



# A novel method to improve vertical accuracy of CARTOSAT DEM using machine learning models

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## Abstract

High quality, accessible Digital Elevation Model (DEM) datasets play a major role in monitoring the changes in the Earth's surface. This study proposes a novel method to increase the vertical precision of CARTOSAT 10 m DEM by blending it with publicly available SRTM (Shuttle Radar Topography Mission) DEM using machine learning methods. Machine learning methods such as Genetic Programming (GP) and Artificial Neural Networks (ANN) are applied to the SRTM-1 DEM and the CARTOSAT DEM in India to generate DEM of improved vertical accuracy. Quantifiable results show that proposed approach improve the vertical accuracy, considering the reference as Ground control Points (GCPs) elevation from Differential Global Positioning System (DGPS) survey data. Significant improvements of 47 and 35% in RMSE are offered by generated DEMs compared to the SRTM-1 and CARTOSAT respectively.

**Keywords** DEM blending · Machine learning · SRTM DEM · CARTOSAT DEM

## Introduction

Digital Elevation Model (DEM) is a 3-dimensional representation of the earth's surface. Its uses are diverse and extensive which includes flood modeling (Setti et al. 2018; Zheng et al. 2015), land use studies (Sridhar et al. 2019), geomorphological studies (Valeriano and Rossetti 2017; Maheswaran et al. 2016), watershed delineation (Freitas et al. 2016; Turcotte et al. 2001), glaciology (Cook et al. 2012), evaluation of natural hazards and geological applications. Generally, the DEMs can be created from i) topographic maps, ii) field data collected through surveying and iii) satellite images. With the advent of technology and availability of resources, remote

sensing satellite based DEMs are preferred over the other sources as it involves less cost and time (Das and Pardeshi 2018). Multitude of satellite DEMs are available across the globe with different resolution and accuracy. Some of these include SRTM DEM (Rajasekhar et al. 2018), ASTER DEM (Rawat et al. 2019), World View (Sefercik et al. 2013), CARTOSAT (Rana and Suryanarayana 2019), TerraSAR (Moreira et al. 2004). Out of these, SRTM DEM is one of the commonly used DEM owing to its public availability and vertical accuracy. Das and Pardeshi (2018) have shown the publicly available SRTM DEM of 30 and 90 m resolution can be used for various purposes. However, these DEMs are limited for applications that require finer resolution. Very recently, the CARTOSAT satellite has gained popularity and has been used extensively for Indian regions. Many studies show that the accuracy of CARTOSAT is comparable with the other DEMs some of these include Rajasekhar et al. (2018) compared the ASTER DEM, SRTM, and CARTOSAT for lineament extraction for a region in southern India and found that the CARTOSAT-DEM are best suited for studying very small areas. Evaluation of various satellite DEMS was carried out by Rawat et al. (2019) using ground control points and the results showed that CARTOSAT-1 DEM showed higher accuracy level when compared to SRTM data sets. Das and Pardeshi (2018) carried a comparative analysis study of

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extraction of lineaments from SRTM, CARTOSAT and ASTER DEM and concluded that the CARTOSAT DEM is best suitable for the lineament extraction in Indian region. There are also other studies (Patel et al. 2016; Rawat et al. 2013) have compared the different DEMs in terms of vertical accuracy and reported that the CARTOSAT DEM has a RMSE on the order of 5–6 m. More recently Venkatesh et al. (2019) showed that CARTOSAT-2 DEM (10 m resolution) have vertical accuracy on order of 5–6 m and are superior in comparison with the SRTM DEM.

These studies show that even though the CARTOSAT-10 m DEM performs better than other publicly available DEMs, the order of the RMSE and the vertical accuracy can be improved. In this study, we aim to develop a framework based on machine learning tools in increasing the vertical (elevation) accuracy of the 10 m CARTOSAT DEM using the publicly available DEMs. The main motivation for using the other DEMs is that these DEMs are derived using different remote sensing principles and have, therefore the capability to capture different features. For example, it is a widely accepted fact that for low relief regions in terms of vertical accuracy, ASTER DEM data is inferior to the SRTM data (Yue et al. 2017) whereas ASTER DEM has shown better performance in mountainous regions (Rawat et al. 2019). Similarly, Mukherjee et al. (2012) report that CARTOSAT has a high error when compared with the SRTM and ASTER for low relief area whereas (Rawat et al. 2019) and (Venkatesh et al. 2019) show CARTOSAT has better performance in terms of vertical accuracy than other counterparts.

One way to improve the performance of the DEM is by combining/blending the DEMs from different sources and scales. Some studies in that direction include Wendi et al. (2016) where the authors attempt to improve the SRTM DEM using LANDSAT images and artificial neural networks. Similarly, Yue et al. (2017) proposed a technique to generate a smooth DEM dataset amalgamation of ASTER GDEM v2, SRTM-1 and ICES at laser altimetry data using ANN. Robinson et al. (2014) used the integration of multi-scale products of DEMs (3-arc GLSDEM, 3-arc SRTM-3 v4.1 and 1-arc ASTER GDEM v2) in the reconstruction of a new DEM of 90 m resolution. Pham et al. (2018) developed a linear method for combining SRTM and ASTER DEMs. In the past, machine learning tools have gained a lot of attention in several research areas viz. hydrological forecasting, spatial interpolation, owing to their ability to capture nonlinear relationship (Makarynska and Makarynsky 2008; Ali Ghorbani et al. 2010; Lima et al. 2013; Guntu et al. 2020, b). In this study, we propose to develop a framework based on Genetic Programming (GP) and Artificial Neural Network (ANN) to generate high quality, DEM by an amalgamation of the SRTM-30 m, CARTOSAT-30 m DEMs. Using the proposed approach, it is possible to develop DEMs of higher accuracy and DEM can be generated in data-scarce regions with the

help of the trained model from its nearby areas which has high accurate data set.

The arrangement of this paper is done in the following manner. Section 2 describes the data used and the Study area. The methodology developed in this study is shown in Section 3. Section 4 explains the results and Section 5 provides the conclusion from the study.

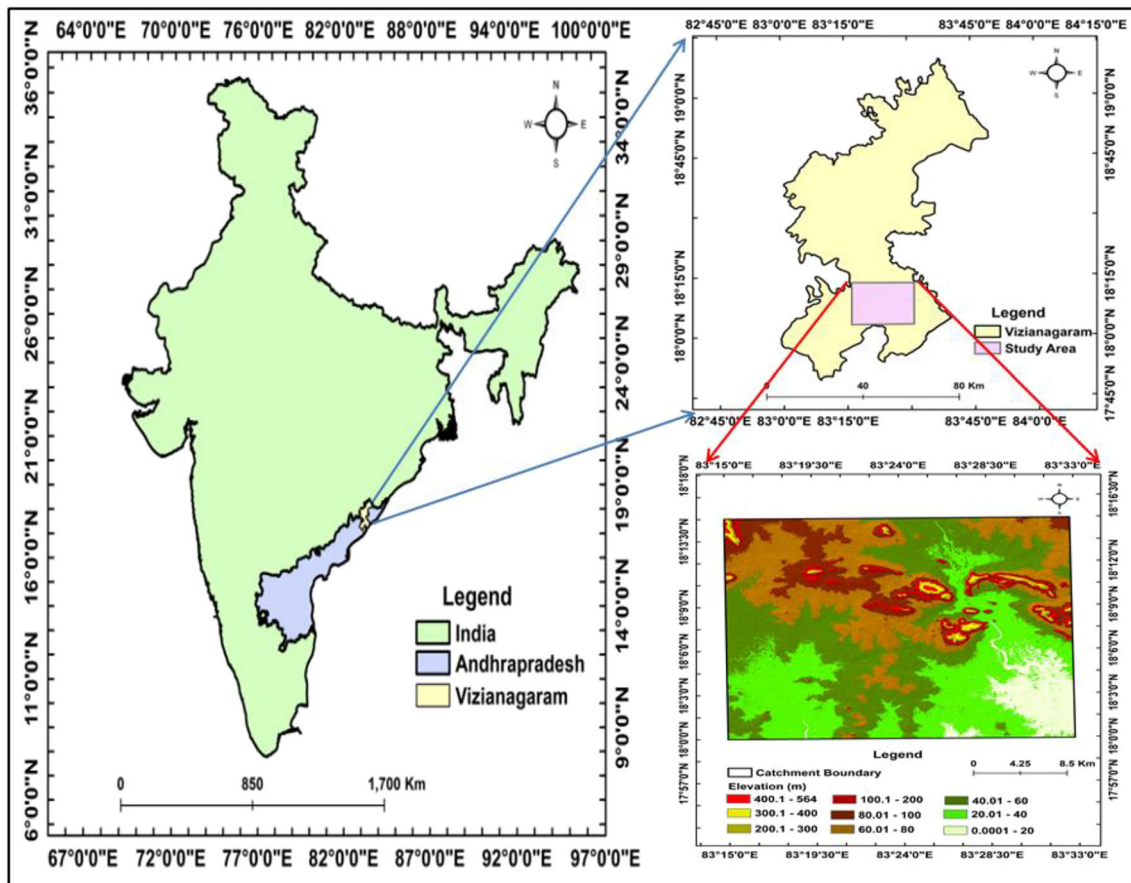
## Study area and data used

### Study area

The study area is a sub-basin (Fig. 1) of the Champavathi River Basin located on the east coast of India having an area of 868 km<sup>2</sup>. The location of the watershed is lies between the latitude of 18° 11' North and longitude of 83° 40' East. The physiography of the watershed is dominated by plain areas with occasional small mountain ranges. The altitude ranges from 26 m to 564 m. A substantial part of the study area is above 50 m elevation above mean sea level. The major land cover and land use include agricultural tracts, urban areas, hill slope, grasslands and water bodies.

### Shuttle radar topography Mission (SRTM 30 m)

The Shuttle Radar Topography Mission (SRTM) is an international project lead by the National Aeronautics and Space Administration (NASA) and National Geospatial-Intelligence Agency (NGA) Launched in February 2000 (Zheng et al. 2015; Yue et al. 2017). It is the modified radar system that flew for an 11-day mission in February 2000 with onboard Space Shuttle Endeavour. By single pass and using radar interferometry, data procurement can be done by using onboard via outboard by antenna system and it also generates earth land elevation datasets in form of Digital Elevation Model (DEM). This DEM datasets product is derived from Interferometry Synthetic Aperture Radar (InSAR) sensor consists of X-band and C-band with a wavelength of 5.6 cm and a frequency of 5.3. The SRTM, Digital Elevation Models (DEM) datasets product collect earth land elevation data over 80% coverage with World Geodetic System (WGS84) horizontal datum and Earth Gravitational Models (EGM96) vertical datum with a near-global scale from 60°N to 56°S where WGS is the reference system for GPS developed by U. S Department of Defense while EGM96 is used as the geoid reference of the World Geodetic System (Farr and Kobrick 2000). SRTM DEM data sets are available in 1 and 3 arc sec i.e., 30 m resolution DEM and 90 m resolution DEM dataset product. These DEM data sets products are available in scenes or tiles in website for free download <https://earthexplorer.usgs.gov/>.



**Fig. 1** Geographical location of the study area. The left panel shows the index map of the study area and the right bottom panel show the terrain of the study area using SRTM DEM-30 m

**CARTOSAT -10 and 30 m DEM**

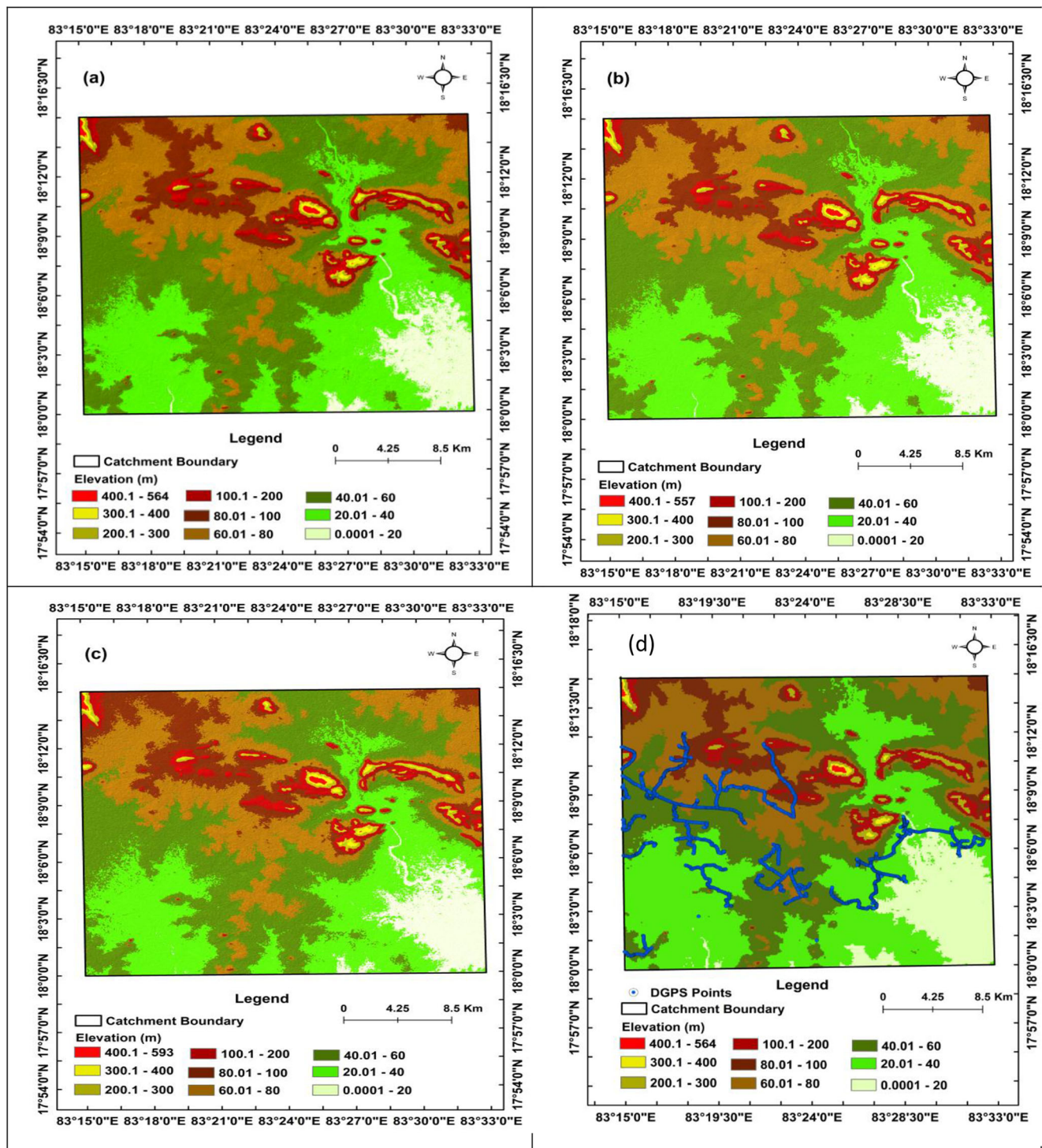
The CARTOSAT -1 spacecraft is an Indian Satellite which is launched in the year 2005 on May 5 by the Indian Space Research Organization (ISRO). CARTOSAT satellite consists of a panchromatic camera i.e., after looking (AFT) and Foreword looking (FORE), which gives along-track of stereo, with a tilt inflight direction of  $\pm 5^\circ$  and  $\pm 26^\circ$ . It covers the minimum and maximum of swath width of  $26 \times 26$  or which is nearly to 30 km and has a breadth/ height ratio of 0.62. CARTOSAT spacecraft gives the stereo images which can be used in wide applications like large scale mapping and terrain modeling etc.

The CARTOSAT DEM datasets products are available in 1 Arc Degree second i.e., 30 M resolution. It can be freely downloaded which is available on Earth Explorer website <https://bhuvan.nrsc.gov.in>. Further, CARTOSAT DEM of higher resolution (10 m) is made available and can be acquired from the National Remote Sensing Centre (NRSC), India. Figure 2 shows the geographical locations of DGPS points used as GCP in this study. For the study area, we have procured CARTOSAT-10 m resolution data. It is to be noted that both (CARTOSAT 10 and 30 m DEMs) datasets were

provided with WGS84 ellipsoid as the datum. However, for comparison with other datasets, it was converted from ellipsoid to spheroid datum. Figure 2d shows the terrain of the study area as obtained from the different DEMs.

**Ground control points**

For calibrating and validating the machine learning models we have used the ground control points obtained from the Differential Global Positioning System (DGPS) survey performed in the study area. The survey was conducted by GEOCON Survey, Visakhapatnam, India as part of their projects related to canal and road alignment. In this survey, they followed a kinematic GNSS approach using a R95 receiver which has a 95% confidence level of accuracy and the horizontal accuracy of the equipment used is up to 0.6 m and a vertical accuracy of 1.7 times the horizontal accuracy of the equipment. For the present study, we had used nearly 4000 Ground Control points. However, in order to develop an effective machine learning model for improvement of existing DEMs, the requirement of GCPs is paramount and these control points should cover at least 40% of the area. Figure 2d shows the location of the GCPs



**Fig. 2** a–c represents the Topography of the study area obtained from CARTOSAT-10 m, CARTOSAT-30 m and SRTM-30 m, respectively and **d** represents the Geographical location of the DGPS points in the

study area. The elevations at the location obtained from the DGPS survey were used for model calibration and for testing the proposed approach

used in the study. These DGPS points can be used as an exact reference elevation points for comparison of Vertical accuracy with available DEMs. Further, the GCPs were used as a reference data set to train and validate our approach.

## Methods

Before, describing the methodology adopted in this study, a brief description of the machine learning tools, ANN and GP are provided.

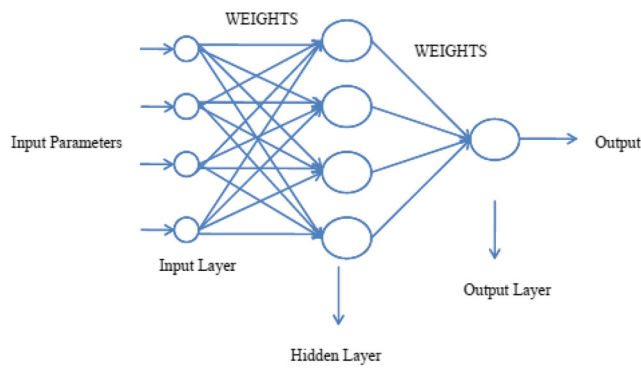


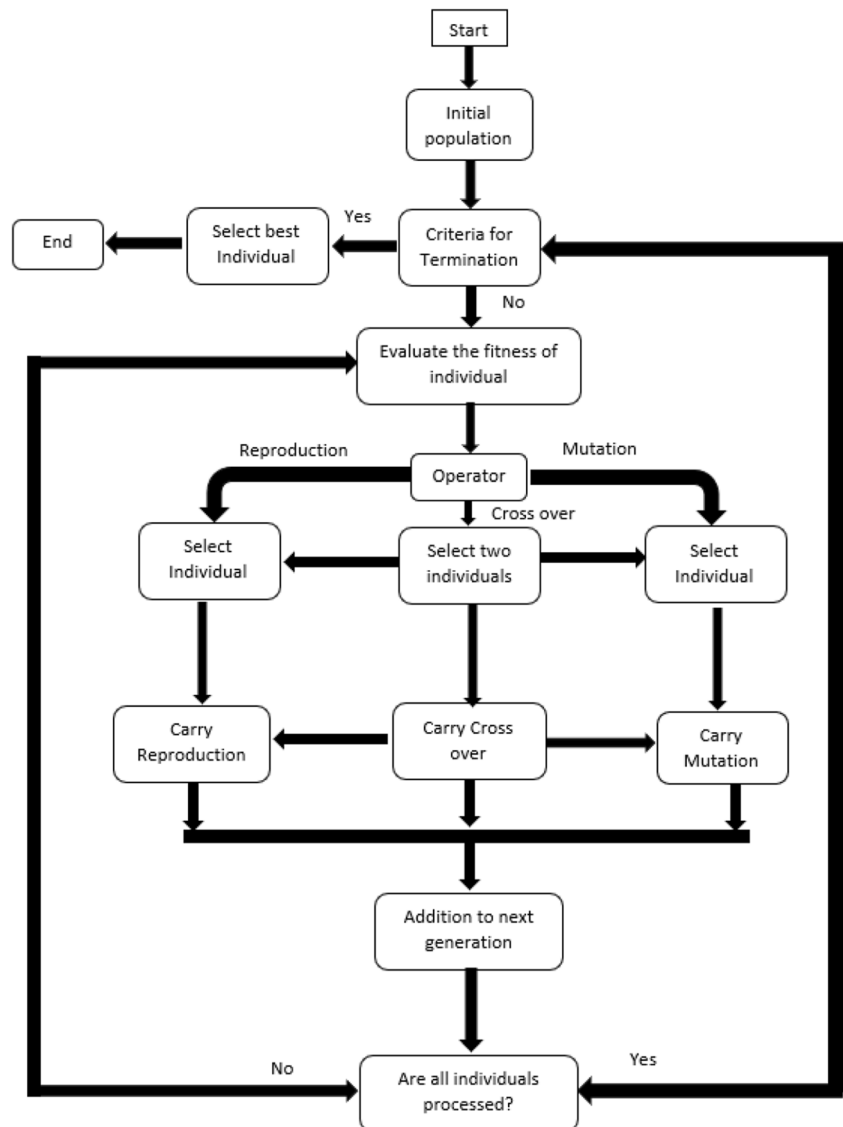
Fig. 3 A typical MLP based ANN model

### Artificial neural networks

Artificial Neural Networks are based on the neural system of a living organism. ANN is an effective method for

understanding the complex nonlinear relationships between inputs and outputs (Alizadeh et al. 2018). ANN’s inherent ability to learn based upon the relationship developed predictors and predictands help in solving complex problems that orthodox models cannot perform. Model functioning and the results from the model are mainly based on the learning algorithm used to develop the network. The learning algorithm determines the relationship between predictors and predictands from the given training data set. During each trial, the neural network model develops a new relationship between the variables and the weights assigned by the network also change for each run of the model until minimum error criteria are satisfied (Maheswaran et al. 2016). In the past, ANN’s have been used in the fields of climatology and hydrology for different kinds of applications. Some of the examples include Kışi (2008), Nourani et al. (2009), Belayneh et al. (2014), Sahay and Srivastava (2014), Okkan and Fistikoglu

Fig. 4 Flow chart of genetic programming



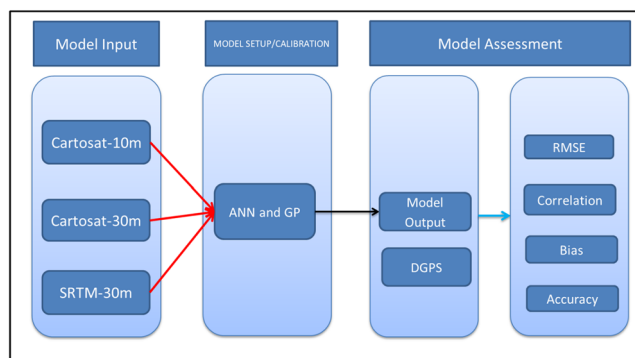


Fig. 5 Schematic of the proposed methodology

(2014), Ahmed et al. (2015), Maheswaran and Khosa (2012), Vu et al. (2016) and Yeditha et al. (2020). For detailed explanation about the readers are referred to (Shanmuganathan 2016). The most widely used neural network is a multi-layer feed-forward network due to its capability to recognize non-linear patterns in a system more effectively than singular models. The architecture of a typical feed-forward multilayer neural network is shown in Fig. 3. Numerous algorithms have been proposed for ANN training and amongst these, the Levenberg–Marquardt (LM) algorithm has found wide acceptance by various studies. de Vos and Rientjes (2009) have shown that the efficiency of the LM algorithm is best in terms of fast convergence and accuracy of results. The LM algorithm has also been adopted in this study. ANNs in this study were trained using supervised training algorithms that sought to minimize an objective function of Mean Squared Error (MSE). The ANN models were developed in MATLAB 8.3.0 (R2014a) using the Neural Networks Toolbox.

**Genetic programming**

Genetic Programming (GP), having roots from the Genetic Algorithm, is an evolutionary algorithm working on the principles of survival of fittest and natural selection. (Sachindra et al. 2018; Sivapragasam et al. 2008). However, it is slightly different from the Genetic Algorithm in the way of utilizing the ‘parse tree’ structure for searching the best solutions. It uses the bottom-up approach and therefore doesn’t involve a priori assumption on the structural relationship between the predictors and predict and rather, GP searches for a suitable relationship may be in the form of i) mathematical expression, ii) logical statements or iii) a set of mathematical functions which are arranged in an unfamiliar pattern (Maheswaran

and Khosa 2011). In general, the GP implementation has two steps: a) creation of parse trees which involves identification of the probable set of basic mathematical functions (such as cos, sin, tan, sum, subtract, exp., multiply, divide, and power), and (b) formation of the terminal set (which includes the predictand and the predictors). The above steps work iteratively to mimic the underlying process. In this study, the terminal set includes the NCEP variables and the local precipitation and the set of functions used were {+, −, exp., /, \*, sqrt, power}. The minimization of the sum of squared error was used as the objective function to evolve the best model structure. We have altered the GP parameters such as no.of generations, initial population, cross over and mutation rate in such a way to get the best results. Discipulus (<https://discipulus.software.informer.com/>) tool is used for developing GP models (Foster 2001) and a typical functioning of Genetic programming can be seen in Fig. 4.

**Proposed approach**

The proposed approach is categorized into three major steps as illustrated in Fig. 5. These are data preprocessing, model setup and result post-processing and model application. The model output is assessed and analyzed for its performance in comparison with the original CARTOSAT DEM in terms of its vertical accuracy.

i Model Input Processing:

Generally, DEM contains voids/gaps (null values) (no elevation value in the cells) (Luedeling et al. 2007) the gaps occur in regions with the water surface, areas covered with low reflecting materials, areas with rough slopes. These voids are required to be removed or corrected. We have corrected the voids using the methods described in (Rawat et al. 2013; Reuter et al. 2007). Further, before the analysis, we have projected all the data set to the same datum (WGS84) and projection system (UTM-44 N). The GCPs points from the DGPS survey were also checked for any missing data and were projected on the same projection system.

ii. Model Setup

In this study for comparison, we have adopted two different models ANN and GP. For both the models, the input data sets are

Table 1 Vertical accuracy of Different DEMs in terms of RMSE

S. No	Statistic	CARTOSAT-10 m	CARTOSAT-30 m	SRTM-30 m
1	Mean elevation (m)	34.08	34.10	34.86
2	Variance of elevation (m)	69.03	68.89	79.87
3	RMSE (m)	5.03	5.89	6.11

**Table 2** Model performance statistics of the ANN and GP Models during calibration and validation

S. No	Model	Calibration			Validation		
		RMSE (m)	Correlation	Bias	RMSE (m)	Correlation	Bias (m)
1	Artificial neural network	2.15	0.98	-0.11	2.19	0.98	-2.49
2	Genetic programming	2.27	0.98	0.45	3.31	0.97	2.27

elevation from CARTOSAT-10 m, CARTOSAT-30 m and SRTM-30 m DEM and the model output was elevation at GCP points. Around 60% of the total GCP points were used for model training, validation was done with 20% and the testing is carried out with the remaining percentage. The testing data is unseen by the model and was used at the application stage to check the applicability of the proposed approach. The model accuracy was analyzed using different performance measures such as RMSE, Correlation Coefficient, and Bias.

iii. Post Processing and Application.

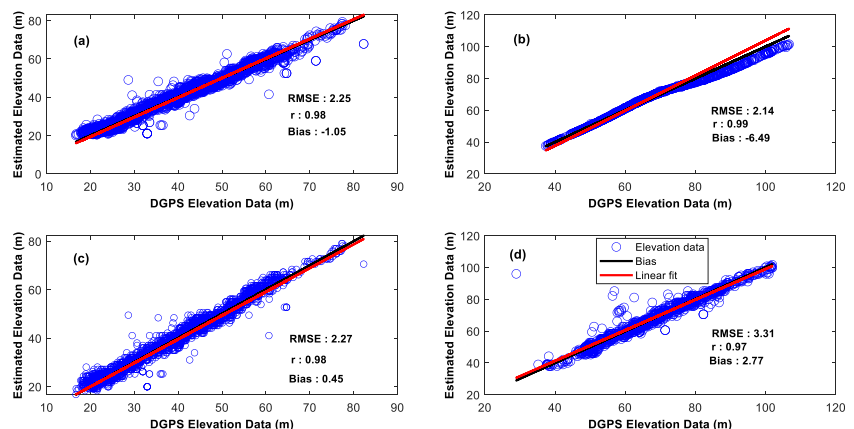
After the models were trained and tested the models were applied to develop the improved DEM using the original DEM datasets. For this purpose, we have resampled data from each of the DEM data sets at 100048 randomly generated points using fishnet. The calibrated model was then used for estimate values. From these elevation values, DEM was generated using different interpolation methods. In this study, we have adopted three commonly used interpolation methods viz. Inverse distance weighting (IDW), Kriging and Spline based interpolation (Ajvazi and Czimer 2019).

From the generated DEM, the elevation accuracy was estimated for the validation dataset and reported for comparison.

The accuracy of the DEMs was evaluated using the following measures: i) RMSE (Root Mean Square Error and ii) Bias.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N \sum (Z_{DGPS}^i - Z_{DEM}^i)^2}{N-1}} \tag{1}$$

**Fig. 6** Scatter plot between elevation values from GCPs and model estimated elevation values from top panel- neural networks during a) calibration and b) validation, bottom panel - genetic programming during c) calibration d) validation



$$Bias (\%) = \frac{\sum_{i=1}^N (Z_{DGPS}^i - Z_{DEM}^i)}{\sum_{i=1}^N (Z_{DGPS}^i)} \times 100 \tag{2}$$

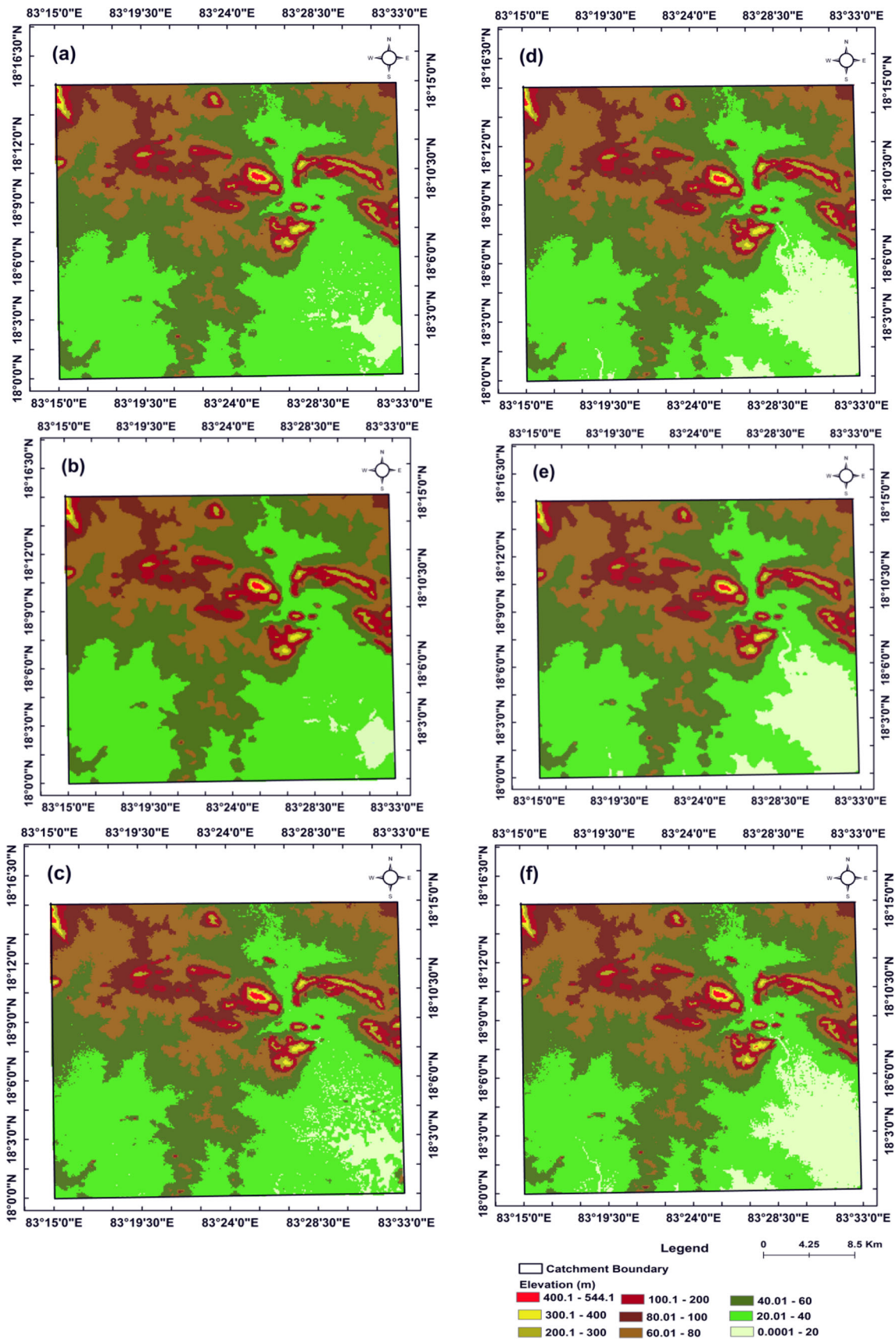
Where:  $Z_{DGPS}^i$  = Elevation obtained using DGPS,  
 $Z_{DEM}^i$  = Elevation obtained using DEM,  
 N is the total no of sampling Points.

RMSE represents the amount of error in the output value of the developed model when compared to the observed value whereas Bias represents the inclination of the results of the model towards underestimation or overestimation when compared to the observed system. Lower the values of RMSE and Bias, the DEM is closer to reality. Positive values of bias indicate DEM are underestimating the elevation concerning the actual values and vice versa.

## Results and discussions

### Comparison of vertical accuracy of the original DEM's

Assuming that the values obtained from the DGPS survey are accurate of all the data sources, we have compared these elevations with the ones obtained from DEMs. Using this difference in elevations, the vertical error analysis was performed for all the DEMs. The RMSE was calculated using 2000 points and the results statistics are tabulated in Table 1. The analysis of the results in terms of RMSE shows that the CARTOSAT 10 m DEM show less deviation from the





◀ **Fig. 7** Left colun: improved DEM obtained from neural network models using a) IDW b) KRIGING c) SPLINE interpolation methods and right column shows DEM obtained from GP models using d) IDW e) KRIGING f) SPLINE interpolation methods

DGPS data whereas the SRTM DEMs show a higher level of error. The RMSE of the CARTOSAT 10 m data is around 5.0 m which is considerably less when compared to the SRTM DEMs.

**Calibration of validation of the machine learning models**

For the GP models, we have chosen the population size to be 500, mutation and cross over rate was kept at high value following Sivapragasam et al. (2008) and Selle and Muttill (2011). We used mean square error as the model fitness function. The mathematical function set was chosen in such a way that a meaningful relationship can be evolved between the predictand and predictors. In this study, we have developed separate GP models for each station and season.

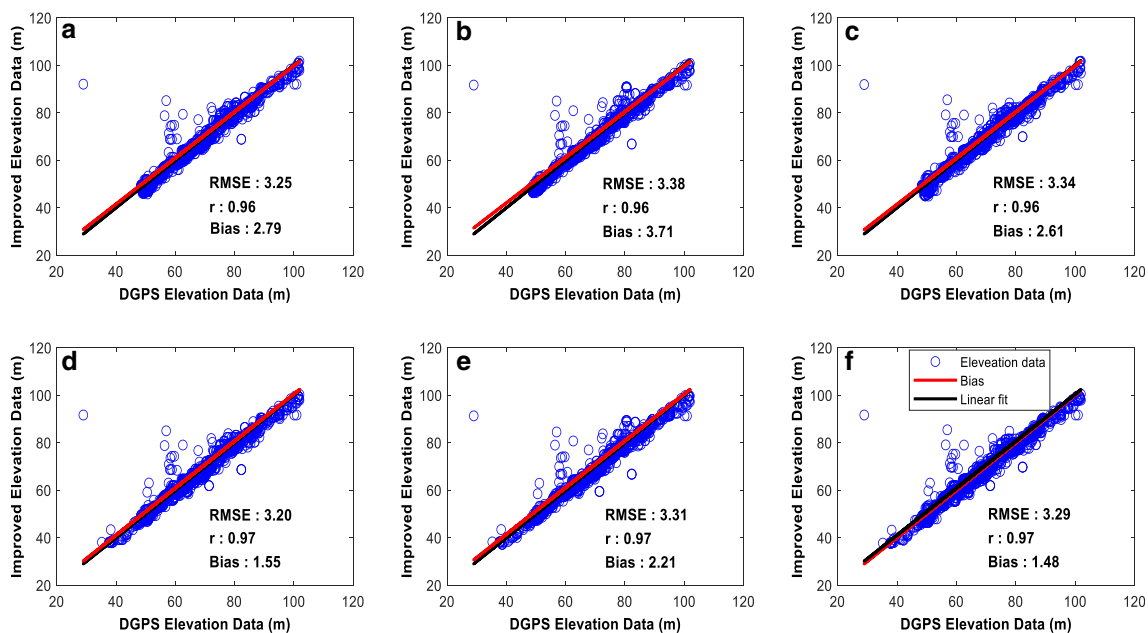
With reference to the ANN-based models, Levenberg–Marquardt (LM) algorithm was used to train the ANN models because of its reliable, accurate, fast results and as well as its processing flexibility (Reuter et al. 2007; Ajvazi and Czimber 2019; Selle and Muttill 2011; Adamowski and Karapataki 2010). The optimal hidden neurons for each of the model was found using trial and error procedure and were varied from 10 to 20 and the best value was chosen based the RMSE.

The calibration and validation result obtained is shown in Table 2. RMSE and correlation between the observed elevation (from GCP) and the modeled elevation values show that both models perform satisfactorily. Figure 6 shows the scatter plot between the observed elevation and the model estimate for both training and validation.

**Application of model for DEM generation**

For the application of the calibrated models in DEM generation, we have extracted elevations from each of the original DEMs at 100048 points, randomly generated using the fishnet tool (du Toit et al. 2020; Heumann et al. 2020) in ArcGIS. This creates a feature class containing a net of rectangular cells. Then using the elevations at the fishnet points, the ANN and GP was run to generate corrected elevations.

From the simulated elevation values at these points, DEM was generated using different interpolation methods. Figure 7 shows the DEM generated for the study area using the proposed approach after interpolation. To verify the accuracy of the generated DEM, we have used the test data GCP points (which were unused for model calibration and validation). Figure 8 shows the elevations scatter plot for the 1000 testing points. Table 3 shows the statistical results obtained from the different combinations of models and interpolation methods. From the results, the ANN- IDW method performs better in terms of RMSE. The RMSE of the resulting DEM is significantly improved from 5.03 m of the original CARTOSAT to 3.25 m (i.e., 35% improvement), and performing far better



**Fig. 8** Scatter plot between elevation from DGPS 1000 and elevation from improved DEM for the 1000 validation points using various methods top row represents the results from neural networks with a)

IDW, b) KRIGING and c) SPLINE. Bottom row shows the results from genetic programming d) IDW, e) KRIGING and f) SPLINE

**Table 3** Statistical results obtained from the different combinations of models and interpolation methods

S. No	Model	Interpolation method	RMSE (m)	Bias (m)	Correlation
1	Artificial Neural Network	IDW	3.25	2.79	0.96
		Kriging	3.38	3.71	0.96
		Spline	3.34	2.61	0.96
2	Genetic Programming	IDW	3.20	1.55	0.97
		Kriging	3.31	2.21	0.97
		Spline	3.29	1.48	0.97

than SRTM 30 m. Similar results were obtained from the GP based DEMs. The RMSE for the GP model results were found to be varying from 3.2–3.29 m and the bias between 1.48–2.21 m. It can very clearly have observed that in comparison with the original DEM, there is a considerable improvement in the vertical accuracy in all the models. This indicates the efficacy of the proposed approach.

## Conclusions

This paper proposed a novel approach for improving the accuracy of CARTOSAT DEM with the use of machine learning methods, available GCP points and other publicly available DEM. The proposed method is applicable in regions where there the spatial data is sparse due to cost, facility and data sharing strategy. The proposed method makes use of reference elevation data from the area which is data-rich to help in developing DEM of better accuracy in data-sparse regions having similar terrain characteristics. The proposed methodology is applied to an area in the Southeastern part of India. Two different machine learning approaches –combined with three interpolation techniques results in six different models. These models were trained, tested and validated using three different data sets. The performance of the proposed approach was an encouraging and significant improvement in RMSE of the order of 35% when compared to the original CARTOSAT DEM. Overall, the proposed approach is shown to be able to improve the CARTOSAT DEM significantly in the selected study area in terms of vertical accuracy and bias. It is important to note that this methodology requires DGPS for areas where improvement is required. However, these can be replaced with GLAS/ICES at data sets for training the model or even high-resolution data can be used if available.

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