	0.28	0.38	0.22	0.26	0.20	0.50
	r^2	0.00	0.10	0.08	0.14	0.05	0.07	0.04	0.25
	(p)	(0.94)	(<0.01)	(0.01)	(<0.01)	(0.02)	(0.01)	(0.04)	(<0.01)

Table 4. Regression coefficients for course mark as dependent variable.

	B	Standard Error	*Beta*	*t*	*p*
A (constant)	0.99	0.64		1.54	0.13
Task II	0.13	0.06	0.20	2.27	0.03
Task III	0.54	0.22	0.21	2.48	0.02
Task IV	0.49	0.12	0.34	4.04	0.00
Task VI	0.32	0.14	0.20	2.33	0.02

The most important tasks to predict the Mark for the course "Topography, Cartography, and Geospatial Technologies" are Tasks III and IV: for each additional point in these tasks, the course mark will rise about 0.5 points (B = 0.54 and B = 0.49, respectively). Each additional point in Task II causes the course mark to rise 0.13 and in Task VI it rises by 0.32. The regression equation would be Predicted Course Mark = 0.99 + 0.13 × Task II + 0.54 × Task III + 0.49 × Task IV + 0.32 × Task VI.

Table 5 shows descriptive statistics for the seven tasks as a direct score adding the corresponding items, the Total TMA Score, and the mark obtained by the students at the end of the "Topography, Cartography and Geospatial Technologies" course.

Table 5. Descriptive statistics of tasks, total score, and course mark.

n = 106	Possible maximum	Min.	Max.	Mean	Standard Deviation
Task I	1	0	1	0.8	0.4
Task II	8	0	8	4.3	2.4
Task III	3	1	3	2.2	0.6
Task IV	7	0	5	3.2	1.1
Task V	3	0	3	2.1	0.8
Task VI	4	0	4	1.4	1.0
Task VII	2	0	2	1.3	0.7
TMA Total Score	28	7	23	15.2	3.8
Course Mark	10	0.7	7.8	4.8	1.6

In order to compare the performance of the different tasks, and given they have different maximum scores, we have calculated for each student the achieved percentage of the maximum score for each task (Table 6).

Table 6. Descriptive statistics of achieved percentage of possible maximum score.

n = 106	Min.	Max.	Mean, %	Standard Deviation
Task I, %	0	100	75.5	43.2
Task II, %	0	100	54.2	29.7
Task III, %	33.3	100	74.5	20.9
Task IV, %	0	71.4	45.4	15.7
Task V, %	0	100	68.6	26.4
Task VI, %	0	100	34.9	24.6
Task VII, %	0	100	63.2	35.4

The MANCOVA 4x2x7 analysis (year, gender, tasks), with age as a covariate, revealed that age is not a covariate and that there are no differences between the performances of tasks (as an achieved percentage) due to the year or gender, or to their interactions. The performances of the several tasks are different (F7, 91 = 8.95, $p < 0.001$, η2 = 0.472). Figure 2 shows the mean achieved percentage with 95% confidence intervals. Posterior pairwise comparations (Sidak adjustment) showed that the best performance was achieved in Tasks I, III, V, and VII, followed by Tasks II and IV. Task VI had the worst performance.

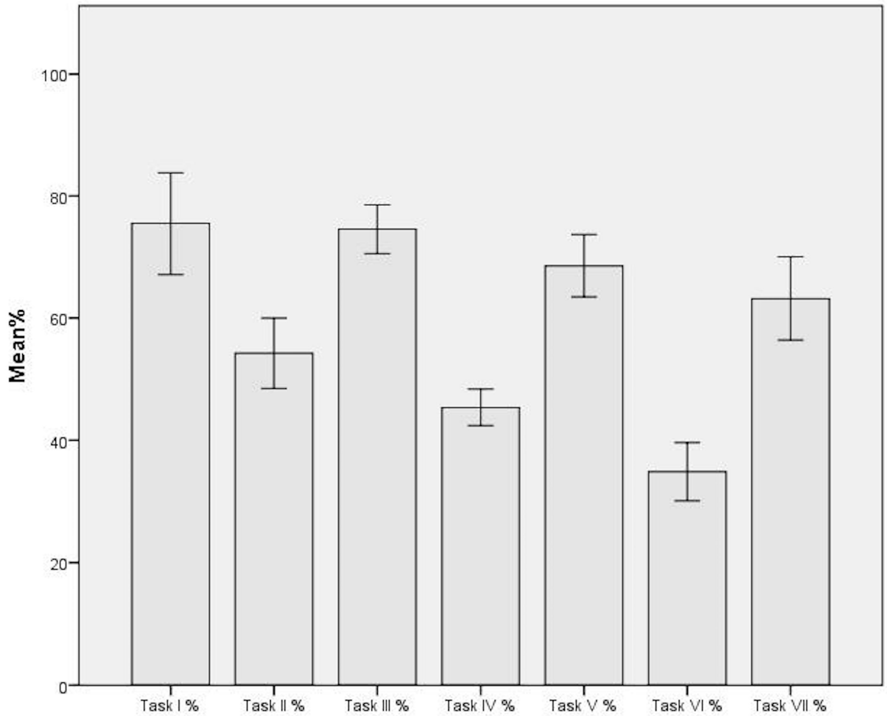

Figure 2. Mean percentage of maximum score for each task with 95% confidence intervals.

Table 7 shows the Pearson's correlations between each pair of tasks. Only Tasks III and V, and Tasks III and VII, share slightly more than 10% ($r > 0.316$), so that the performances in tasks are nearly independent of each other.

Table 7. Pearson's correlations between tasks.

n = 106		Task II, %	Task III, %	Task IV, %	Task V, %	Task VI, %	Task VII, %
Task I, %	*r*	0.00	−0.21	−0.03	−0.04	0.05	−0.22
	(p)	(0.99)	(0.03)	(0.79)	(0.67)	(0.60)	(0.02)
Task II, %	*r*		0.24	0.11	0.19	0.16	0.26
	(p)		(0.01)	(0.26)	(0.05)	(0.10)	(0.01)
Task III, %	*r*			0.03	0.32	0.00	0.33
	(p)			(0.73)	(0.00)	(0.99)	(0.00)
Task IV, %	*r*				−0.06	0.08	0.11
	(p)				(0.57)	(0.40)	(0.26)
Task V, %	*r*					0.17	0.25
	(p)					(0.09)	(0.01)
Task VI, %	*r*						0.22
	(p)						(0.03)

5. Discussion

The multiyear study carried out in the present research throughout four academic years (2014-15, 2015-16, 2016-7, and 2018-19) provides data that serve to detect deficiencies in geospatial tasks necessary to work with maps and geospatial applications. In the field of environmental sustainability and landscape management, when using maps and geospatial applications, geospatial tasks such as those studied in the present research need to be performed. In this sense, it would be a good strategy to help struggling students with these tasks [27]. For this reason, and in agreement with what Ishikawa and Kastens [27] stated in their recent research on the perception of 3D landforms, it would be a good strategy to help struggling students with geospatial tasks.

This strategy, in addition to developing their geospatial thinking, would help them achieve a better course mark. As shown by the Pearson's correlations, tasks are independent of each other, so it takes individualized training in particular tasks to allow each student to reach their top performance.

The deficiencies/strengths that students present when solving geospatial tasks have a remarkable correlation ($r = 0.5$, $p < 0.001$) with their failure/success in the course "Topography, Cartography, and Geospatial Technologies," part of the degree in Agronomic Engineering. Going into detail, the regression model showed that Tasks II, III, IV, and VI are the best at predicting the course mark, so they are the ones that most influence the final grade. These tasks explain nearly 30% ($R^2 = 0.274$) of the variability in the course mark. The MANCOVA analysis showed that Tasks II (Mean% = 54.2), IV (Mean% = 45.4), and VI (Mean% = 34.9) are precisely those at which students perform less well on average. The students who perform best on these tasks are the ones who get a better final course mark. On the other hand, Task III (Mean% = 74.5) has good average performance, but students who perform worse at this task get a worse course mark.

For this purpose, previous studies with different 3D and geospatial technologies have been shown to be effective for the development of geospatial thinking [13,24–26,42]. Dold and Goopman [19] discussed the role of these technologies as a tool for the development of geospatial intelligence. The data from these previous studies, which were performed with Augmented Reality (AR), SketchUp Make 2017 with Sandbox Tools plugin, Autodesk 123D Make, and Spatial Data Infrastructure (SDI), have shown different significant gains for each of the geospatial tasks analyzed in the present research. AR showed a gain of 17% in geospatial thinking for tasks related to route searching (path, Task I); for stream/water flow (Task II) the gain was 37.5%, and in elevation points (Task V) the gain was 20.87%. SketchUp Make 2017 with the Sandbox Tools plugin and Autodesk 123D Make showed gains of 19.33% in Task III (slope) and Task IV (visibility). Spatial Data Infrastructures showed gains of 14.25% and 36% in Task VI (photo-interpretation relief) and Task VII (profile), respectively.

Authors such as Cinderby, Lange, Steiner et al., and Meng [35,51–53] have previously highlighted the potential of AR for landscape visualization. Related to the present research, Turan, Meral, and Sahin [38] concluded that AR is a useful tool to improve the performance of university students in geomorphology (study of landforms) topics. Digital terrain models play an important role in representing, classifying, and interpreting landforms [39]. In the present research, digital terrain models have been created with different tools such as Autodesk 123D Make and SketchUp Make, which have been shown to be effective for this purpose. Diaz et al. [54] showed the effectiveness of manufacturing tangible digital terrain models with Autodesk 123D Make for improving cartographic interpretation. The same occurs in a digital 3D rendering environment like SketchUp Make 2017 with Sandbox Tools plugin, in which 3D modeling tools facilitate these tasks. In this sense, authors such as Wang [55] highlighted the versatility of SketchUp for landscape design, planting design, planning, and designing. In fields related to energy efficiency for sustainable architectural environments, SketchUp has also been shown to be useful [56,57]. Spatial Data Infrastructure geoportals have been shown to be effective in developing geospatial thinking [40–42]. Furthermore, there is an active field of research related to the use of Spatial Data Infrastructures in the field of sustainable development [7,58–61] and environmental education [62].

6. Conclusions

The correlation between students' ability to solve geospatial tasks and their final grade coincides with previous studies that correlated a high level of geospatial thinking with the success of students in STEM degrees [18,46–48]. The results of the present study focus on geospatial tasks frequently used in landscape analysis.

These findings will also help teachers to know which geospatial tasks are the most challenging for students, which will allow them to focus on teaching planning focused on these geospatial tasks.

Knowing which tasks are the most predictive of the course mark can help the student in planning their study from the beginning of the course. In addition, the present research shows the versatility of various technologies that have been effective in solving these tasks. Now, what is the most appropriate technology for each task?

AR is an appropriate technology for tasks related to route searching (path, Task I), stream/water flow (Task II), and elevation points (Task V). The versatility that RA offers, when used with a touch-screen device such as an iPad, allows the user to make turns, rotations, perspectives, and scale changes with hand gestures. In this way, relief exaggeration effects that allow for intuitive 3D visualization can be created, which helps to visualize routes or single points, or to detect water flows.

SketchUp Make 2017 with Sandbox Tools plugin and Autodesk 123D Make showed their potential to solve tasks related to terrain slope (Task III) and visibility analysis (Task IV). Autodesk 123D Make allows the user to work with contour lines that it prints. By gluing each curve in ascending order, a tangible model of the terrain is made. The tangible models facilitate the appreciation of which slope is greater or lesser, as well as detecting if one area or point is at a higher altitude than another.

Spatial Data Infrastructure (SDI) is the geospatial technology that has given the best results in tasks related to the photointerpretation of the relief (Task VI) or to the topographic profiles of the terrain (Task VII). Spatial Data Infrastructures offer different displays of geovisualization such us LiDAR digital surface model, slope models, high-resolution orthophotos, digital elevation models, and topographic maps. These geo-visualization modes facilitate the photointerpretation of the relief. In addition, the commands on the SDIs toolbar allow for obtaining topographic profiles.

A limitation of this research is that it focused on a limited number of geospatial tasks. In a future work, research could be carried out analyzing more geospatial tasks related to environmental sustainability and landscape management.

Another future line of research would be to check whether, indeed, better training in geospatial thinking is synonymous with an improvement in the daily practice of the engineering profession. For this, it would be necessary to monitor graduate students who could provide information about their professional situation.

Author Contributions: Conceptualization, C.C.-C., J.L.S. and S.H.-M.; methodology, S.H.-M.; software, J.L.S.; validation, C.C.-C. and S.H.-M.; formal analysis, S.H.-M.; investigation, C.C.-C.; resources, C.C.-C. and J.L.S.; data curation, C.C.-C., J.L.S. and S.H.-M.; writing—original draft preparation, C.C.-C.; writing—review and editing, C.C.-C., J.L.S. and S.H.-M.; visualization, J.L.S. and S.H.-M.; supervision, J.L.S. and S.H.-M.; project administration, C.C.-C.; funding acquisition, C.C.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The authors appreciate the work of the editor and the reviewers.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ehrlich, P. *The Population Bomb*; Buccaneer Books: New York, NY, USA, 1968.
2. Goldsmith, E. *Blueprint for Survival*; Houghton Mifflin: Boston, MA, USA, 1974; Volume 7830.
3. Meadows, D.H.; Meadows, D.L.; Randers, J.; Behrens, W.W. *The Limits to Growth*; New American Library: New York, NY, USA, 1972.
4. Kates, R.W.; Clark, W.C.; Corell, R.; Hall, J.M.; Jaeger, C.C.; Lowe, I.; Faucheux, S. Sustainability science. *Science* **2001**, *292*, 641–642. [CrossRef]
5. Hwang, S. Placing GIS in sustainability education. *J. Geogr. High. Educ.* **2013**, *37*, 276–291. [CrossRef]
6. Yarnal, B.; Neff, R. Whither parity? The need for a comprehensive curriculum in human-environment geography. *Prof. Geogr.* **2004**, *56*, 28–36.
7. Scott, G.; Rajabifard, A. Sustainable development and geospatial information: A strategic framework for integrating a global policy agenda into national geospatial capabilities. *Geo-Spat. Inf. Sci.* **2017**, *20*, 59–76. [CrossRef]
8. Martin, G.J. *All Possible Worlds: A History of Geographical Ideas*; OUP Catalogue: Oxford, UK, 2005.

9. Association for Advancement of Sustainability in Higher Education (AASHE). Sustainability-Focused Academic Degree Programs. 2012. Available online: http://www.aashe.org/resources/academic-programs (accessed on 18 November 2012).
10. Nielsen, C.P.; Oberle, A.; Sugumaran, R. Implementing a high school level geospatial technologies and spatial thinking course. *J. Geogr.* **2011**, *110*, 60–69. [CrossRef]
11. Huynh, N.T.; Sharpe, B. An assessment instrument to measure geospatial thinking expertise. *J. Geogr.* **2013**, *112*, 3–17. [CrossRef]
12. Ishikawa, T. Spatial thinking in geographic information science: Students' geospatial conceptions, map-based reasoning, and spatial visualization ability. *Ann. Am. Assoc. Geogr.* **2016**, *106*, 76–95. [CrossRef]
13. Carbonell-Carrera, C.; Hess-Medler, S. 3D Landform Modeling to Enhance Geospatial Thinking. *Isprs Int. J. Geo-Inf.* **2019**, *8*, 65. [CrossRef]
14. Kainz, W. Cartography and the others—Aspects of a complicated relationship. *Geo-Spat. Inf. Sci.* **2020**, *23*, 52–60. [CrossRef]
15. Bednarz, R.S.; Bednarz, S.W. The effect of explicit instruction in spatial thinking. In Proceedings of the 5th International Conference on Geographic Information Systems, Istanbul, Turkey, 2–5 July 2008; Fatih University Publications: Buyukcekmece, Istanbul, Turkey, 2008; pp. 649–655.
16. Lobben, A.; Lawrence, M. Synthesized model of geospatial thinking. *Prof. Geogr.* **2015**, *67*, 307–318. [CrossRef]
17. La Necesidad de Integrar el Pensamiento Espacial en Educación. GI Learner. Creando una Línea de Aprendizaje Basada en el Pensamiento Espacial. Available online: http://www.gilearner.ugent.be/wp-content/uploads/GI-Learner-O7_ES.pdf (accessed on 18 May 2020).
18. NRC. *National Research Council. Learning to Think Spatially*; National Academy Press: Washington, DC, USA, 2006.
19. Dold, J.; Groopman, J. The future of geospatial intelligence. *Geo-Spat. Inf. Sci.* **2017**, *20*, 151–162. [CrossRef]
20. Chueca, M.; Salcedo, F.; Ferrer, J.; Galán, L.; Olivé, J. *White Paper Title Engineer Degree in Geomatics and Surveying*; National Agency for Quality Assessment and Accreditation (ANECA): Madrid, Spain, 2004; pp. 118–148.
21. Lee, J.; Bednarz, R. Effect of GIS learning on spatial thinking. *J. Geogr. High. Educ.* **2009**, *33*, 183–198. [CrossRef]
22. Lee, J.; Bednarz, R. Components of spatial thinking: Evidence from a spatial thinking ability test. *J. Geogr.* **2012**, *111*, 15–26. [CrossRef]
23. Goodchild, M.F.; Janelle, D.G. Toward critical spatial thinking in the social sciences and humanities. *GeoJournal* **2010**, *75*, 3–13. [CrossRef] [PubMed]
24. Hammond, T.C.; Bodzin, A.; Anastasio, D.; Holland, B.; Popejoy, K.; Sahagian, D.; Rutzmoseer, S.; Carrigan, J.; Farina, W. "You know you can do this, right?" developing geospatial technological pedagogical content knowledge and enhancing teachers' cartographic practices with socio-environmental science investigations. *Cartog. Geog. Inf. Sci.* **2018**, *45*, 305–318. [CrossRef]
25. Schlemper, M.B.; Athreya, B.; Czajkowski, K.; Stewart, V.C.; Shetty, S. Teaching Spatial Thinking and Geospatial Technologies Through Citizen Mapping and Problem-Based Inquiry in Grades 7–12. *Cartog. Geog. Inf. Sci.* **2018**, *118*, 21–34. [CrossRef]
26. Carbonell-Carrera, C.; Hess-Medler, S. Interactive Visualization Software to Improve Relief Interpretation Skills: Spatial Data Infrastructure Geoportal versus Augmented Reality. *Prof. Geogr.* **2019**, *71*, 725–737. [CrossRef]
27. Ishikawa, T.; Kastens, K. Why Some Students Have Trouble with Maps and Other Spatial Representations. *J. Geosc. Educ.* **2018**, *53*, 184–197. [CrossRef]
28. Kastens, K.A.; Ishikawa, T. Spatial thinking in the geosciences and cognitive sciences: A cross-disciplinary look at the intersection of the two fi elds. In *Earth and Mind: How Geologists Think and Learn about the Earth: Geological Society of America Special Paper 413*; Manduca, C.A., Mogk, D.W., Eds.; Geological Society of America: Boulder, CO, USA, 2006; pp. 53–76. [CrossRef]
29. Sındır, K.O.; Martinov, M.; Skaljic, S.; Djevic, M.; Oztekın, S.; Ros, V.; Kosutic, S. The role of agricultural engineering in sustainable rural development in SEE (South Eastern Europe) countries. *J. Agric. Sci.* **2008**, *53*, 151–158.
30. Jacovina, M.; Ormand, C.; Shipley, T.F.; Weisberg, S. Topographic Map Assessment. 2014. Available online: http://www.spatiallearning.org/index.php/resources/testsainstruments (accessed on 12 March 2017).

31. Golledge, R.G.; Marsh, M.; Battersby, S. Matching geospatial concepts with geographic educational needs. *Geogr. Res.* **2008**, *46*, 85–98. [CrossRef]
32. Palmer, J.F. A Landscape Assessment Framework for Visual Impact Assessment in the USA. *J. Digit. Landsc. Archit.* **2016**, *1*, 10–17.
33. Ayer, S.K.; Messner, J.I.; Anumba, C.J. Assessing the impact of using photographic images to influence building retrofit design education. In *AEI 2013: Building Solutions for Architectural Engineering*; American Society of Civil Engineers: Reston, VA, USA, 2013; pp. 34–43.
34. Barrado-Timón, D.A.; Hidalgo-Giralt, C. The Historic City, Its Transmission and Perception via Augmented Reality and Virtual Reality and the Use of the Past as a Resource for the Present: A New Era for Urban Cultural Heritage and Tourism? *Sustainability* **2019**, *11*, 2835. [CrossRef]
35. Meng, L. An IEEE value loop of human-technology collaboration in geospatial information science. *Geo-Spat. Inf. Sci.* **2020**, *23*, 61–67. [CrossRef]
36. Gabajová, G.; Furmannová, B.; Medvecká, I.; Grznár, P.; Krajčovič, M.; Furmann, R. Virtual Training Application by Use of Augmented and Virtual Reality under University Technology Enhanced Learning in Slovakia. *Sustainability* **2019**, *11*, 6677. [CrossRef]
37. Nakamae, E.; Qin, X.; Tadamura, K. Rendering of landscapes for environmental assessment. *Landsc. Urban Plan.* **2001**, *54*, 19–32. [CrossRef]
38. Turan, Z.; Meral, E.; Sahin, I.F. The impact of mobile augmented reality in geography education: Achievements, cognitive loads and views of university students. *J. Geogr. High. Educ.* **2018**, *3*, 427–441. [CrossRef]
39. Galin, E.; Guérin, E.; Peytavie, A.; Cordonnier, G.; Cani, M.P.; Benes, B.; Gain, J. A Review of Digital Terrain Modeling. *Comput. Graph. Forum* **2019**, *38*, 553–577. [CrossRef]
40. Carbonell-Carrera, C.; Hess Medler, S. Spatial Orientation Skill Improvement with Geospatial Applications: Report of a Multi-Year Study. *ISPRS Int. J. Geo-Inf.* **2017**, *6*, 278. [CrossRef]
41. Carbonell Carrera, C. Spatial-thinking knowledge acquisition from route-based learning and survey learning: Improvement of spatial orientation skill with geographic information science sources. *J. Surv. Eng.* **2017**, *143*, 05016009. [CrossRef]
42. Álvarez-Otero, J.; De Lázaro y Torres, M.L. Spatial Data Infrastructures and Geography Learning. *Eur. J. Geogr.* **2017**, *3*, 19–29.
43. Atit, K.; Weisberg, S.M.; Newcombe, N.S.; Shipley, T.F. Learning to interpret topographic maps: Understanding layered spatial information. *Cogn. Res. Princ. Implic.* **2016**, *1*, 2. [CrossRef] [PubMed]
44. Newcombe, N.S.; Weisberg, S.M.; Atit, K.; Jacovina, M.E.; Ormand, C.J.; Shipley, T.F. The lay of the land: Sensing and representing topography. *Balt. Int. Yearb. Cogn. Log. Commun.* **2015**, *10*, 6. [CrossRef]
45. Carbonell-Carrera, C.; Jaeger, A.J.; Shipley, T.F. 2D Cartography Training: Has the Time Come for a Paradigm Shift? *Isprs Int. J. Geo-Inf.* **2018**, *7*, 197. [CrossRef]
46. Sorby, S.A. Educational research in developing 3-D spatial skills for engineering students. *Int. J. Sci. Educ.* **2009**, *31*, 459–480. [CrossRef]
47. Liben, L.S.; Kastens, K.A.; Christensen, A.E. Spatial foundations of science education: The illustrative case of instruction on introductory geological concepts. *Cogn. Instr.* **2011**, *29*, 45–87. [CrossRef]
48. Uttal, D.H.; Meadow, N.G.; Tipton, E.; Hand, L.L.; Alden, A.R.; Warren, C.; Newcombe, N.S. The malleability of spatial skills: A meta-analysis of training studies. *Psychol. Bull.* **2013**, *139*, 352. [CrossRef]
49. Pak, R.; Czaja, S.J.; Sharit, J.; Rogers, W.A.; Fisk, A.D. The role of spatial abilities and age in performance in an auditory computer navigation task. *Comput. Hum. Behav.* **2006**, *24*, 3045–3051. [CrossRef]
50. IBM Corp. *IBM SPSS Statistics for Windows*, version 21.0; Released 2012; IBM Corp: Armonk, NY, USA, 2012.
51. Cinderby, S. How to reach the ‘hard-to-reach’: The development of Participatory Geographic Information Systems (P-GIS) for inclusive urban design in UK cities. *Area* **2010**, *42*, 239–251. [CrossRef]
52. Lange, E. 99 volumes later: We can visualise. Now what? *Landsc. Urban Plan.* **2011**, *100*, 403–406. [CrossRef]
53. Steiner, F.; Simmons, M.; Gallagher, M.; Ranganathan, J.; Robertson, C. The ecological imperative for environmental design and planning. *Front. Ecol. Environ.* **2013**, *11*, 355–361. [CrossRef]
54. Díaz, D.M.; Carbonell Carrera, C.C.; Pérez, J.L.S.; De la Torre Cantero, J.; Dorta, N.M. Digital manufacturing of 3D DTM models to enhance cartographic interpretation & creative competence. *Adv. Build. Educ.* **2017**, *1*, 11–26. [CrossRef]
55. Wang, X. Landscape based on three-dimensional SketchUp modelling to get visualization applications. *Comput. Model. New Technol.* **2014**, *18*, 142–146.

56. Rojas-Fernández, J.; Galán-Marín, C.; Rivera-Gómez, C.; Fernández-Nieto, E.D. Exploring the Interplay between CAD and FreeFem++ as an Energy Decision-Making Tool for Architectural Design. *Energies* **2018**, *11*, 2665. [CrossRef]
57. Guo, Y.; Bart, D. Optimization of Design Parameters for Office Buildings with Climatic Adaptability Based on Energy Demand and Thermal Comfort. *Sustainability* **2020**, *12*, 3540. [CrossRef]
58. Ayanlade, A.; Orimoogunje, I.O.O.; Borisade, P.B. Geospatial data infrastructure for sustainable development in sub-Saharan countries. *Int. J. Digit. Earth* **2008**, *1*, 247–258. [CrossRef]
59. Ray, N.; Lacroix, P.M.A.; Giuliani, G.; Upla, P.; Rajabifard, A.; Jensen, D. Open spatial data infrastructures for the sustainable development of the extractives sector: Promises and challenges. In *Spatial Enablement in a Smart World*; GSDI Association Press: Needham, MA, USA, 2016.
60. Rigby, M.; Eagleson, S. Spatial data infrastructure challenges for addressing the Sustainable Development Goals in Australia. In Proceedings of the International Symposium on A Smart Sustainable Future for All: Enhancing Resilience in a Changing Landscape, Melbourne, Australia, 24–26 September 2018.
61. Álvarez Otero, J.; De Lázaro y Torres, M.L. Education in Sustainable Development Goals Using the Spatial Data Infrastructures and the TPACK Model. *Educ. Sci.* **2018**, *8*, 171. [CrossRef]
62. Pokojski, W.; Angiel, J.; Pokojska, P. Importance of digital spatial data in environmental education. *Edukacja Biologiczna i Środowiskowa* **2018**, *1*, 34–38. [CrossRef]