

VERTICAL ACCURACY ASSESSMENT OF OPEN ACCESS DIGITAL ELEVATION MODELS: BUCARAMANGA-COLOMBIA CASE STUDY

Jhonathan APONTE SARAIVIA ^{*}

Faculty of Natural Sciences and Engineering, Unidades Tecnológicas de Santander, Bucaramanga, Colombia

Received 20 January 2021; accepted 10 March 2022

Abstract. Digital Elevation Models (DEMs), are fundamental data that allow to represent topographic information continuously. They are widely used in various applications such as geoscience, and in the graphical representation of the landscape surface. Performing the analysis by using DEMs in which the real shape of the surface is adjusted, this would contribute significantly in obtaining their results as we would be approaching the actual occurrence of the object of study in the landscape. Currently, several global DEMs are freely available. However, various investigations have produced different results, so there are uncertainties as to which model is more appropriate for some areas. In that sense, the research was aimed at comparing the vertical accuracy of four DEMs in the city of Bucaramanga using central tendency statistical methods such as mean analysis, standard deviation and root mean squared error. As a result, the model that showed the best vertical accuracy was the one generated by the Advanced Land Observation Satellite program – Synthetic Aperture Radar and X-band Shuttle Radar Topography Mission, with a root mean squared error of 8.22 and 8.55 m respectively. Moreover, the one that best represented the shape of the landscape was the X-band Shuttle Radar Topography Mission X model.

Keywords: vertical uncertainty, digital surface model, accuracy assessment, Free DEM comparison.

Introduction

Digital Elevation Models are a dataset that allows the continuous representation of land topography using quantitative values (Li et al., 2005). They are one of the most important attributes for terrain modelling (Yahaya & Azzab, 2019), which has multiple applications in the survey and analysis of geographic objects that are bounded to the Earth's surface (Florinsky, 2016; Yahaya & Azzab, 2019). They are classified into two groups: Digital Terrain Models (DTM), which describe objects at the ground level, and Digital Surface Models (DSMs), which reflect the Earth's surface including all man-made objects and natural objects (Martha et al., 2010; Florinsky, 2016).

Currently, several organizations have released digital surface model data generated through indirect methods, some of which have global coverage. In addition, in recent years these data have reportedly improved their performance in describing the shape of the land surface. This is the case of the SRTM program, which has released DSM data in different periods (version 1, version 2 and version 3). For example, at the end of 2014 the version 3 of the SRTM model generated in the C-band (SRTM C) was released by Jet Propulsion Laboratory (2020). Similarly,

SRTM data generated in the X-band (SRTM X) were also published by the German Space Agency (DLR). Also, the DSMs of the Advanced Land Observation Satellite [ALOS] program launched in 2006 by Japan Aerospace Exploration Agency (JAXA) (Tadono et al., 2014) are free and publicly available in digital repositories.

These DSMs have been successfully used in various applications, such as: Hydrological modelling (Wilson & Gallant, 2000), glaciology studies (Mölg et al., 2017), geomorphology studies (Florinsky, 2016), environmental studies (Li et al., 2005), civil engineering applications (Li et al., 2005), soil mapping and prediction (Florinsky, 2016), spatial distribution of vegetation (Jelaska, 2009), meteorological applications (Emeis & Knoche, 2009), among others. Therefore, it is essential to know the DSMs generation processes and their levels of uncertainty with respect to the real shape of the Earth's surface.

However, DSMs have several errors, which affect the representation of the Earth's surface. One of them are random errors that may be associated with the altitude variable. In turn, they are categorized by their spatial scale into long-wavelength absolute biases (Rodríguez et al., 2006; Dowling et al., 2011). Also, the DSMs can be affected by systematic errors, which are caused by the tree canopies in

^{*}Corresponding author. E-mail: japonte@correo.uts.edu.co

forested areas (O'Loughlin et al., 2016). Moreover, there is evidence of these errors in areas without vegetation cover—especially in areas with a steep slope (González-Moradas & Viveen, 2020).

When the DSMs are obtained, the metadata generally indicates the values of precision and accuracy. However, it is understood that these values are a global reference, and in some parts of the Earth the terrain shape is abrupt and complex, especially in mountainous landscapes. Therefore, landscape analyses in areas with complex terrain topography generate results with unknown levels of uncertainty. In addition, research has shown that vertical accuracy values vary according to slope (Vaka et al., 2019; Yahaya & Azzab, 2019), where the Root Mean Squared Error (RMSE) varies between ± 4.22 and ± 27.58 m (Sharma et al., 2010). Moreover, SRTM version 4.1 with a pixel size of 90 m for South America shows an RMSE of approximately 11.2 m (Mukul et al., 2017). Thus, these results are still very general.

On the other hand, it is essential to know which model allows to present with greater accuracy and precision the continuous description of the data associated with the altitude variable and its spatial location; it is crucial for the success of many applications in geoscience, engineering and other areas (Vaka et al., 2019). After all, using accurate data in landscape modelling processes and their interactions will provide results that are highly correlated with real-world situations. Accordingly, it may be possible to understand why certain complex processes are occurring in the landscape (Wechsler, 2007). Thus, the aim of the research was to compare the vertical accuracy of four open-access DEMs from different sources for the city of Bucaramanga, the area has different types of surfaces, such as: surfaces with rugged topography and areas where the surface has been modified by human activity, in addition,

few investigations have evaluated the performance of DEMs in Latin America.

1. Materials and methods

1.1. Study area

The study area is located in the city of Bucaramanga, northeast of Colombia's capital, on the north-eastern side of the Andes Mountains, in the geographic coordinates ($7^{\circ}7'8.79''$ N; $73^{\circ}7'21.65''$ W). The study area is made up of a variety of terrain types relief such as: Hills, valleys, depressions, plains, plateaus, and mountain elevations in the most extreme parts. The study area covers approximately 263.22 km², see Figure 1. This whole area has a diverse topography, where land slopes of less than 12% predominate. There are also small flat and semi-flat areas, where the city of Bucaramanga, outlying cities and agricultural production areas are located. And in the areas where the land slope varies between 12% and 25%, there are creeks and small valleys. The areas where the land topography is higher than 25% correspond to the highest parts of the selected area, especially in the north-east.

1.2. Data

The data used for this study were collected from the SRTM X digital surface model, which was developed by the National Aeronautics and Space Administration [NASA] in cooperation with the National Geospatial-Intelligence Agency (NGA), the German Space Agency (DLR) and the Italian Space Agency (ASI) (German Space Agency, 2020b), using the SAR technique, in the X-band, whose wavelength is 3.1 cm (Farr et al., 2007). Additionally, the DSM metadata indicates that it has a relative vertical accuracy of around 6 m and an absolute vertical accuracy of

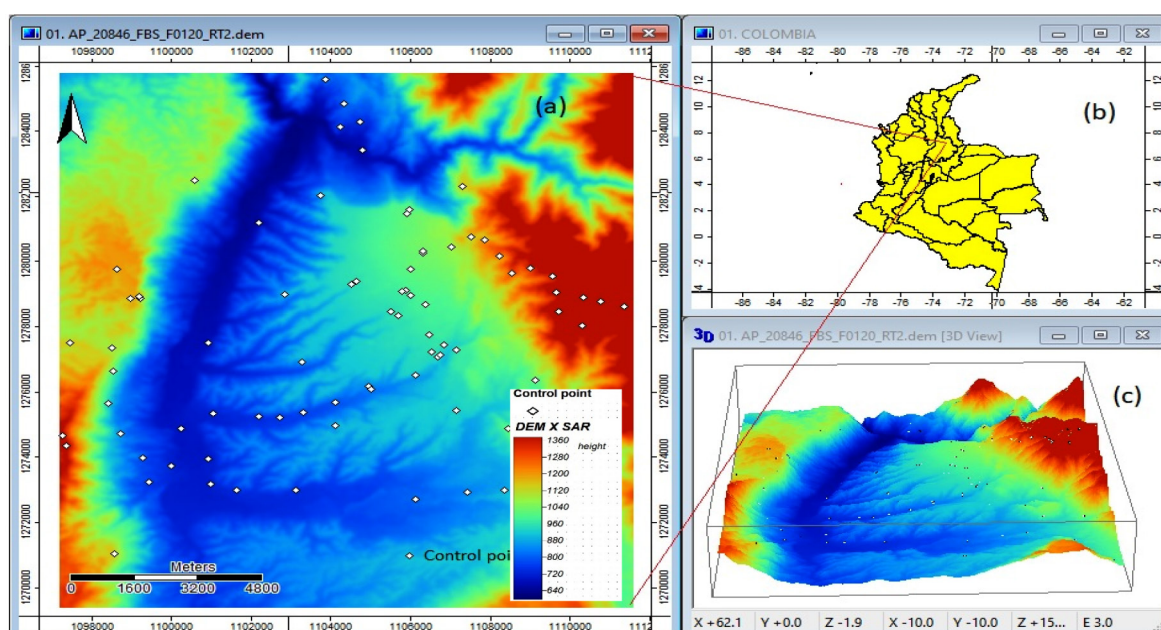


Figure 1. Shows the location of the study area: a – study area coverage using continuous DEM data; b – the location of the study area in the territory of Colombia; c – the presentation of the study area in a 3D model

around ± 16 m at the 90% confidence level (German Space Agency, 2020a).

Similarly, the SRTM C version 3 digital surface model was used, which was generated using the SAR technique, in the C-band, wavelength of 5.6 cm (Farr et al., 2007), with spatial resolution similar to the SRTM X model. Its purpose was to obtain data that did not exceed the 16 m vertical accuracy error at 90% confidence level (Mukul et al., 2017). This version was released in 2015 (National Aeronautics & Space Administration, 2015).

The ALOS digital surface model was also used, which consisted in a project called ALOS World 3D (AW3D) version 3.1, developed by the JAXA and launched in January 2006 (Tadono et al., 2017). It used more than three million satellite images to create 3D topographic data, applying the traditional technique of optical stereo matching of panchromatic images: Panchromatic Remote Sensing Instrument for Stereo Mapping (PRISM) (Takaku et al., 2014), with a vertical mean squared error of less than 4 m (Tadono et al., 2017).

In addition, a digital surface model developed by the PALSAR program (ALOS SAR) was used – a project developed by JAXA and the Japan Resource Observation System (JAROS) using the SAR technique. This data was polarimetrically obtained in the L-band frequency, generated from a horizontal polarization (HH) and a horizontal-vertical polarization (HV) (Advanced Land Observing Satellite, 2020), see Figure 2.

Furthermore, for the vertical accuracy assessment of digital surface models, 88 high precision checkpoints (vertices of the national geodetic network of Colombia) were used, configured in the National Geocentric Reference Framework, densification of the Geocentric Reference System for the Americas MAGNA SIRGAS (Sanchez, 2004). The data were configured in the Geo-Col2004 Geoidal Model, which represents the direct relationship between the geoid and the quasigeoid, and is equivalent to the difference of orthometric and normal heights (Sánchez Rodríguez, 2003). These data are available in the geoportal of Instituto Geográfico Agustín Codazzi.

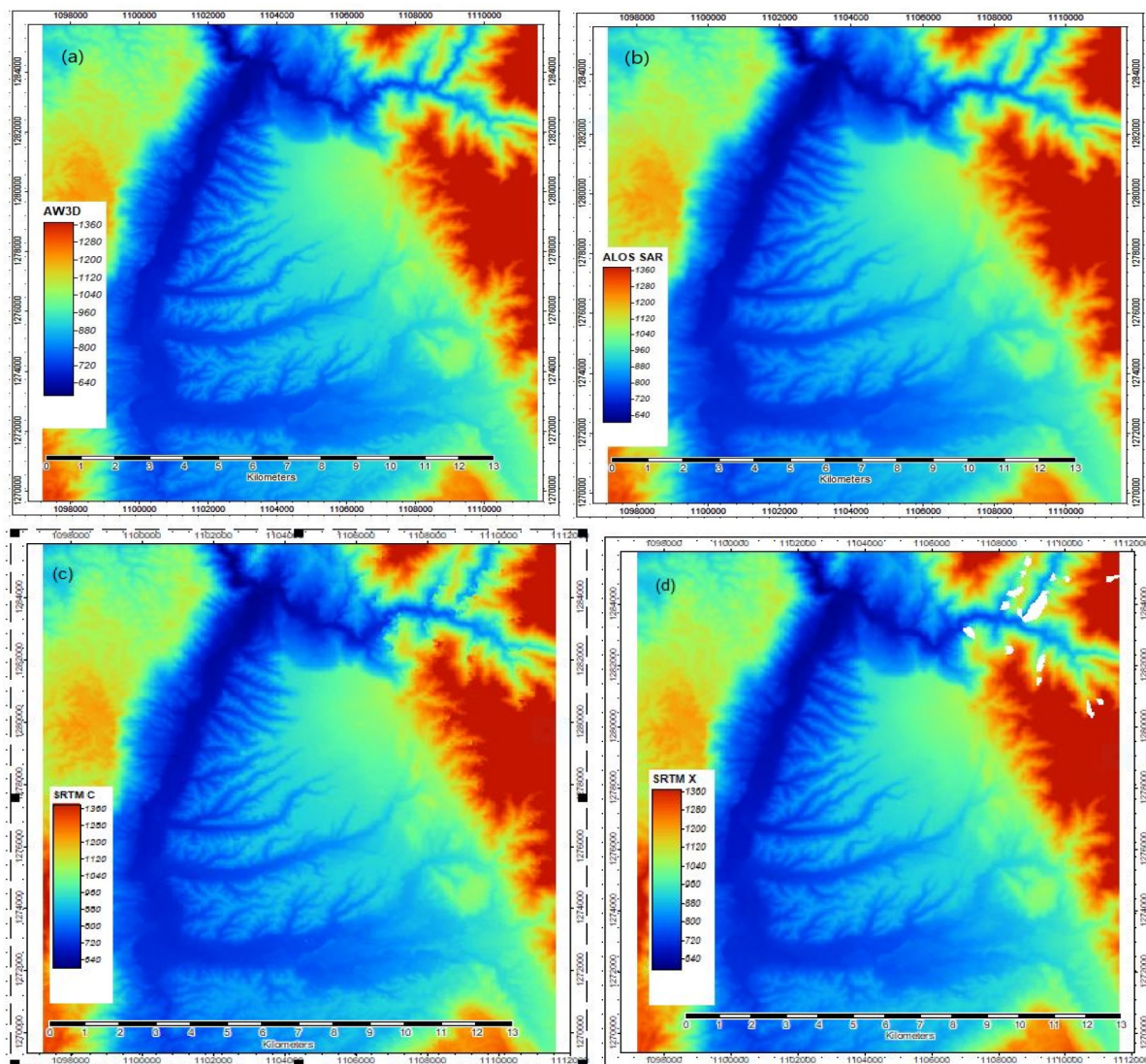


Figure 2. Presents the visual comparison of the digital elevation models, the blue pixels indicate the zones of lower altitude and the red zones show the zones of higher altitude: a – DEM AW3D; b – DEM ALOS SAR; c – DEM SRTM C; d – DEM SRTM X

Table 1. Presents the descriptive statistical distribution of the altitudes of the digital elevation models of the selected area and the number of pixels covered by the grid.

Data	Height min.	Height Max.	Mean	SD	Datum vertical	No data cells
AW3D	581.04	1773.03	959.48	209.42	WGS84	0
ALOS SAR	599.96	1784.92	967.06	208.84	EMG96	0
SRTM C	592.65	1774.80	957.87	208.75	EMG96	0
SRTM X	485.33	1813.40	968.68	208.07	WGS84	1206

1.3. Methods

After downloading and organizing data, both in the digital surface models and in the checkpoints (geodesic points), they were converted into flat coordinates, in order to have data in the same reference system. The DEMs associated with the area of interest were then extracted, with pixel sizes of 30 m. for each of the DEMs. Subsequently, the descriptive statistical exploration, as well as the verification of the vertical datum, were performed on these selected data as shown in Table 1.

Similarly, a preliminary analysis of the checkpoints (geodetic points) revealed that these data contained geometric height and undulation values. Thus, it was possible to convert data into ellipsoidal heights, since digital surface models denote ellipsoidal heights. For such purpose, the equation applied by Yahaya and Azzab (2019) was used.

The pixel values of DEMs that match the horizontal position of the checkpoints were then extracted. Subsequently, statistical assessments of vertical accuracy comparison analysis were performed, using the System for Automated Geoscientific Analyses (SAGA), R Package and RStudio for data processing and analysis, example the differences between the height of the checkpoints (h_{point}) and the height of the DEMs (h_{DEM}) were calculated (Ibrahim Yahaya & El Azzab, 2019). The vertical accuracy analysis is based on the analysis of statistical parameters such as: Mean (ME), Standard Deviation (SD) and RMSE (Vaka et al., 2019; Wessel et al., 2018). For this purpose, the mean residual values were calculated using the following expression:

$$ME = \frac{1}{n} \sum_{i=1}^n h_{point} - h_{DEM} = \frac{1}{n} \sum_{i=1}^n \Delta h_i, \quad (1)$$

where Δh_i are the residual error values, and n is the number of checkpoints. These values were converted into absolute values for their analysis. This expression was also applied by González-Moradas and Viveen (2020). In addition, SD (American Society for Photogrammetry and Remote Sensing [ASPRS], 2015) was calculated on each model using the following equation:

$$SD = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\Delta h_i - ME)^2}. \quad (2)$$

Similarly, the RMSE – which is a widely used metric for measuring the accuracy of continuous variables in

geoscience as well as in DEMs (Vaka et al., 2019; Wessel et al., 2018; González-Moradas & Viveen, 2020) – was calculated using the following expression:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (h_{point} - h_{DEM})^2}, \quad (3)$$

where n is the number of points used in the sample, (h_{point}) is the height of the checkpoints and (h_{DEM}) is the height of the digital elevation model.

Then, assuming that the values of the vertical errors have a normal distribution and the linear error is proportional to the standard error (Grohmann, 2018) and in accordance with the American Society for Photogrammetry and Remote Sensing (ASPRS) standards for these processes (ASPRS, 2015; González-Moradas & Viveen, 2020), the confidence intervals were calculated at 95% using the following expression.

$$LE95\% = 1.9600 \times SD. \quad (4)$$

Similarly, the residual distribution was assessed to understand how these values are distributed according to the slope, which was also assessed in similar studies by González-Moradas and Viveen (2020) and Vaka et al. (2019). In the same way, linear correlation between the height of the checkpoints and the height of the DEMs was analysed in order to identify the model with the highest correlation value.

Then, the digital surface models were compared. For this process, data referring to the DSM that provides the most accurate statistical analysis was considered. It was then compared with the other less precise models, following the criteria applied by González-Moradas and Viveen (2020), using the following relation:

$$\Delta DEM = DEM_{ref} - DEM_i, \quad (5)$$

where ΔDEM , are the residual values of the models, DEM_{ref} is the reference model, and DEM_i is the model selected for comparison. After obtaining the residual values of the digital elevation models, the absolute value was calculated and comparisons were made with the pending topographic attribute generated from the most accurate DEM, in order to observe the statistical and spatial behaviour in different landforms.

2. Results and discussions

The following describes the most important results of the vertical uncertainty assessment process for the different

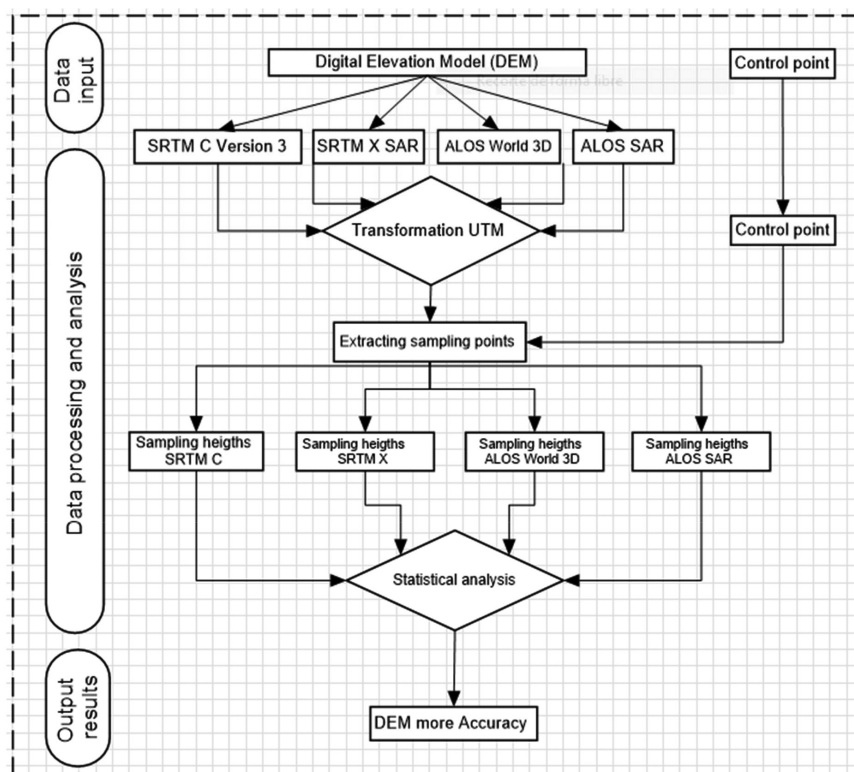


Figure 3. Presents the methodological scheme of the research process, indicating the entry, data analysis and obtaining the results of vertical accuracy

global digital surface models. Also, the presentation and comparison of the results was done using the R package software product, RStudio and the presentation of surface profiles in SAGA.

Table 2. Presents the descriptive statistical distribution of the residual errors between the control points and the digital surface models

Data Statistics	AW3D	ALOS SAR	SRTM C	SRTM X
Absolute maximum residual (m)	21.02	20.70	28.75	24.07
Absolute minimum residual (m)	0.30	0.10	0.40	0.35
Absolute mean residual (m)	10.13	6.13	11.27	6.32
SD	4.63	5.51	7.18	5.79
RMSE	11.13	8.22	13.34	8.55
LE 95%	9.07	10.79	14.07	11.34

From the vertical comparison analysis of digital surface models with high-precision checkpoints, it is evident that the ALOS SAR model has the lowest RMSE, followed by SRTM X. It also has the lowest SD values, except in AW3D, indicating that the residual error dataset is clustered in a relatively small range. However, AW3D and SRTM C have the highest mean squared errors, which indicates a greater uncertainty, see Table 2. Similar to Florinsky et al. (2018), who also mentioned that the SRTM model is more inaccurate than AW3D–RMSE of 17.91

and 7.87 respectively – Alganci et al. (2018) stated that the ALOS model showed a greater accuracy than SRTM C. Whereas, González-Moradas and Viven (2020) mentioned that the SRTM C model has higher vertical accuracy when compared to other models such as: ASTER GDEM2, AW3D. Other research has shown more accurate results as described in (Alganci et al., 2018). Therefore, it is important to make these comparisons, because vertical accuracy depends significantly on landscape conditions and geographic locations.

On the other hand, when analysing the behaviour of the residual errors according to the slope, it can be seen that the SD increases as the slope increases. This indicates that the vertical accuracy is greater in areas where the slope is less than 2.5%, and that the higher the slope, the lower the vertical accuracy, see image (a) in Figure 4. This criterion is generally met in all four DEMs, which is consistent with Vaka et al. (2019) findings. Model SRTM X errors showed greater vertical accuracy in landscapes where land topography is less than 2.5% and uncertainty is higher in areas where land topography is greater than 7.5% compared to other models. While ALOS SAR residual errors show lower SD in areas where the slope is greater than 20%, this model shows less uncertainty for the study area on various slope types, see Table 2 and Image (a) in Figure 4.

Thus, there are different vertical accuracy behaviours in various types of vegetation cover, see image (b) of Figure 3, which shows a greater vertical accuracy in areas considered as flat and semi-flat areas, where there is

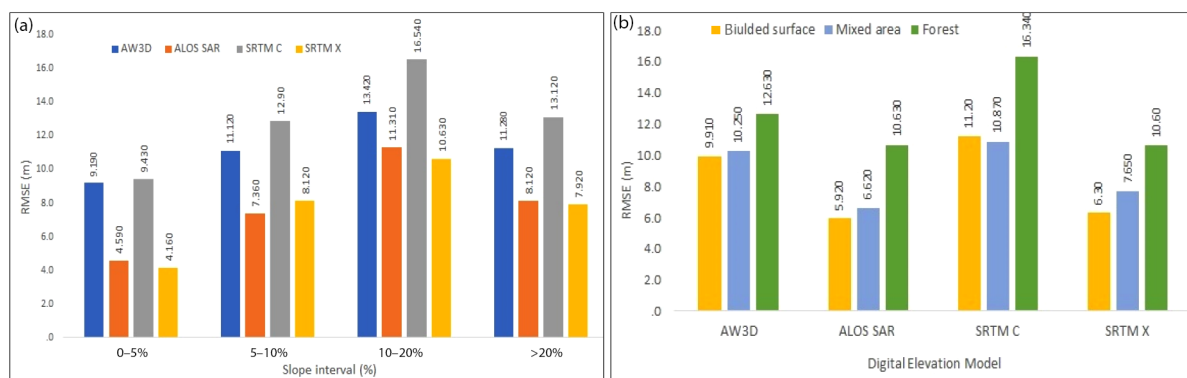


Figure 4. Shows the behavior of residual errors: a – SD in different slope ranges; b – SD in different types of coverage

little vegetation and no urban constructions. This pattern is consistent in all models, and uncertainty is greater in mixed areas (constructed areas, areas with vegetation and open spaces); RMSE is higher in areas with dense vegetation and abrupt topography, revealing a greater uncertainty in these places. It is inferred that dense vegetation and urban constructions are the components that significantly increase the uncertainty of the global DEMs generated by indirect methods, which is consistent with the findings of Vaka et al. (2019), Florinsky et al. (2018), Alganci et al. (2018).

From the analysis of the surface profile, the model which best describes the shape of the landscape at surface level is the SRTM X model, since this model – in areas with dense vegetation and a slope greater than 20% – is able to describe the surface profile in greater detail, including the peaks of the surface profiles in the most prominent trees, see image (a) and (b), in Figure 5. Thus, in urban areas it manages to represent in greater detail the surface profiles of the buildings and vegetation, followed by the AW3D model, which also represents the shape of the surface, but in less detail, as shown in picture (c), (d), (g) and (h) in Figure 5. Similarly, in areas with little bush vegetation and topography of less than 20%, the pixels of the SRTM X model describe in greater detail the shape of the landscape at the surface level.

The images (d) and (h) of Figure 5, shows the surface profiles of different digital elevation models, where it allows us to show with better performance the description of the surface of each model, because this section represents surfaces with abrupt slopes generating a more complex surface edge, see images (c) and (g) of the same figure, also the length of the profile section is shorter, achieving to observe the surface profiles with greater detail in the SRTM X model and the AW3D model. On the other hand, the images (f) and (j) do not help to visually differentiate the performance of the model in the process of describing the surface, even though the profile section is located in surfaces with smooth, abrupt undulations, where the vegetation does not have significant heights, generating confusion. In this sense, these data generate inaccurate surface

models because the pixel size is large and this does not allow to generate surfaces with a high level of detail, however, it is appropriate to generate cartographic information with a low level of detail.

Considering that the ALOS SAR digital surface model is the one with the highest vertical accuracy, it was used as a reference model to perform the residual error calculation on the other models with lower vertical accuracy, in order to describe and assess the behaviour of residual errors using the central trend descriptive criteria. The results are shown in Figure 6.

From the analysis of the residual data (between ALOS SAR – SRTM C), it is observed that the central trend of data is 2.078, with this value being the closest to zero with respect to the other models, see Figure 6. The above shows that most residual data is concentrated between –6.499 and 9.655 m, while the other residual datasets are within greater ranges, despite the fact that SD values are lower. Hence, the higher residual values observed when comparing the most accurate model with the others suggest a greater uncertainty. Given this criterion, the model that presented higher residual values is ALOS SAR – SRTM X. This is because the model SRTM X represents in greater detail the landscape surface shape, see Figure 4. On the other hand, the ALOS SAR model represents the surface shape in less detail, i.e. the description of the surface shape is more homogeneous. However, the residual values of ALOS SAR – SRTM C show less uncertainty, probably because the characteristics of both models provide a more homogeneous description of the landscape shape. In other words, these models do not represent the surface shape in much detail. However, this assessment is not statistically relevant because there are few data with high residual values, see Figure 6.

Conclusions

From the vertical accuracy comparison analysis of the models evaluated, the ones that showed the greatest vertical accuracy were ALOS SAR and SRTM X, whose mean squared error values are 8.22 and 8.55, respectively. On the other hand, the models that better described the shape of

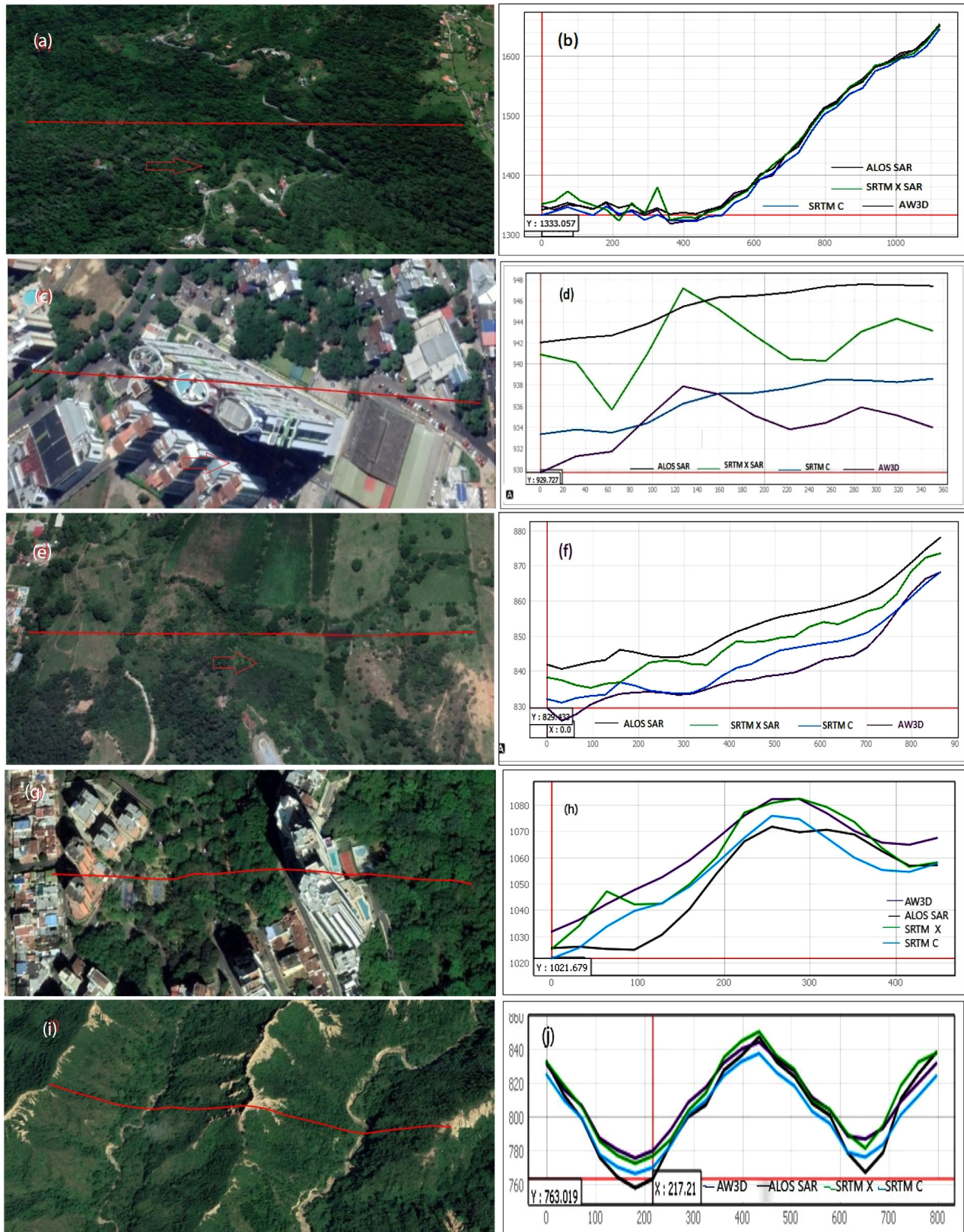


Figure 5. Shows the behaviour of the surface profiles in different types of coverings: a – vegetation coverage in topography of land greater than 20%; b – surface profile behaviour in vegetation zones; c – the image shows urban infrastructure; d – surface profile of different digital surface models in urban areas; e – shows zones with scarce vegetation and areas of flat and semi-flat slopes; f – indicates the surface profile in areas of low vegetation; g – the image shows urban infrastructure and in areas with dense vegetation; h – shows the surface profile in areas of urban structures and in areas with dense vegetation; i – shows the image in areas where the slope varies between 30% and 52%; j – surface profile in rugged areas

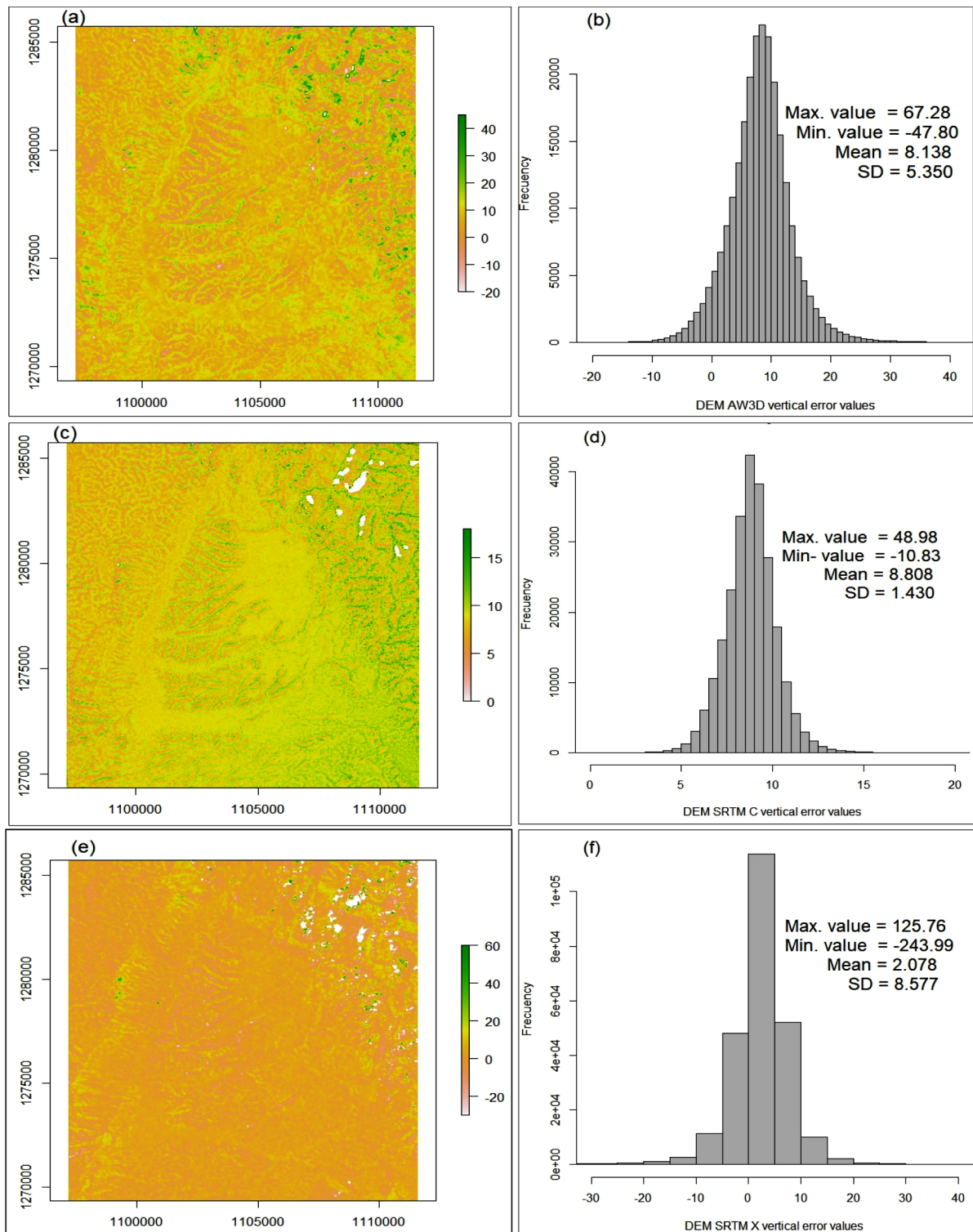


Figure 6. Shows the spatial distribution of the residual errors values of the DEM: a – residual error of the difference between ALOS SAR and AW3D; b – distribution of the residual data of the difference between ALOS SAR and AW3D; c – residual error of the difference between ALOS SAR and SRTM C models; d – distribution of residual difference errors of ALOS SAR and SRTM C models; e – spatial distribution of the difference errors between ALOS SAR and SRTM X; f – difference residual error histogram of ALOS SAR and SRTM X models

the landscape were SRTM X and AW3D. Specifically, the SRTM X model tries to represent in greater detail the elevations of urban structures and dominant trees. However, the models that represent the terrain shape more homogeneously were ALOS SAR and SRTM C, because these models failed to represent the edges of urban structures or dominant trees.

Accordingly, it can be deduced that for the study area the SRTM X model has a high potential to make adjustments for the landscape modelling at surface level. On the other hand, the ALOS SAR model has no potential to describe the shape of the surface even though it presented the lowest mean square error value.

Acknowledgements

My deepest thanks to the research group “Grupo de Investigación Medio Ambiente y Territorio – GRIMAT”, for giving me the necessary time to conclude this investigation and the manuscript.

Author contributions

Jhonathan Aponte Saravia, has contributed to the design, data collection, data analysis, interpretation of results and construction of the manuscript.

Disclosure statement

The author of the manuscript has no interest in financial, professional or personal issues regarding the publication of this document, but on the contrary the purpose is to share the results of the research with the scientific community.

References

- Advancend Land Ovserving Satellite. (2020). *Palsar phased array type l-band synthetic aperture radar*. Retrieved July 2020, from <https://www.eorc.jaxa.jp/ALOS/en/about/palsar.htm>
- Alganci, U., Besol, B., & Sertel, E. (2018). Accuracy assessment of different digital surface models. *ISPRS International Journal of Geo-Information*, 7(3), 114. <https://doi.org/10.3390/ijgi7030114>
- American Society for Photogrammetry and Remote Sensing. (2015). ASPRS positional accuracy standards for digital geospatial data. *Photogrammetric Engineering & Remote Sensing*, 81(3), A1–A26. <https://doi.org/10.14358/PERS.81.3.A1-A26>
- Dowling, T. I., Brooks, M., & Read, A. M. (2011, December). Continental hydrologic assessment using the 1 second (30 m) resolution Shuttle Radar Topographic Mission DEM of Australia. In *19th International Congress on Modelling and Simulation*. Perth.
- Emeis, S., & Knoche, H. R. (2009). Applications in meteorology. In T. Hengl & H. Reuter (Eds.), *Developments in soil science: Vol. 33. Geomorphometry – concepts, software, applications* (pp. 603–622). Elsevier. [https://doi.org/10.1016/S0166-2481\(08\)00026-3](https://doi.org/10.1016/S0166-2481(08)00026-3)
- Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., & Alsdorf, D. (2007). The shuttle radar topography mission. *Reviews of Geophysics*, 45(2), 1–33. <https://doi.org/10.1029/2005RG000183>
- Florinsky, I. (2016). Digital terrain modeling: A brief historical overview. In *Digital terrain analysis in soil science and geology* (2nd ed.). Elsevier Inc. <https://doi.org/10.1016/B978-0-12-804632-6.00001-8>
- Florinsky, I., Skrypitsyna, T., & Luschikova, O. (2018). Comparative accuracy of the AW3D30 DSM, ASTER GDEM, and SRTM1 DEM: A case study on the Zaoksky testing ground, Central European Russia. *Remote Sensing Letters*, 9(7), 706–714. <https://doi.org/10.1080/2150704X.2018.1468098>
- German Space Agency. (2020a). *Shuttle Radar Topography Mission SRTM product*. Retrieved December 2022, from https://geoservice.dlr.de/resources/licenses/srtm_xsar/DLR_SRTM_XSAR_ReadMe.pdf
- German Space Agency. (2020b). *The SRTM X-SAR digital elevation model*. Retrieved December 2020, from https://geoservice.dlr.de/web/dataguide/srtm/#further_information_mission
- González-Moradas, M., & Viveen, W. (2020). Evaluation of ASTER GDEM2, SRTMv3.0, ALOS AW3D30 and TanDEM-X DEMs for the Peruvian Andes against highly accurate GNSS ground control points and geomorphological-hydrological metrics. *Remote Sensing of Environment*, 237, 111509. <https://doi.org/10.1016/j.rse.2019.111509>
- Grohmann, C. H. (2018). Evaluation of TanDEM-X DEMs on selected Brazilian sites: Comparison with SRTM, ASTER GDEM and ALOS AW3D30. *Remote Sensing of Environment*, 212, 121–133. <https://doi.org/10.1016/j.rse.2018.04.043>
- Ibrahim Yahaya, S., & El Azzab, D. (2019). Vertical accuracy assessment of global digital elevation models and validation of gravity database heights in Niger. *International Journal of Remote Sensing*, 40(20), 7966–7985. <https://doi.org/10.1080/01431161.2019.1607982>
- Jelaska, S. D. (2009). Vegetation mapping applications. In T. Hengl & H. Reuter (Eds.), *Developments in soil science: Vol. 33. Geomorphometry – concepts, software, applications* (pp. 481–496). Elsevier. [https://doi.org/10.1016/S0166-2481\(08\)00021-4](https://doi.org/10.1016/S0166-2481(08)00021-4)
- Jet Propulsion Laboratory. (2021). *U.S. releases enhanced shuttle land elevation data*. California Institute of Technology. Retrieved January 2021 from <https://www2.jpl.nasa.gov/srtm/>
- Li, Z., Zhu, C., & Gold, C. (2005). *Digital terrain modeling: Principles and methodology*. CRC Press.
- Martha, T. R., Kerle, N., Jetten, V., van Westen, C. J., & Kumar, K. V. (2010). Characterising spectral, spatial and morphometric properties of landslides for semi-automatic detection using object-oriented methods. *Geomorphology*, 116(1–2), 24–36. <https://doi.org/10.1016/j.geomorph.2009.10.004>
- Mölg, N., Ceballos, J. L., Huggel, C., Micheletti, N., Rabatel, A., & Zemp, M. (2017). Ten years of monthly mass balance of conejeas glacier, colombia, and their evaluation using different interpolation methods. *Geografiska Annaler: Series A, Physical Geography*, 99(2), 155–176. <https://doi.org/10.1080/04353676.2017.1297678>
- Mukul, M., Srivastava, V., Jade, S., & Mukul, M. (2017). Uncertainties in the Shuttle Radar Topography Mission (SRTM) heights: Insights from the Indian Himalaya and Peninsula. *Scientific Reports*, 7, 41672. <https://doi.org/10.1038/srep41672>
- National Aeronautics and Space Administration. (2015). *The Shuttle Radar Topography Mission (SRTM) collection user guide*. Retrieved June 2015, from https://lpdaac.usgs.gov/documents/179/SRTM_User_Guide_V3.pdf

- O'Loughlin, F. E., Paiva, R. C., Durand, M., Alsdorf, D. E., & Bates, P. D. (2016). A multi-sensor approach towards a global vegetation corrected SRTM DEM product. *Remote Sensing of Environment*, 182, 49–59. <https://doi.org/10.1016/j.rse.2016.04.018>
- Rodríguez, E., Morris, Ch. S., & Belz, J. E. (2006). A Global assessment of the SRTM performance. *Photogrammetric Engineering & Remote Sensing*, 72(3), 249–260. <https://doi.org/10.14358/PERS.72.3.249>
- Sánchez Rodríguez, L. (2003). *Determinación de la superficie vertical de referencia para Colombia* [Master's Thesis]. Technische Universität Dresden. <https://www.igac.gov.co/sites/igac.gov.co/files/modelogeoidalgeocol2004.pdf>
- Sanchez Rodriguez L. (2004). *Aspectos Prácticos de la Adopción del Marco Geocéntrico Nacional de Referencia MAGNA SIRGAS como datum oficial de Colombia* (Tech. Rep.). Subdirección de Geografía y Cartografía. Instituto Geográfico Agustín Codazzi. <https://www.igac.gov.co/sites/igac.gov.co/files/aspectospracticos.pdf>
- Sharma, A., Tiwari, K., & Bhadoria, P. (2010). Vertical accuracy of digital elevation model from Shuttle Radar Topographic Mission – a case study. *Geocarto International*, 25(4), 257–267. <https://doi.org/10.1080/10106040903302931>
- Tadono, T., Ishida, H., Oda, F., Naito, S., Minakawa, K., & Iwamoto, H. (2014). Precise global DEM generation by ALOS PRISM. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2(4), 71–76. https://www.aw3d.jp/wp/wp-content/themes/AW3DEnglish/technology/doc/pdf/technology_03.pdf
- Tadono, T., Takaku, J., Ohgushi, F., Doutsu, M., & Kobayashi, K. (2017). Updates of 'AW3D30' 30 M-MESH global digital surface model dataset. In *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)* (pp. 5656–5657). <https://doi.org/10.1109/IGARSS.2017.8128290>
- Takaku, J., Tadono, T., & Tsutsui, K. (2014). Generation of high-resolution global DSM from ALOS PRISM. *ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences*, 2(4), 243–248. https://www.aw3d.jp/wp/wp-content/themes/AW3DEnglish/technology/doc/pdf/technology_02.pdf
- Vaka, D. S., Kumar, V., Rao, Y., & Deo, R. (2019, July). Comparison of various DEMs for Height accuracy assessment over different terrains of India. In *IGARSS 2019 – 2019 IEEE International Geoscience and Remote Sensing Symposium* (pp. 1998–2001). Yokohama, Japan. <https://doi.org/10.1109/IGARSS.2019.8898492>
- Wechsler, S. P. (2007). Uncertainties associated with digital elevation models for hydrologic applications: A review. *Hydrology and Earth System Sciences*, 11(4), 1481–1500. <https://doi.org/10.5194/hess-11-1481-2007>
- Wessel, B., Huber, M., Wohlfart, C., Marschall, U., Kosmann, D., & Roth, A. (2018). Accuracy assessment of the global TanDEM-X Digital Elevation Model with GPS data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 139, 171–182. <https://doi.org/10.1016/j.isprsjprs.2018.02.017>
- Wilson, J. P., & Gallant, J. C. (Eds.) (2000). *Terrain analysis: Principles and applications*. Wiley.
- Yahaya, S. I., & Azzab, D. E. (2019). Vertical accuracy assessment of global digital elevation models and validation of gravity database heights in Niger. *International Journal of Remote Sensing*, 40(20), 7966–7985. <https://doi.org/10.1080/01431161.2019.1607982>