AN EVALUATION OF LIDAR, EU-DEM AND SRTM-DERIVED TERRAIN PARAMETERS FOR HYDROLOGIC APPLICATIONS IN ȚIBLEȘ AND RODNEI MOUNTAINS (ROMANIA)

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ABSTRACT. An Evaluation of Lidar, EU-DEM and SRTM-Derived Terrain Parameters for Hydrologic Applications in Tibles and Rodnei Mountains (Romania). Over the years numerous geospatial data sets have become accessible to users in the form of various types of digital elevation models (DEMs) at different resolutions. DEMs are often used to study the behavior and hydrological response of watersheds, and so came to be considered as a reflection of their physiographic characteristics. Accurate determination of a catchment's morphometric parameters plays a crucial role in distributed hydrological modelling and river flow estimation. This study is divided into two parts and objectives; the first part examines the accuracy of DEMs from different sources (EU-DEM, SRTM and LIDAR) in deriving terrain attributes by comparison, and the second one investigates the ability of resampling the 3 m LIDAR DEM to coarser cell resolutions, to accurately represent the extracted hydrological features. In order to evaluate the quality and precision of SRTM and EU-DEM, the high-resolution 3 m LIDAR DEM was used as a reference data set due to its higher degree of accuracy. Firstly, this data set was resampled to 25 m and 30 m to match the EU-DEM and SRTM cell size, and all of them were re-projected in order to have the same Stereo 70 coordinate system for Romania. A comparison has been carried out between the derived hydrologic and terrain variables of the different DEMs. For the second part of this research, LIDAR DEM was also resampled to 10 m and subsequently, another similar evaluation was made, but this time with regards to different cell resolutions (3 m, 10 m, 25 m and 30 m). Several catchments of various drainage areas (Tibles, Runc, Sălăuța and Valea Caselor) located in Tibles and Rodnei Mountains were chosen as study areas for this research.

Several resampling techniques available in ArcMap were evaluated, and the comparative analyzes were carried out using the R software. Results revealed not only the LiDAR's superior accuracy as compared to the other data sets, but also the possibilities offered by the latter for deriving the hydrological characteristics of a mountainous area, contingent upon what the user aims to achieve.

Keywords: Digital elevation models, LIDAR, SRTM, EU-DEM, resample, accuracy, morphometry, R, Rstudio, geospatial analysis

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1. INTRODUCTION

A detailed morphometric analysis of topographic areas is an essential tool in drainage delineation, water resources assessment, soil erosion, landslides, flood susceptibility, and surface runoff modelling, respectively. In this context, over the past few decades, geospatial databases such as digital elevation models (DEMs) have been used to automatically extract and determine morphometric parameters, such as drainage patterns and density, basin relief, the length of watercourses, watershed area, and shape, slope, and aspect, etc.

The evolution of techniques for digital elevation models generation allowed for continuous development in terms of quality and increasingly detailed spatial resolution. Thus, if the available elevation models with global coverage had a spatial resolution of 1 km (The Global Land 1 km-Base Elevation Project-GLOBE) before the 2000s, during the last decade higher resolution DEMs were developed, such as Shuttle Radar Topograraphy Mission (SRTM) with a resolution of 90 and 30 m; Advanced Land Observation STLT (ALOS) at 30 m spatial resolution; Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) with a resolution of 30 m (Niyazi et al., 2019); Digital Elevation Model over Europe (EU-DEM) at 25 m spatial resolution and Light Detection and Ranging (LIDAR), available at a high horizontal resolution of 1 m or even higher. According to Saran et al. (2009) high-resolution DEMs provide higher accuracies in deriving watershed, watercourses, and terrain features.

The resolution and information content of DEMs are critical factors affecting the extraction of morphometric features used in hydrological and climatological studies (MacMillan et al., 2014). Due to their applicability and relatively easy processing in a GIS environment, for multiple applications, DEMs have been worldwide used as part of many scientific works. Most studies focused on a comparative analysis of different DEMs in terms of absolute surface heights and vertical accuracies (Yao et al., 2020; Kasi et al., 2020; Abdel-Wahab, 2019), but numerous works have been worldwide conducted assessing the differences in morphometric parameters at watershed scale (Das et al., 2016; Niyazi et al., 2019; Wang et al., 2010; Jacques et al., 2014, Niculiță et al., 2020). Furthermore, by comparing three types of DEMs, namely USGS, SRTM, and LIDAR, Wang and Wade (2008), modeled the extent and volumetric capacity of the Randleman Reservoir in North Carolina. Mohtashami et al. (2022), computed depth-to-water maps using digital elevation models, in order to identify wetlands for planning logging operations.

A variety of studies were carried out in Romania, for which DEMs were the basis for deriving the morphometric parameters used for hydrological modeling purposes (Kocsis et al., 2020; Strapazan et al., 2021, Haidu & Strapazan, 2019), flood vulnerability (Kocsis et al., 2022) and soil erosion risk assessment (Ciotină et al., 2021; Ciotină et al., 2022; Costea et al., 2022).

Therefore, the general objective of this study is to evaluate the accuracy of data from various sources used as the main input for distributed hydrological modeling, worldwide applied and improved in recent years. The assessment of the quality and capacity of DEMs from different sources (EU-DEM, SRTM, and LIDAR) in deriving the terrain attributes was carried out through a comparative analysis, in terms of elevation, morphological and hydrological parameters differences, resulting from downsampling the LIDAR digital elevation model (3 m) to lower resolutions, similar to those of the other DEMs, namely SRTM (30 m), and EU-DEM (25 m). This study also sought to examine each resampling method's ability to accurately determine the watersheds' hydrological characteristics. The R and ArcMap softwares were chosen for DEMs processing and accuracy assessment purposes. Several studies have been conducted over the past few years, in which R was used for spatial analysis (Blangiardo & Camaletti, 2016; Niculiță, 2018; Legendre, 2023), and morphological parameters computation from DEMs (Niculită, 2016), due to its multiple functionalities and relatively short processing time.

2. STUDY AREA

The study area is located in the northern half of Bistriţa-Năsăud county, in the middle reaches of the Someşul Mare River, being bounded to the north by the high peaks of the Țibleş (1840 m) and Rodnei (2303 m) Mountains, to the south by the Someşul Mare corridor, to the east by the Rebra valley, and to the west by the Ilişua valley (Fig. 1)

This study comprises an area of 571 km² and includes the Ţibleş, Runc, Sălăuta and Caselor river basins. The mountainous landform allowed for the development of a radial drainage network with a somewhat parallel pattern, determining the orientation of the main valleys towards the north-south direction, with pronounced falls towards the corridor of Someşului Mare. Ţibleş, for instance, has an average slope of 38 m/km, over a distance of 32 km. Thus, draining several landforms, the study area is characterized by the presence of water courses showing torrential characteristics and implicitly, an excessive transport of alluvium, thus causing a permanent alteration of the hydrological and morphometric river characteristics, being the most sensitive and elements of this landscape (Thomas, 2001).



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Fig. 1. Țibleș, Runc, Sălăuța, and Valea Caselor catchment area location

3. DATA AND METHODS

The proposed methodology relies on several stages of digital elevation models analysis.

The SRTM v1 data (Shuttle Radar Topography Mission Data) at 30 m spatial resolution, is available for free usage and was downloaded from the website: https://earthexplorer.usgs.gov/. The European digital surface model EU-DEM v1.1 (European Digital Elevation Model) at 25 m spatial resolution was downloaded from the website: https://land.copernicus.eu/, also being publicly available.

The LIDAR data for the study area were retrieved from PPPDEI (2014). This data set was resampled to 25 m and 30 m spatial resolution, in order to match the EU-DEM and SRTM pixel size, and all DEMs were re-projected to have the same extent and Stereo 70 coordinate system for Romania. The comparative

analysis involved the terrain and hydrological characteristics resulting from different DEMs processing. The LIDAR-DEM was also resampled at 10 m spatial resolution and a similar assessment was subsequently carried out, but in this case with respect to different resolutions (3 m, 10 m, 25 m, and 30 m) resulting from the resampling methods.

The comparison assessment was carried out, mainly using the R (version 4.2.1) and ArcGIS softwares. Given the fact that the statistical analysis process is quite difficult itself and time-consuming, involving a series of possible errors for its execution, the R software was considered to be the best option for evaluating the accuracy of the digital elevation models. The import and export of data, as well as the relatively short execution time of all R functionalities through code lines running, is of great advantage to such data analyses and is freely available under the GNU General Public License (R Core Team, 2022). The code was executed within RStudio, the main IDE (Integrated Development Environment) for R (RStudio Team, 2022), (Fig. 2).



Fig. 2. Executing the R code for DEM analysis under RStudio

Thus, the first stage of the analysis was carried out on the application of various resampling techniques available in the data management tools within ArcMap, namely Nearest neighbor, Bilinear interpolation, and Cubic convolution, in order to evaluate whether different resampling techniques generate vastly different results or values, and if so, how different from the reference raster (LIDAR with 3 m spatial resolution).

The second stage of analysis considered the differences between different pairs of DEMs: LIDAR (30 m) and SRTM (30 m), as well as LIDAR (25 m) and EU-DEM (25 m).

In the third stage, the correlation between each of the two pairs of DEMs

was analysed. According to Wuensch and Evans (1996), the value of the Pearson coefficient must fall within the following ranges: 1. 0.00-0.19: - very weak; 2. 0.20-0.39: - weak; 3. 0.40-0.59: - moderate; 4. 0.60-0.79: - strong, and 5. 0.80-1.0: - very strong.

Finally, the Topographic Wetness Index, $TI = (TWI, ln(a/tan\beta))$ was calculated, using the semi-distributed Dynamic TOPMODEL hydrological model, "dynatopmodel package" (Metcalfe et al., 2018), within R version 3.6.0, for compatibility purposes.

4. RESULTS AND DISCUSSIONS

At first, the LIDAR data was resampled to lower resolutions of 10, 25, and 30 m using the above-mentioned techniques. The resulting rasters were then imported into R through a series of code lines which allowed data reading and manipulation. The preliminary analysis results related to the resampling techniques are given in Table 1.

DEM					CKENN	Quantile						
DEIVI	IVIIIN	IVIAX	WEAN	SID DEV.	SKEW	0%	25%	50%	75%	100%		
LIDAR 3	286.2	1837.8	742.5	260.2	0.8	286.2	549.9	701.5	897.0	1837.8		
Nearest neighbour												
LIDAR 10	286.2	1837.6	742.5	260.2	0.8	286.2	550.0	701.5	897.0	1837.6		
LIDAR 25	286.3	1837.1	742.6	260.4	0.8	286.3	549.9	701.5	897.1	1837.1		
LIDAR 30	286.3	1837.0	742.5	260.4	0.8	286.3	549.8	701.4	897.0	1837.0		
				Bi	ilinear							
LIDAR 10	286.2	1837.6	742.5	260.2	0.8	286.2	550.0	701.5	897.0	1837.6		
LIDAR 25	286.3	1836.9	742.6	260.4	0.8	286.3	549.9	701.5	897.1	1836.9		
LIDAR 30	286.4	1836.7	742.5	260.3	0.8	286.4	549.8	701.4	897.0	1836.7		
				Cubic o	convolution							
LIDAR 10	286.2	1837.6	742.5	260.2	0.8	286.2	550.0	701.5	897.0	1837.6		
LIDAR 25	286.3	1837.0	742.6	260.4	0.8	286.3	549.9	701.5	897.1	1837.0		
LIDAR 30	286.4	1836.8	742.5	260.4	0.8	286.4	549.8	701.4	897.0	1836.8		

Table 1. Results of statistical analyzes between resample methods

Since the statistical indicators did not reveal high differences among the results, the Nearest Neighbor resample technique was chosen for the next stage of the analysis, considering its widely usage for digital elevation models evaluation. A subsequent investigation was carried out with the aim of computing the differences between the following pairs of DEMs: LIDAR-EU-DEM (25 m) and LIDAR-SRTM (30 m). It should be noted that all calculations that were performed for the entire study area were carried out using the R programming language and software, the raster package (Hijmans, 2022) along with ggplot2 (Wickham, 2016) providing the reading, analysis and graphical representation of the imported raster files into the program (Fig. 3, 4). Packages like hydroGOF (Zambrano-Bigiarini, 2020), e1071 (Meyer et al., 2022), ggpubr (Kassambara, 2022), gridExtra (Auguie, 2017) were also used for data analysis.



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Fig. 3. LIDAR digital terrain model, EU-DEM and the resulting difference (25m)



Fig. 4. LIDAR digital terrain model, SRTM and the resulting difference (30 m)

The histogram of relative frequencies gives us an overview of the distribution tendency of DEM errors, as well as the symmetry or asymmetry of

the frequency distribution. It can be noted that most errors fall within the range (-40,+40) m, and low errors (values close to 0), have a distribution of approximately 70% with respect to LIDAR – SRTM comparison. On the other hand, the distribution of errors between LIDAR and EUDEM is much more flattened, with only ~ 20% of the errors being close to 0 (Fig. 5).



Fig. 5. Histogram of differences between reference DEM (LIDAR) and EU-DEM, respectively SRTM

At the same time, the distribution of errors between LIDAR and EU-DEM is platykurtic, a fact that is also revealed by the "kurtosis" flattening index, which is < 0. However, the values fall within the deviation of a normal distribution of (-2, +2), (George & Mallery, 2018). Regarding the differences between LIDAR and SRTM, the distribution appears to be leptokurtic, with a kurtosis coefficient almost equal to 1.5 (Table 2). These differences have a slightly asymmetric distribution to the left, suggesting higher values of SRTM compared to LIDAR with a skewness index < 0, unlike the errors between EU-DEM and LIDAR which reveal a slightly asymmetric distribution to the right, indicating that most of the EU-DEM values are smaller than LIDAR ones. Considering all of the DEMs, the differences between the important statistical indicators do not seem very large (Table 3).

 Table 2. Results of statistical analyzes for elevation errors

Comparison/Difference	MIN	MAX	MEAN	STD DEV.	SKEW	KURT	RMSE
LIDAR-EUDEM	-118.80	149.50	-4.73	27.94	0.04	-0.09	28.34
LIDAR-SRTM	-93.04	48.51	-3.40	10.99	-0.83	1.45	11.50

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DEM	MIN	MAX	MEAN	STD DEV.	SKEW	KURT
EUDEM25	283.0	1815.7	747.3	262.4	0.7	0.3
LIDAR25	286.3	1837.1	742.6	260.4	0.8	0.4
SRTM30	282.0	1831.0	745.9	262.1	0.7	0.3
LIDAR30	286.3	1837.0	742.5	260.4	0.8	0.4

Table 3. Results of statistical analyzes at the level of DEMs

A set of 1000 points was extracted for the correlation plot, given the large number of cells within each raster (over 1000000). An extremely strong linear relationship can be observed between the rasters, with Pearson coefficients close to 1 in both cases (Fig. 6).



Fig. 6. Correlation between EU-DEM and LIDAR, as well as between SRTM and LIDAR

The boxplot shows significant differences within the forest areas codes 311, 312, and 313), a fact that can be explained by the SRTM data acquisition methods. However the LIDAR interpolation isn't the most precise (Fig. 7).



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Fig. 7. Boxplot showing the differences between EU-DEM and LIDAR, as well as between SRTM and LIDAR, by usage category

Originally developed by Beven & Kirkby (1979), the Topographic Wetness Index is one of the most important factors indicating the potential for runoff generation by taking into account the upstream runoff contribution area and the slope (Kocsis et al., 2022). In other words, high TWI values indicate high runoff generation potential and vice versa. Also, for flood risk assessment, this factor can be used as a quick method to identify flood-prone areas (Fig. 8). Statistical analysis regarding TWI show higher EU-DEM values when compared to LIDAR and a larger value range corresponding to SRTM, but with a higher mean compared to LIDAR (Table 4).

Topographic wetness index	MIN	MAX	MEAN	STD DEV.	SKEW
EUDEM25	2.5	23.7	7.0	2.2	2.2
LIDAR25	2.1	24.2	6.6	2.3	2.7
SRTM30	1.8	24.7	7.0	2.4	2.5
LIDAR30	2.5	24.2	6.7	2.4	2.6

Table 4. Results of statistical analysis on TWI at the level of DEMs



Fig. 8. Topographic Wetness Index (TWI)

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Differences were observed for the whole study area both in terms of the river lengths, slopes, and elevation, as well as watershed areas (Table 5).

				S	RTM30									
	River lengths	Watershed area	Drainage density	S	ope (de	g)		Strahle	r (km)		Ele	vation m	n RAW D	EM
Watershed	(km)	(sq.km)	(km/km)	mean	max	std.dev	1	2	3	4	min	max	mean	std.dev
TIBLES	74.4	98.9	0.8	17.0	50.1	8.6	26.8	23.0	24.6		283.0	1831.0	715.1	280.2
RUNC	36.7	48.7	0.8	15.2	42.4	7.0	19.1	13.6	4.0		296.0	884.0	598.3	124.0
SALAUTA	289.4	414.3	0.7	19.0	61.6	8.2	149.9	60.9	43.5	35.1	298.0	1829.0	785.5	245.7
V.CASELOR	7.1	9.0	0.8	14.0	44.9	7.3	7.1				318.0	811.0	564.5	132.7
				EUDEM25										
	River lengths	Watershed area	Drainage density	S	ope (de	g)		Strahle	r (km)		Ele	vation m	n RAW D	EM
Watershed	(km)	(sq.km)	(km/km)	mean	max	std.dev	1	2	3	4	min	max	mean	std.dev
TIBLES	72.7	98.9	0.7	15.6	50.5	8.1	27.8	20.9	24.1		283.0	1808.9	715.2	279.2
RUNC	37.1	48.7	0.8	13.9	40.8	6.4	18.6	8.8	9.6		292.0	872.0	596.3	124.3
SALAUTA	293.7	414.1	0.7	17.8	60.1	7.8	150.8	63.8	44.1	35.0	297.0	1806.3	786.0	244.7
V.CASELOR	6.5	7.9	0.8	13.4	40	6.4	6.5				314	800.4	590.4	114.7
				LI	DAR30									
	River lengths	Watershed area	Drainage density	S	ope (de	g)		Strahle	r (km)		Ele	vation m	RAW D	EM
watersned	(km)	(sq.km)	(km/km)	mean	max	std.dev	1	2	3	4	min	max	mean	std.dev
TIBLES	77.6	98.8	0.8	18.4	49.3	8.9	25.9	25.7	26.0		286.6	1836.2	713.9	278.6
RUNC	41.2	52.2	0.8	16.4	48.1	7.3	19.4	11.8	10.0		297.1	886.7	602.5	124.2
SALAUTA	294.6	411.8	0.7	20.2	59.1	8.5	152.9	62.9	43.4	35.5	302.6	1833.5	782.8	245.3
V.CASELOR	6.5	7.9	0.8	16.1	43.0	7.0	6.5				315.9	814.8	591.2	112.8
LIDAR25														
					DAILES									
Wetershed	River lengths	Watershed area	Drainage density	S	ope (de	g)		Strahle	r (km)		Ele	vation m	RAW D	EM
Watershed	River lengths (km)	Watershed area (sq.km)	Drainage density (km/km)	Si mean	ope (de max	g) std.dev	1	Strahle 2	r (km) 3	4	Ele min	vation m max	RAW D mean	EM std.dev
Watershed TIBLES	River lengths (km) 75.8	Watershed area (sq.km) 98.8	Drainage density (km/km) 0.8	mean 18.7	ope (de max 52.0	g) std.dev 9.1	1 26.2	Strahle 2 25.2	r (km) 3 24.4	4	Ele min 286.4	vation m max 1837.1	RAW D mean 713.9	EM std.dev 278.6
Watershed TIBLES RUNC	River lengths (km) 75.8 40.9	Watershed area (sq.km) 98.8 51.6	Drainage density (km/km) 0.8 0.8	mean 18.7 16.8	ope (de max 52.0 50.7	g) std.dev 9.1 7.5	1 26.2 19.2	Strahle 2 25.2 11.8	r (km) 3 24.4 10.0	4	Ele min 286.4 297.3	vation m max 1837.1 886.7	RAW D mean 713.9 605.3	EM std.dev 278.6 122.1
Watershed TIBLES RUNC SALAUTA	River lengths (km) 75.8 40.9 294.9	Watershed area (sq.km) 98.8 51.6 411.8	Drainage density (km/km) 0.8 0.8 0.7	5 mean 18.7 16.8 20.5	ope (de max 52.0 50.7 60.8	g) std.dev 9.1 7.5 8.6	1 26.2 19.2 152.4	Strahle 2 25.2 11.8 63.4	r (km) 3 24.4 10.0 43.2	4	Ele min 286.4 297.3 302.6	vation m max 1837.1 886.7 1836.3	RAW D mean 713.9 605.3 782.8	EM std.dev 278.6 122.1 245.4
Watershed TIBLES RUNC SALAUTA V.CASELOR	River lengths (km) 75.8 40.9 294.9 6.6	Watershed area (sq.km) 98.8 51.6 411.8 9.0	Drainage density (km/km) 0.8 0.8 0.7 0.7	Si mean 18.7 16.8 20.5 15.2	ope (de max 52.0 50.7 60.8 44.9	g) std.dev 9.1 7.5 8.6 7.8	1 26.2 19.2 152.4 6.6	Strahle 2 25.2 11.8 63.4	r (km) 3 24.4 10.0 43.2	4	Ele min 286.4 297.3 302.6 317.5	vation m max 1837.1 886.7 1836.3 814.9	RAW D mean 713.9 605.3 782.8 563.7	EM std.dev 278.6 122.1 245.4 130.6
Watershed TIBLES RUNC SALAUTA V.CASELOR	River lengths (km) 75.8 40.9 294.9 6.6	Watershed area (sq.km) 98.8 51.6 411.8 9.0	Drainage density (km/km) 0.8 0.8 0.7 0.7	Si mean 18.7 16.8 20.5 15.2	ope (de max 52.0 50.7 60.8 44.9 DAR10	g) std.dev 9.1 7.5 8.6 7.8	1 26.2 19.2 152.4 6.6	Strahle 2 25.2 11.8 63.4	r (km) 3 24.4 10.0 43.2	4	Ele min 286.4 297.3 302.6 317.5	vation m max 1837.1 886.7 1836.3 814.9	RAW D mean 713.9 605.3 782.8 563.7	EM std.dev 278.6 122.1 245.4 130.6
Watershed TIBLES RUNC SALAUTA V.CASELOR	River lengths (km) 75.8 40.9 294.9 6.6 River lengths	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area	Drainage density (km/km) 0.8 0.8 0.7 0.7 0.7 Drainage density	mean 18.7 16.8 20.5 15.2	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de	g) std.dev 9.1 7.5 8.6 7.8 7.8	1 26.2 19.2 152.4 6.6	Strahle 2 25.2 11.8 63.4 Strahle	r (km) 3 24.4 10.0 43.2 r (km)	4	Ele min 286.4 297.3 302.6 317.5 Ele	vation m max 1837.1 886.7 1836.3 814.9 vation m	RAW D mean 713.9 605.3 782.8 563.7 RAW D	EM std.dev 278.6 122.1 245.4 130.6 EM
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km)	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area (sq.km)	Drainage density (km/km) 0.8 0.8 0.7 0.7 0.7 Drainage density (km/km)	mean 18.7 16.8 20.5 15.2 LL S mean	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max	g) std.dev 9.1 7.5 8.6 7.8 g) std.dev	1 26.2 19.2 152.4 6.6	Strahle 2 25.2 11.8 63.4 Strahle 2	r (km) 3 24.4 10.0 43.2 r (km) 3	4 35.8 4	Ele min 286.4 297.3 302.6 317.5 Ele min	vation m max 1837.1 886.7 1836.3 814.9 vation m max	RAW D mean 713.9 605.3 782.8 563.7 RAW D mean	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area (sq.km) 98.7	Drainage density (km/km) 0.8 0.7 0.7 0.7 Drainage density (km/km) 0.8	mean 18.7 16.8 20.5 15.2 LL SI mean 19.7	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0	8) std.dev 9.1 7.5 8.6 7.8 8.6 7.8 std.dev 9.8	1 26.2 19.2 152.4 6.6 1 26.3	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8	r (km) 3 24.4 10.0 43.2 r (km) 3 25.0	4 35.8 4	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2	vation m max 1837.1 886.7 1836.3 814.9 vation m max 1837.0	RAW D mean 713.9 605.3 782.8 563.7 RAW D mean 714.0	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES RUNC	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1 42.2	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area (sq.km) 98.7 52.4	Drainage density (km/km) 0.8 0.7 0.7 0.7 Drainage density (km/km) 0.8 0.8	si mean 18.7 16.8 20.5 15.2 Li Si mean 19.7 17.7	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 58.0	g) std.dev 9.1 7.5 8.6 7.8 7.8 5td.dev 9.8 8.5	1 26.2 19.2 152.4 6.6 1 26.3 19.8	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8 12.1	r (km) 3 24.4 10.0 43.2 r (km) 3 25.0 10.3	4 35.8 4	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0	vation m max 1837.1 886.7 1836.3 814.9 vation m max 1837.0 888.5	RAW D mean 713.9 605.3 782.8 563.7 RAW D mean 714.0 601.7	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES RUNC SALAUTA	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1 42.2 300.0	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area (sq.km) 98.7 52.4 411.9	Drainage density (km/km) 0.8 0.7 0.7 Drainage density (km/km) 0.8 0.8 0.8 0.7	si mean 18.7 16.8 20.5 15.2 Li Si mean 19.7 17.7 21.5	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 58.0 73.9	g) std.dev 9.1 7.5 8.6 7.8 g) std.dev 9.8 8.5 9.4	1 26.2 19.2 152.4 6.6 1 26.3 19.8 155.6	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8 12.1 64.1	r (km) 3 24.4 10.0 43.2 43.2 7 (km) 3 25.0 10.3 44.0	4 35.8 4 36.2	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0 302.4	vation m max 1837.1 886.7 1836.3 814.9 vation m max 1837.0 888.5 1836.8	RAW D mean 713.9 605.3 782.8 563.7 RAW D mean 714.0 601.7 782.8	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0 245.4
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES RUNC SALAUTA V.CASELOR	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1 42.2 300.0 8.6	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area (sq.km) 98.7 52.4 41.9 10.0	Drainage density (km/km) 0.8 0.7 0.7 Drainage density (km/km) 0.8 0.8 0.7 0.9	Image mean 18.7 16.8 20.5 15.2 mean 19.7 17.7 21.5 15.6	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 58.0 73.9 53.4	g) std.dev 9.1 7.5 8.6 7.8 std.dev 9.8 8.5 9.4 8.5	1 26.2 19.2 152.4 6.6 7 26.3 19.8 155.6 8.4	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8 12.1 64.1 0.3	r (km) 3 24.4 10.0 43.2 r (km) 3 25.0 10.3 44.0	4 35.8 4 36.2	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0 302.4 315.4	vation m max 1837.1 886.7 1836.3 814.9 vation m max 1837.0 888.5 1836.8 815.1	RAW D mean 713.9 605.3 782.8 563.7 RAW D mean 714.0 601.7 782.8 553.2	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0 245.4 130.1
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES RUNC SALAUTA V.CASELOR	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1 42.2 300.0 8.6	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area (sq.km) 98.7 52.4 411.9 10.0	Drainage density (km/km) 0.8 0.7 0.7 Drainage density (km/km) 0.8 0.8 0.7 0.9	Image mean 18.7 16.8 20.5 15.2 Image 19.7 17.7 21.5 15.6	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 58.0 73.9 53.4 IDAR3	std.dev 9.1 7.5 8.6 7.8 (std.dev 9.8 8.5 9.4 8.5	1 26.2 19.2 152.4 6.6 1 26.3 19.8 155.6 8.4	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8 12.1 64.1 0.3	r (km) 3 24.4 10.0 43.2 r (km) 3 25.0 10.3 44.0	4 35.8 4 36.2	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0 302.4 315.4	vation m max 1837.1 886.7 1836.3 814.9 vation m max 1837.0 888.5 1836.8 815.1	RAW D mean 713.9 605.3 782.8 563.7 RAW D mean 714.0 601.7 782.8 553.2	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0 245.4 130.1
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES RUNC SALAUTA V.CASELOR	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1 42.2 300.0 8.6 River lengths	Watershed area (sq.km) 98.8 51.6 411.8 90.0 Watershed area (sq.km) 98.7 52.4 411.9 10.0 Watershed area	Drainage density (km/km) 0.8 0.7 0.7 Drainage density (km/km) 0.8 0.8 0.8 0.7 0.9 Drainage density	Si mean 18.7 16.8 20.5 15.2 Image: Signal and S	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 58.0 73.9 53.4 DAR3 ope (de	std.dev 9.1 7.5 8.6 7.8 std.dev 9.8 std.dev 9.8 8.5 9.4 8.5 9.4 8.5	1 26.2 19.2 152.4 6.6 1 26.3 19.8 155.6 8.4	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8 12.1 64.1 0.3 Strahle	r (km) 3 24.4 10.0 43.2 r (km) 3 25.0 10.3 44.0 r (km)	4 35.8 4 36.2	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0 302.4 315.4	vation m max 1837.1 886.7 1836.3 814.9 vation m max 1837.0 888.5 1836.8 815.1 vation m	RAW D mean 713.9 605.3 782.8 563.7 RAW D mean 714.0 601.7 782.8 553.2	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0 245.4 130.1 EM
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 42.2 300.0 8.6 River lengths (km)	Watershed area (sq.km) 98.8 51.6 411.8 90 Watershed area (sq.km) 98.7 52.4 411.9 10.0 Watershed area (sq.km)	Drainage density (km/km) 0.8 0.7 0.7 0.7 Drainage density (km/km) 0.8 0.8 0.8 0.7 0.9 Drainage density (km/km)	mean 18.7 16.8 20.5 15.2 LI SI mean 19.7 17.7 21.5 15.6 L SI SI mean	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 58.0 73.9 53.4 DAR3 ope (de max	std.dev 9.1 7.5 8.6 7.8 std.dev 9.8 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5	1 26.2 19.2 152.4 6.6 7 26.3 19.8 155.6 8.4 7 1	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8 12.1 64.1 0.3 Strahle 2	r (km) 3 24.4 10.0 43.2 r (km) 3 25.0 10.3 44.0 r (km) 3	4 35.8 4 36.2 4	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0 302.4 315.4 Ele min	vation m max 1837.1 1836.3 814.9 vation m max 1837.0 888.5 1836.8 815.1 vation m max	RAW D mean 713.9 605.3 782.8 563.7 RAW D 601.7 782.8 553.2 RAW D mean RAW D	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0 245.4 130.1 EM std.dev
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES Watershed TIBLES	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1 42.2 300.0 8.6 River lengths (km) 77.6	Watershed area (sq.km) 98.8 51.6 411.8 90.0 Watershed area (sq.km) 98.7 52.4 411.9 10.0 Watershed area (sq.km) 99.8	Drainage density (km/km) 0.8 0.7 0.7 Drainage density (km/km) 0.8 0.8 0.7 0.9 Drainage density (km/km) 0.8	mean 18.7 16.8 20.5 15.2 15.2 15.6 19.7 17.7 21.5 15.6 L S mean 20.0	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 58.0 73.9 53.4 DAR3 ope (de max 73.1	std.dev 9.1 7.5 8.6 7.8 std.dev 9.8 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4	1 26.2 19.2 152.4 6.6 1 26.3 19.8 155.6 8.4 155.6 8.4	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8 12.1 64.1 0.3 Strahle 2 Strahle 2 25.2	r (km) 3 24.4 10.0 43.2 r (km) 3 25.0 10.3 44.0 r (km) 3 25.2	4 35.8 4 36.2 4	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0 302.4 315.4 Ele min 286.2	vation m max 1837.1 886.7 1836.3 814.9 vation m max 1837.0 888.5 1836.8 815.1 vation m max 1837.2	RAW D mean 713.9 605.3 782.8 563.7 RAW D 601.7 782.8 553.2 RAW D 601.7 782.8 553.2 RAW D	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0 245.4 130.1 EM std.dev 280.1
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES RUNC Watershed TIBLES RUNC	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1 42.2 300.0 8.6 River lengths (km) River lengths (km) 77.6 44.6	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area (sq.km) 98.7 52.4 411.9 10.0 Watershed area (sq.km) 99.8 53.9	Drainage density (km/km) 0.8 0.7 0.7 Drainage density (km/km) 0.8 0.8 0.7 0.9 Drainage density (km/km) 0.9	mean 18.7 16.8 20.5 15.2 15.6 19.7 17.7 21.5 15.6 L 15.6 L 15.6 L 15.6 L 15.6 L 15.6 L 15.6 L 15.6 L 15.6 L 15.6 L 15.2 L 15 L 15 L 15 L 15 L 15 L 15 L 15 L 1	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 58.0 73.9 53.4 DAR3 ope (de max 73.1 70.8	std.dev 9.1 7.5 8.6 7.8 std.dev 9.8 8.5 9.4 8.5 9.4 8.5 9.4 std.dev 9.8 8.5 9.4 std.dev 10.2 9.0	1 26.2 19.2 152.4 6.6 7 7 26.3 19.8 155.6 8.4 7 7 27.2 22.0	Strahle 2 25.2 11.8 63.4 2 Strahle 2 25.8 12.1 64.1 0.3 Strahle 2 25.2 12.1 64.1 0.3 Strahle 2 25.2 12.1	r (km) 3 24.4 10.0 43.2 	4 35.8 4 36.2 4	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0 302.4 315.4 Ele min 286.2 297.0 302.4 297.0	vation m max 1837.1 886.7 1836.3 814.9 vation m max 1837.0 888.5 1836.8 815.1 vation m max 1837.2 889	RAW D mean 713.9 605.3 782.8 563.7 RAW D 601.7 714.0 601.7 782.8 553.2 RAW D 601.7 782.8 553.2 RAW D	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0 245.4 130.1 EM std.dev 280.1 128.4
Watershed TIBLES RUNC SALAUTA V.CASELOR Watershed TIBLES RUNC SALAUTA Watershed TIBLES RUNC SALAUTA	River lengths (km) 75.8 40.9 294.9 6.6 River lengths (km) 77.1 42.2 300.0 8.6 River lengths (km) 77.6 44.6 302.9	Watershed area (sq.km) 98.8 51.6 411.8 9.0 Watershed area (sq.km) 98.7 52.4 411.9 10.0 Watershed area (sq.km) 99.8 53.9 412.0	Drainage density (km/km) 0.8 0.7 0.7 Drainage density (km/km) 0.8 0.9 Drainage density (km/km) 0.8 0.9 0.9 0.9	si mean 18.7 16.8 20.5 15.2 U Si mean 19.7 17.7 21.5 15.6 L Si mean 20.0 18.0 22.0	ope (de max 52.0 50.7 60.8 44.9 DAR10 ope (de max 60.0 53.0 73.9 53.4 IDAR3 ope (de max 73.1 70.8 83.8	std.dev 9.1 7.5 8.6 7.8 std.dev 9.8 std.dev 9.8 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.4 8.5 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 8.6 9.5 9.5 8.6 9.5 8.6 9.5 9.5 9.5 8.6 9.5 9.5 9.5 9.5 9.5 9.5 9.5 9.5 9.5 9.5	1 26.2 19.2 152.4 6.6 26.3 19.8 155.6 8.4 155.6 8.4 127.2 22.0 156.8	Strahle 2 25.2 11.8 63.4 Strahle 2 25.8 12.1 64.1 0.3 Strahle 2 25.2 12.1 64.1 0.3 Strahle 2 25.2 12.1 65.4	r (km) 3 24.4 10.0 43.2 7 r (km) 3 25.0 10.3 44.0 3 25.2 10.5 44.0	4 35.8 4 36.2 4 36.7	Ele min 286.4 297.3 302.6 317.5 Ele min 286.2 297.0 302.4 315.4 Ele min 286.2 296.4 301.9	vation n max 1837.1 886.7 1836.3 814.9 vation n max 1837.0 888.5 1836.8 815.1 vation n max 1837.2 889 1837.1	RAW D mean 713.9 605.3 782.8 563.7 RAW D 601.7 782.8 553.2 RAW D 601.7 782.8 553.2 RAW D 782.8	EM std.dev 278.6 122.1 245.4 130.6 EM std.dev 278.7 125.0 245.4 130.1 EM std.dev 280.1 128.4 245.5

Table 5. The results of the statistical analysis for the study catchments

The results obtained by resampling the LIDAR data to 30, 25, and 10 m, reveal the largest overall differences in parameter values for the Sălăuța river basin. In the case of Țibleş and Runc catchments, the greatest differences are noted for the LIDAR 25 in terms of river lengths and drainage area, unlike the rest of the watersheds, where the greatest differences are noted, as it should be, within the larger resamplings (LIDAR 30).

Considering the Strahler classification, the largest differences can be seen for the 1st order stream lengths and very small differences in terms of drainage density. The average slope values remain generally unchanged, with the largest differences in the case of the maximum slopes, but this fact can be justified by pixel resizing, which takes its value according to the closest cell.

An interesting fact could be observed for the case of minimum and average elevations (note the large difference in average elevation values within the V. Caselor catchment area), with higher resulting values, when applying the resampling procedure, and at the same time lower maximum values, resulting in lower values of maximum slopes.

Analysis of slope distribution patterns, through the shape of their cumulative frequency curves (Fig. 9, 11) and the histograms of their percentage distribution (Fig. 10, 12), indicate higher LIDAR values for all the 4 catchment areas studied. Results reveal greater differences between the reference digital elevation model and the EU-DEM, than those related to the SRTM data (Fig. 11), although the latter has a somewhat coarser resolution than the former.

Regarding the results at the basin scale, the largest differences between SRTM and LIDAR were mostly noted for low slopes, especially in the case of the smallest-sized basin (V. Caselor), at slopes $< 10^{\circ}$, followed by Runc (mainly at slopes ranging between 10-20°), Ţibleş (especially at small slopes ranging between 5-15°, but also at steeper slopes between 25-35°) and Sălăuța (especially at slopes falling in the range between 5-15°).

On the other hand, the differences between EU-DEM and LIDAR reveal another distribution pattern of the results, with the largest differences observed, both at small slopes and at steeper slopes, in the case of Ţibleş (as is the case for SRTM, especially at slopes ranging between $5-15^{\circ}$, as well as between $25-35^{\circ}$), followed by Runc (mainly at slopes between $20-30^{\circ}$, but also at slopes $<15^{\circ}$), Sălăuța (both at slopes in the range between $5-15^{\circ}$ and steeper slopes between $25-35^{\circ}$) and Valea Caselor (especially at slopes $<15^{\circ}$).

Considering the LIDAR DEM resampling results, it can be stated that as the size of the pixel increases and the resolution decreases, the slopes decrease, as was to be expected, the closest values to the given 3 m LIDAR reference ones, being those derived from the 10 m LIDAR model (Fig. 13). Results derived from the resampling procedure of LIDAR DEM at spatial resolutions of 25 and 30 m respectively, show quite close differences among all catchment areas considered (the only larger differences could be observed at gentle slopes, < 15-20⁰), with the exception of the V. Caselor drainage basin, with significantly varying slope angles derived from LIDAR 30 m (Fig. 14).



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Fig. 9. Cumulative slope frequency curves derived from EUDEM 25 and LIDAR 25



Fig. 10. Histograms of slope classes derived from SRTM 30 and LIDAR 30



AN EVALUATION OF LIDAR, EU-DEM AND SRTM-DERIVED TERRAIN PARAMETERS ...

Fig. 11. Cumulative slope frequency curves derived from EUDEM 25 and LIDAR 25



Fig. 12. Histograms of slope classes derived from EUDEM 25 and LIDAR 25



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Fig. 13. Cumulative slope frequency curves generated from different LIDAR resolutions



Fig. 14. Histograms of slope classes generated from different LIDAR resolutions

5. CONCLUSIONS

The choice of a digital terrain model for calculations, analysis and drainage characteristics processing at watershed scale, is of crucial importance, especially if one opts for the workflow automation process rather than the time-consuming process of working with topographical materials. Digital terrain models are the basis for deriving various characteristics related to watersheds, useful not only for analysis but also for runoff modelling, such as the hydraulic length, drainage area and slope, with major implications on the water velocity and movement as well as the time of flow concentration. Gentler slopes generally result in lower water velocities during a rainfall event, while steeper slopes produce a faster water runoff rate and concentration with major influence on the results of surface runoff modeling.

The objective of the present study was to conduct a comparative analysis in terms of river basin characteristics resulting from processing different digital elevation models at a wide area scale comprising various-sized drainage systems. The purpose was to determine the range of differences that can be found in such a case. Although relatively larger differences were noticed within the study area as regards the EU-DEM-derived characteristics when compared to the reference model, it does not mean that this type of DEM cannot and should not be used for hydrological analysis purposes. In the case of hydrological models with lumped or semi-distributed parameters, if this type of data were to be used, it would certainly meet the requirements for this particular area (maybe even in the case of a distributed runoff model, depending on the purpose of the study). It is very important to account for all the possibilities offered by each data source, contingent upon what the user aims to achieve.

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