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ANN-Based DEM Fusion and DEM Improvement Frameworks in Regions of Assam and Meghalaya using Remote Sensing Datasets

Priti Girohi and Ashutosh Bhardwaj

ABSTRACT

The Digital Elevation Models (DEMs) are a key and primary input to a large number of modelling processes such as disaster risk monitoring, flood modelling, hydrology, geology, geomorphology, climatology, and environmental study applications. The DEM serves as an important source of topographic information representing the continuous surface of the earth in 3 dimensions with x, y and z coordinates of any point in a grided raster form or a vector TIN form. This study is based on developing a new method using the universal approximation capability of neural networks for the fusion and improvement of L-band and X-band SAR (Synthetic Aperture Radar) DEMs in the complex terrain of Assam and Meghalaya states of the Indian geographic region using the DEM fusion technique. The high-spatial-resolution ALOS PALSAR RTC HR 12.5 m DEM products are used in a fusion framework designed with neural network models. The network adaptively learns the terrain information to produce fused DEM products. The neural network models generate the relationship between the input elevation information from ALOS PALSAR DEMs and precise reference elevation from ICESat-2 spaceborne altimetry as target data. The training and testing data samples are prepared and filtered by checking the correct range of elevation from the toposheets of this region. Different models are used to separately train for the relatively plain valley portion of the Assam region and mountainous portions of the highland Shillong plateau. The obtained fused DEMs from the developed neural net structure are assessed for their quality and accuracy by estimating the RMSE parameter. The fused DEM attains an RMSE value of 7 meters for the complete region which is a significant improvement over the input DEM RMSE of approximately 11 meters. The plain area points and mountainous region points are assessed separately to analyze the predictions from neural nets in the two types of terrains observed in this study site. Moreover, TanDEM-X 90 m DEM is improved using the neural network modeling in the geometric distortions affected areas, which shows an improvement of around 33% overall at the study site. The assessment of plain and mountainous region points for near-ground points shows an improvement of 47% and 55% respectively. The fusion framework designed using the neural network models is an effective and efficient method for obtaining fused DEMs as well as for the improvement of the existing DEMs for complex terrain.

Keywords: Artificial Neural Network (ANN), DEM Fusion, ICESat-2 Altimetry, Interferometry SAR.

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I. INTRODUCTION

Digital Elevation Models (DEMs) are an important input that influences a large number of applications using topographic information. These applications include hydrological modelling, geomorphological, agricultural, soil sciences, glaciological, climate studies, forestry, urban, infrastructure planning, disaster risk monitoring and management and environment-related research works. A DEM is a 3D representation of the continuous earth's surface depicting its elevation profile or height variations. It possesses the latitude, longitude and elevation information in a given coordinate system for representation of the earth's surface in a gridded raster format or a vector Triangulated Irregular Network (TIN) form [1]. The synonymous terms used very often to denote an elevation model are DTM (Digital Terrain Model) and DSM (Digital Surface Model). DEM is the most widely accepted and used term in regards to an elevation model. The DSM represents the top-reflective surface of the earth and its objects like buildings, trees, or vegetation while the DTM is termed as a bare earth elevation model excluding any building or tree canopy height. [2]. Several traditional and advancing, remote sensing technologies are employed for the generation of DEM in varying terrains with the availability of different types of sensor data. The available sensors provide elevation information in different ways such as the stereo-images from optical sensors, SAR (Synthetic Aperture Radar) image pairs from the space-based satellites for SAR Interferometry (InSAR or IfSAR) and Radargrammetry, discrete point clouds from the LiDAR (Light Detection and Ranging) devices which can be placed on spaceborne or terrestrial platforms, and a more traditional method is to digitize the contour maps. Thus based on the type of available data various DEM generation techniques are Photogrammetry [3], Radargrammetry [4], Photoclinometry [5], Radarclinometry [6], Altimetry or LiDAR [7], [8], and SAR Interferometry (InSAR) [9], [10].

Several global DEMs are available in open access at a high spatial resolution for the research community such as the SRTM (Shuttle Radar Topography Mission), TanDEM-X, ALOS PALSAR (Advanced Land Observing Satellite Phased Array L-band type SAR) DEM, ASTER GDEM (Advanced Spaceborne Thermal Emission and Reflection Radiometer Global DEM), NASADEM, COPDEM (Copernicus DEM), and so on providing elevation information around the globe. Any improvement in the existing or generated DEMs will in turn produce quality-based outputs from the specific applications where DEMs are considered as inputs. This will add up to the potential value resulting in the enhancement of several modelling and quantifying processes directly improving the outputs or products, specifically for an engineering project. Further, combining the data from multiple sources or sensors, and multi-temporal data in an intelligent manner produces better and improved results using the capabilities of the Neural Nets. This technique of combining the various datasets is known as data fusion [11], [12]. DEM assimilation or fusion methods have been studied by various researchers and research groups using different methods namely, feature-based fusion [13], Kalman Optimal Interpolation [13], Sparse Representation [14], and artificial neural network (ANN) approaches [15], [16]. Similarly, the fusion of DEMs has been mainly focused on Optical-Optical datasets [13], Optical-InSAR [15], [17]–[19], InSAR- InSAR datasets [20]. Other organizations, space agencies, and universities working in this direction have come out with improved DEMs using a fusion approach such as the NASADEM which is an improvisation of DEM obtained by combining data from SRTM, ASTER GDEM, ALOS PRISM, NED and Alaska's DEM available at 30 m resolution. It also relies on ICESat (Ice, Cloud and Land Elevation Satellite) GLAS LiDAR data for attaining an improved geolocation accuracy [21]–[23]. The EarthEnv- 90 m DEM is obtained by fusion of ASTER GDEM 2 and SRTM 90 m DEM under NASA's ErathEnv project [24], [25], and MERIT (Multi-Error Removed Improved Terrain) DEMs which are available in 90 m resolution is obtained by fusion of SRTM (version 2.1) and AW3D-30 m (version 1) along with some other datasets to remove the error from the existing DEMs mainly focusing in hydrological modelling [26]–[29].

A. *Geometric Distortions in SAR images*

One of the major concerns in the generation of DEMs is the terrain or topographic effects which produce geometric distortions like foreshortening, layover and shadows in the SAR images due to its side-looking geometry. These are mainly dependent on the radar's transmitting frequency, the shape of the antenna pattern and the viewing geometry of the sensor. The geometric distortions occur in SAR images where the range to each target changes in accordance with the target ground location and its height, due to the surface topography [30], [31]. In the side-looking geometry system, the upward slopes oriented towards the sensor appear narrower than the alike downward slopes. The foreshortening appears in the images when the slopes facing the sensor appear distorted and compression or thinning of slopes takes place on the face oriented towards the radar while an elongation on the other side that is not illuminated. These foreslopes appear shortened in the radar image which makes the feature as it is leaning toward the sensor as they are steeper. If the depression angles increase, the SAR geometry makes the slope appear progressively decreasing, thus increasing the severity of foreshortening. The amount of this effect varies according to the incidence angle and the steepness of the slope. Layover is the extreme version of foreshortening. The top or peak of a feature would appear nearer to the nadir than its base. The effect is such that in the radar image slope appears as inverted and leaning or laid over. Layover mainly occurs when the look angle is less than the angle of slope. These geometric distortions are prominent in the mountainous terrain and with small incidence angles, hence the slope is the crucial factor here. Another effect seen in the hilly and mountainous terrain is that of shadow. It's the region in the radar image where the sensor receives no echo from the target. This area either appears black or defined sharply lacking any information. The shadow is the silence region where either that region is not illuminated or echo is not received due to any obstacle while imaging the earth's surface. It is important to consider and overcome these distortions while using SAR-based DEMs. Further, the existing global DEMs can be improved through fusion techniques for the complex undulating terrains where slope effects and geometric distortions are highly prominent to obtain better quality DEM.

A precise reference data which can substitute the requirement of ground truth data is provided by the ICESat-2 (Ice, Cloud and Land Vegetation Satellite) spaceborne altimetry mission from NASA launched in September, 2018. The ICESat-2 mission provides global coverage with a large number of laser footprints serving as reference elevations for carrying out such studies. ICESat-2 provides various elevation products specific to applications like geolocated photon data (ATL03), Land-ice height (ATL06), Sea-ice height (ATL07), Land-vegetation height (ATL08) and so on [32]. The vertical and horizontal accuracy of ICESat-2 products is assessed and used as a reference elevation in several research works [33]. The accuracy of ICESat-2 in providing ground elevation for the Alaska region is validated using airborne LiDAR data along with other factors such as slope, vegetation cover and vegetation heights [34]. The accuracy of the ICESat-2 ATL06 product has also been tested successfully in the mountainous region using around 208 footprints with Continuously Operating Reference System (CORS) and UAV datasets [35]. The global coverage of ICESat-2 data is widely used in DEM accuracy assessment such as for open access InSAR DEMs in parts of the Himalayas comparing accuracies of TanDEM-X 90 m and ALOS PALSAR RTC HR DEMs [36]. Similarly, SRTM 90 m DEM is assessed with the ICESat-2 altimetry data in regions of Australia for bare ground as well as areas with tree cover and vegetation heights, concluding in improved accuracy in plain areas comparable to SRTM DEM and showing positive differences in vegetation areas for ATL08 product [37]. The open-access DEMs like TanDEM-X and CartoDEM are assessed for ICESat-2 data and it is also used for retrieval of building heights in urban and rural areas [38], [39].

The main objective of this research study is to develop a DEM fusion and improvement framework using the neural network models for complex terrain of the North-East region of India in the states of Assam and Meghalaya. The study utilizes the ALOS PALSAR Radiometrically Terrain Corrected (RTC) high-resolution (HR) 12.5 m DEM and TanDEM-X 90 m DEM in the ANN-based fusion framework for implementing the DEM fusion and their improvement. The evolvement of machine learning and neural network modelling has provided a whole new perspective in finding solutions for remote sensing and signal processing problems. The adaptive learning and universal approximation of the neural network models provide scope for developing methods and tools for DEM fusion to improve the quality of DEMs. Further, the use of the precise elevation information from ICESat-2 can be explored in the development of ANN-based fusion approaches specifically for Indian study sites.

II. Literature Review

An Artificial Neural Network (ANN) or simply Neural Network (NN) belongs to the subset class of Machine Learning. The fundamental unit of a NN model is a neuron that is analogous to the biological neurons and it acts in the same way as a human brain works. The simplest structure of a NN model contains several layers which are interconnected. It possesses the special characteristics of adaptative learning and universal approximation. This makes these models highly effective to be used as a tool for solving several practical problems in domains like remote sensing and signal processing [40]. The first introduction of the neural network came forward from the work of McCulloch and Pitts in 1943, where they presented a single neuron that has two main parts, a net function (u) and an activation function (a). The net function is the summation of the weighted average of all the inputs and biases. The activation functions are mathematical equations (linear or non-linear) that transform the inputs to desired outputs (1).

$$u = \sum_{j=1}^{N} w_j y_j + \theta; \; a = f(u) \qquad (1)$$

Where u denotes the net function of the neuron giving a summation of inputs yj multiplied by weights wj and θ is the threshold or bias used in the model and a is the activation function.

The neural networks are a non-linear and non-parametric computational model that can handle the complex relationship between variables. The structure of a neural network consists of the parallel combination of the input layer, hidden layer(s) and an output layer. Each layer has a neuron unit that works parallelly to convert the input to the desired output. The ANN operates by receiving input information from the outside world through the input layer, which is passed to the next connected layer called the hidden layer. The hidden layer uses a transfer or activation function for transforming the input into a meaningful output. The input data contains values of attributes/features of different samples that belong to different classes. The edges of each connection are assigned with random weights initialized arbitrarily based on the importance of the inputs having an influence on the outputs. The activation functions are the mathematical equations which are differentiable in a definite range that computes the sum of the product of weights and inputs with biases. The activation function checks whether a neuron should be activated or not if the value of a neuron crosses the threshold. The most commonly used activation functions are Sigmoid (logsig, tansig), Hyperbolic tangent (tanh), Linear, Rectified Linear unit (ReLU), Softmax and so on [40], [41]. The term Forward Propagation explains the phenomena of data traversing through the network from input to output layer via hidden layers. The network finally produces an error between the reference or target output and the predicted output.

The backpropagation algorithm was first proposed in the Widrow-Hoff gradient descent procedure during the 1960s. The behaviour of a single neuron was studied and it was found that the learning of a neural network is useful in reducing the error to the greatest extent possible. The backpropagation defines the way in which the gradient is computed for the non-linear networks. Several backpropagation algorithms are developed and used nowadays, the standard one being the gradient descent algorithm. The gradient is referred to as the direction of the steepest descent for the learning algorithm to fetch the global minima from several local minima [42]. During backpropagation, the gradient of error is calculated and weights are updated. The gradient of error is an indication of the change in error in relation to the change in weights.

$$w_{ij}^{L}(t+1) = w_{ij}^{L}(t) + \eta . \sum_{k=1}^{K} \delta_i^{L}(k) z_j^{L-1}(k) + \mu\left[w_{ij}^{L}(t) - w_{ij}^{L}(t-1)\right] + \varepsilon_{ij}^{L}(t) \qquad (2)$$

Here, the updated weight $w_{ij}^{L}(t+1)$ is given by the summation of weight at instant t $w_{ij}^{L}(t)$ (first term of above equation), the gradient of the mean square error with respect to weight w_{ij}^{L} (second term), momentum (third term) and the delta error (fourth term) on the right side of equation 2. The relation between momentum and error gradient is such that, momentum is gained when the error gradient vector indicates in the same direction for each successive epoch. The learning rate (η) and momentum (μ) lie in the range of 0 to 1. The learning rate is generally selected between 0 to 0.3 and kept smaller. The momentum values are selected between 0.6 to 0.9 as suitable to run the backpropagation algorithm.

A Feed-Forward Multilayer Neural Network finds applications in solving classification, regression, pattern recognition and prediction problems. The best-fit model is designed by applying a heuristic approach to exactly find the number of hidden layers, neurons of each layer, type of transfer function, type of neural network, type of backpropagation algorithms, selection of optimizer and other model parameters (such as batch size, epochs. learning rate and momentum), that will be suitable for a particular application [43], [44]. The MATLAB Neural Network Toolbox (nntool) provides a platform for developing and implementing the neural network-based fusion approach in this research study. This commercial software has in-built applications for designing several types of neural network models such as the classification learner, deep network designer, neural network fitting, regression learner and pattern recognition networks. The training and target data samples are preprocessed and applied in the form of input and target matrix sequentially or concurrently. These input and target vectors are used to train the designed model until input vectors are associated with output vectors. The transfer functions can be chosen from the available linear (purelin) and sigmoid (logsig and tansig) activation functions. It is equipped with more robust and faster converging backpropagation algorithms other than the standard gradient descent. Other available variations of basic algorithms having variable learning rates are batch gradient descent without/with momentum (TRAINGD, TRAINGDM), resilient backpropagation (TRAINRP) and algorithms using numerical optimization like conjugate gradient (TRAINCGF, TRAINCGB, TRAINSCG), Quasi-Newton (TRAINBGF) and Levenberg Marquardt (TRAINLM). Among these, the fastest converging is the Levenberg-Marquardt algorithm and it works best on function approximation problems. The TRAINLM algorithm is highly useful in training typical feedforward networks which has the performance function in the form of the sum of squares of the input values. It can approach the second-order training speed without having to compute the Hessian matrix [45].

There has been extensive use of machine learning and neural network models in the remote sensing domain for solving several practical problems like classification, feature extraction, object detection, regression, and making predictive modelling. Several researchers have used ANN models in the improvement of digital elevation models and performed the fusion of DEMs. A fusion framework is designed using ANN as a predictive weight mapping model for weighted averaging to perform the fusion of TanDEM-X and Cartosat-1 elevation datasets in different sub-classes of the urban area of Munich, Germany [15]. The SRTM DEM is improved in another study by combining it with Sentinel-2 multispectral data in an ANN model specifically for flood modelling applications in dense urban cities of Nice (France) and Singapore resulting in an improved SRTM with a 38% reduction in RMSE [16]. Along with these study sites, the open-access SRTM DEM is improved using an ANN-based approach for the coastal areas of the US and Australia by employing a multilayer perceptron model. It has used the LiDAR data as ground truth to train the model and in addition to vegetation cover indices, variables like neighboring elevation values, slope values, population density and height errors between the local SRTM and ICESat data were used. The obtained RMSE from this study were reduced by one-half at both locations [46].

An alternative to the interpolation technique is developed using MATLAB-based multilayer perceptron models to estimate the unknown heights in a DTM [47]. Developing a cost-effective method for deriving a good quality DEM in the dense urban city of Nice and Singapore a multi-channel CNN (Convolutional Neural Network) model was used. Here, the SRTM DEM quality is improved by combining the information from Sentinel-2 and Google satellite images as input data and high-precision DEM as target data in a U-Net structure of the CNN model designed in the Deep Learning toolbox of MATLAB. The improvement of SRTM DEM has attained an RMSE of 4.8 m reduced to almost half of the RMSE of the original DEM [48]. A recent study has shown the implementation of an ANN-based DEM fusion approach in plain and hilly terrains of India including study sites from Ghaziabad and Dehradun cities. This study is based on firstly, the generation of multiple InSAR DEMs for the two regions and further, improving the DEM by fusion using DEM derivatives as well as land use land cover classes of the regions as input data and ICESat-2 altimetry as a reference or target data. Models were designed using a programming-based ANN sequential model in Keras and MATLAB NN-toolbox. The RMSE is estimated using TanDEM- X 90 m DEM is about 3.46 m in plain terrain region and 10.95 m in hilly undulating terrain region in contrast to higher RMSE values for input DEMs [49].

Although the literature survey shows extensive use of machine learning and ANN models for developing fusion frameworks, no such work has been implemented on the Indian study sites. This research work is an attempt to study the diverse terrain of the Indian geographic region and hence, produce high-quality DEMs that can be applied as a key input to various remote sensing applications. The focus of this research work is to develop neural network-based fusion frameworks for SAR-based DEM fusion, and DEM improvement in the complex terrains of the North-eastern Himalayan region of India. The wide number of applications for high-quality DEMs emphasizes the requirement of methods/models that can produce high-quality DEM fusion techniques.

III. Study Area and Dataset Used

A. A. Study Area

The study area from the North-Eastern Himalayan Region of India is selected which covers several districts of Assam and Meghalaya states (Fig.1). The geographic extent of this region covers from 25.40’ to 26.85’ N Latitude and 91.61’ and 93.07’ E Longitude. The study site has Darrang, Kamrup, Karbi, Anglong, Marigaon, Nagaon, Nalbari, North Cachar Hills, Guwahati, Tezpur, Lakhimpur and Sonitpur districts from the state of Assam while East Khasi Hills, Jaintia Hills, Ri-Bhoi, West-Khasi hills are included from the Meghalaya state.

The region of Assam includes the Northern Himalayas, Brahmaputra plain and plateau in the southern parts. The geomorphology of this area can be described as having large plains and dissected hills across the region. The Brahmaputra River which is older than the Himalayas is the antecedent river that flows through this state. Crossing higher altitudes and eroding at a greater pace, the river forms steep gorges and creates floodplains in the region of Brahmaputra valley. Assam has a temperate and tropical rainforest-type climate and observes heavy rainfall with humidity. The average height of the hills in this area ranges from 300 to about 2000 m. This region is highly prone to natural disasters due to high rainfall, deforestation and other factors leading to annual floods. The region has also observed several earthquakes and mild tremors, which are common.

On the other hand, the Meghalaya region has the geologically important Shillong plateau. Several faults such as the Dauki in the south, Kopili to the east, Brahmaputra fault in the north and Dubri in the west bounds this region. The river Brahmaputra separates this site from the Indo-Myanmar Mobile belt and the eastern Himalayas. The geology of this region contains the oldest rocks from the Precambrian gneissic complex to the new alluvium formations. This region observes active tectonic activities caused by the collision of the Indian plate and Tibetian landmass in the north and the east. There is a subduction process experienced in the Shan Tenasserim block and the Indian plate. This site is also prone to erosions as well as continuous upliftment. Geologically, this region comprises different types of rocks like the Khasi greenstone, Granite pluton in lower Gondwana, Sylhet trap in the Therriaghat river, and so on. The range of elevations across the whole study area varies from the lowest at 1 m to the highest peaks at 2000 m (approx.).

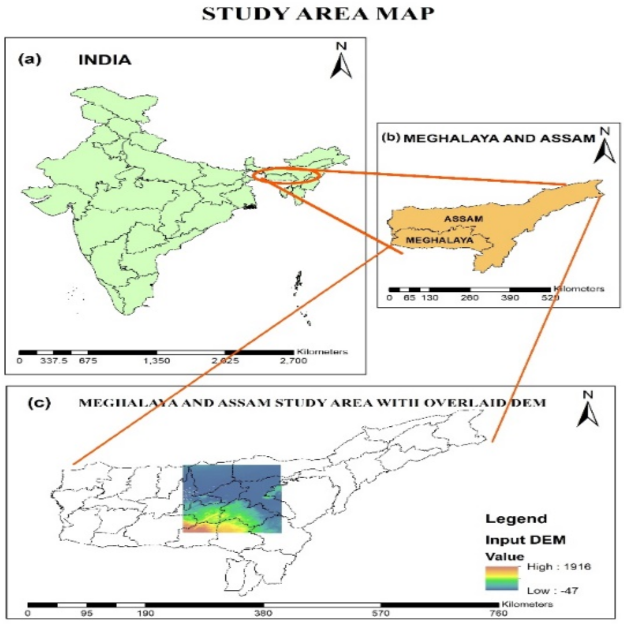


Fig. 1. Study area map: (a). India; (b). Meghalaya and Assam state; and (c). The extent of the study area in the Meghalaya and Assam region with overlaid DEM. The legend depicts the elevation value of DEM.

TABLE I: DATASET USED AND THEIR SPECIFICATIONS

Product used	Purpose	Specifications	Product IDs of DEM tiles with date
1. ALOS PALSAR RTC HR 12.5 m DEM	Input DEMs to be fused	**Sensor**- ALOS (Advanced Land Observing Satellite) PALSAR (Phased Array type L band SAR) **Wavelength**- L band (24.6 cm) **Spatial Resolution**- 12.5 m HR (High-Resolution) RTC (Radiometrically Terrain Corrected) Product **Polarization**- Full Beam Single (FBS); HH polarization **Beam Mode**- Ascending	**Input DEM 1:** ALPSRP055520520 (08/02/2007) ALPSRP055520510 (08/02/2007) ALPSRP055520500 (08/02/2007) ALPSRP058000520 (25/02/2007) ALPSRP058000510 (25/02/2007) ALPSRP058000500 (25/02/2007) ALPSRP053770520 (27/01/2007) ALPSRP080610510 (30/07/2007) ALPSRP080610500 (30/07/2007) **Input DEM 2:** ALPSRP115910520 (28/03/2008) ALPSRP115910510 (28/03/2008) ALPSRP115910500 (28/03/3008) ALPSRP104970520 (13/01/2008) ALPSRP104970510 (13/01/2008) ALPSRP104970500 (13/01/2008) ALPSRP107450520 (30/01/2008) ALPSRP107450510 (30/01/2008) ALPSRP114160500 (16/03/2008)
2. TanDEM-X 90 m DEM	DEM improvement in geometric distortion areas, Accuracy assessment of fused output DEM	**Sensor**- TanDEM-X active microwave sensor **Wavelength**- X-band (0.35 cm) **Spatial Resolution**- 90 m Absolute Vertical and Horizontal accuracy- 10 m (approx.) **Projection system and datum**- World Geographic System; WGS 84	**TanDEM-X 90 m DEM product used for Meghalaya and Assam region:** TDM1_DEM_30_N25E091 TDM1_DEM_30_N25E092 TDM1_DEM_30_N25E093 TDM1_DEM_30_N26E091 TDM1_DEM_30_N26E092 TDM1_DEM_30_N26E093
3. ICESat-2 altimetry data	Reference data in neural network training; Accuracy assessment of Fused output DEMs	**Sensor/Detector**- Spaceborne altimetry/Laser photon counting **Wavelength**- 532 nm **Orbit inclination and coverage**- 92˚; covering up to 88˚ N to -88˚ S latitude Tracks available- 6 tracks from one laser beam in three pairs; each pair having a strong and weak laser beams **Footprint diameter**- 17 m **Along-track & Across-track spacing**- 0.7 m and 3 km (between the 3 pairs) respectively; 90 m (within each pair) Product used- ATL08 Land and Vegetation heights	**Track IDs used:** 553 (strong and weak), 821 (strong and weak), 1384 (strong and weak)
4. SOI Toposheets	Check for the elevation ranges of Fused output DEMs	**Type**- Open Series Maps **Scale**- 1:50000	**Toposheet numbers:** 78N/9,10,11,12,13,14,15,16; 78O/9,10,11,13,14,15; 83B/1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,8 3C/1,2,3,5,6,7,9,10,11,13,14,15

This study area is selected due to its geological and geomorphological importance. It is useful to research and obtain an improved elevation model for such complex terrains including large river flood plains as well as highland plateaus. The obtained improved DEMs are crucial in various disaster risk monitoring, management, and infrastructure planning applications. Moreover, the use of precise ICESat-2 photon data in the fusion and improvement of open access SAR-based DEMs is studied. DEM improvement is useful in the areas affected by foreshortening, layover, and shadow distortions which can be observed in complex terrain like the North-East Himalayan region of India.

A. Dataset

The high-resolution (HR) L-band SAR DEMs from the ALOS PALSAR RTC 12.5 m DEM products are processed in the neural network fusion framework to obtain the fused output DEMs with improved accuracy. The global open-access TanDEM-X 90 m DEM [50] is processed in the neural network framework for the improvement of existing DEM in the areas affected by geometric distortions. The ICESat-2 spaceborne altimetry photon data is used as target elevation for providing accurate training of the neural network models. This is also used in point-based accuracy assessment of the fused DEMs produced from the neural networks in plain and mountainous portions of the study area separately as well as for the whole region. The precise ICESat-2 data is used in assessing the percentage improvement of TanDEM-X 90 m DEM over the areas affected by foreshortening, layover and shadows. The toposheets from the Open Map Series product from the Survey of India (SOI) are referred to check the correct range of elevations in the fused outputs.

The details of the datasets are provided in Table I along with the sensor and data specifications. Several tiles covering the study area from ALOS PALSAR RTC HR 12.5 m DEM products are used, three laser tracks of ICESat-2 ATL08 Land and Vegetation product are used as a reference and precise TanDEM-X 90 m DEM is improved over the geometric distortion affected areas.

The map in Fig. 2 depicts the input ALOS PALSAR RTC 12.5 m HR DEMs (ALOS DEM 1 and ALOS DEM 2) to be fused using the ANN-based approach. Two input DEMs are processed here, and the ICESat-2 ATL08 footprints distributed over the study area provide the precise reference elevation values to carry out the study. The elevation values in this region range from a low of -47 m to as high as 1918 m. This study site comprises a plain portion around the Assam valley region which is also referred to as the Brahmaputra floodplain having lower elevation values (depicted in blue colour in Fig. 2 and Fig. 3). On the other side, it also contains the Meghalaya highland plateau region, which is a tectonically active area and has various hills with higher values of elevation (lower left portion depicted in red to green colours in Fig. 2 and Fig. 3).

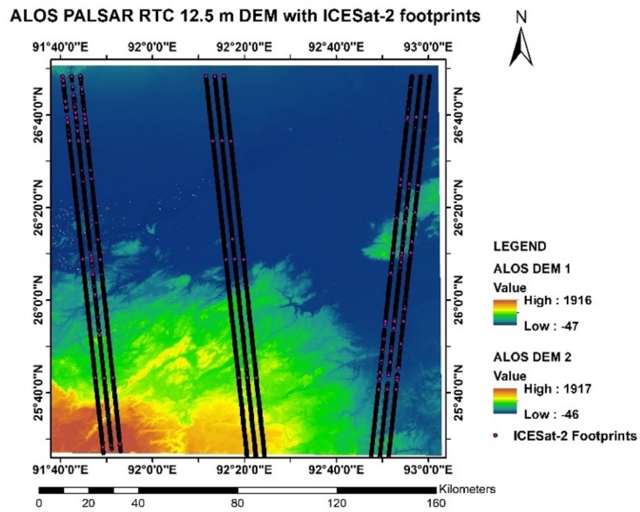


Fig. 2. ALOS PALSAR RTC 12.5 m DEMs* with ICESat-2 footprints (* value in the legend refers to the elevation values for the DEMs).

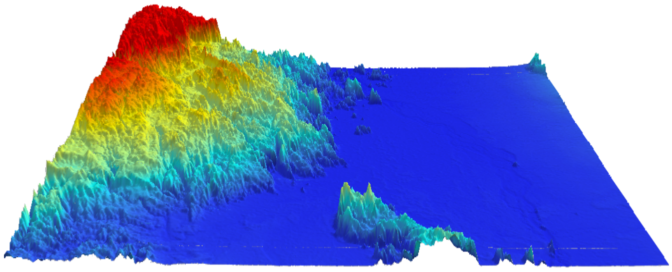


Fig. 3. ALOS PALSAR DEM 3D image (rotated) for the depiction of complex terrain in the Meghalaya and Assam region.

IV. METHODOLOGY

The steps followed for developing the DEM fusion framework and improving the existing DEM are shown in fig. 4. Two independent processes are performed here first for the fusion of ALOS PALSAR RTC HR 12.5 m DEMs in the Assam and Meghalaya region, and second for the improvement of TanDEM-X 90 m DEM in areas affected by foreshortening, layover, and shadow regions.

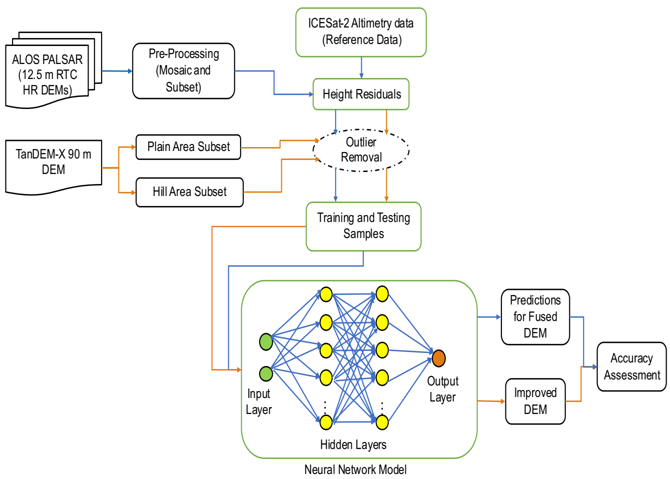


Fig. 4. Flowchart of ANN-based DEM fusion and improvement framework.

The neural network fusion framework is developed for the fusion of SAR-based DEMs from ALOS PALSAR RTC 12.5 m products. Several tiles of this product are accessed and downloaded from the ASF (Alaska Satellite Facility) vertex data search tool covering the study area. These products are mosaicked and a subset is taken for producing the input DEMs. The training samples for the NN are prepared by extracting the elevation values from the input DEMs at every ICESat-2 footprint location and estimating the height residuals by subtracting the elevation values from the reference ICESat-2 elevations. The training data is filtered using the values within the range of the second standard deviation of the mean for removing the outliers. The appropriate NN model architecture is selected by applying a heuristic approach in several iterations. The Feed-Forward Network with Backpropagation algorithm is selected for each of the fusion processes implemented on the complete study site as well as the plain and mountainous portions separately. The faster converging TRAINLM (Levenberg Marquardt) backpropagation algorithm is used here with different suitable transfer/activation functions in plain and mountainous regions distinctly. The target samples are prepared from the precise reference elevation values from the ICESat-2 ATL08 product, which is distributed across the study area. Similarly, these data samples are separated into the plain and mountain portions for evaluating the two types of terrains independently. The trained model is then simulated on new data samples which are not included in the training samples. The elevation values of the fused DEMs are checked with the toposheets of the region to check the correct range. The fused DEMs are analyzed for accuracy assessment using the ICESat-2 altimetry data in a point-based assessment on near-ground points (having height error in the range of 0 to 0.5 m) and using TanDEM-X 90 m DEM for area-based assessment by calculating it's ME (Mean Error) and RMSE (Root Mean Square Error).

Due to the complex hilly terrain in this study area, the DEMs are affected by geometric distortions such as foreshortening, layover and shadows in the SAR images. The global open-access TanDEM-X 90 m DEM is improved using the neural network model. The training data includes the elevation values from the TanDEM-X 90 m DEM and the target data samples include the precise ICESat-2 altimetry elevation data. The Linear transfer function is used in a Feed-Forward neural network using TRAINLM backpropagation algorithm. The relationship between the training and target data is modelled and predictions are made for the improved DEM. The obtained values are checked with the range given in toposheets and these are evaluated to find the percentage improvement. The statistical parameters used for the accuracy assessment of the results include the mean error (ME), root mean square error (RMSE), and percentage improvement factor (%IF). Mathematically, the mean error is simply the average of the sum of all errors (3) while RMSE measures the spread out of errors and is given by the square root of the average of the squared differences between the predicted and the reference values (4). Further, the percentage improvement factor accounts for the amount of improvement achieved in output over the input and is given by the percentage of input RMSE to the RMSE of predicted output (5) [51]–[54].

$$ME = \frac{\sum_{i=0}^{n} H_{i(Input)} - H_{i(Ref)}}{n} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(H_{i(Input)} - H_{i(Ref)}\right)^2}{n}} \quad (4)$$

$$\% IF = \frac{\sqrt{\frac{1}{N}\sum_{j=1}^{N}(H_{i(input)} - H_{i(Ref)})^2} - \sqrt{\frac{1}{N}\sum_{j=1}^{N}(H_{i(fused)} - H_{i(Ref)})^2}}{\sqrt{\frac{1}{N}\sum_{j=1}^{N}(H_{i(input)} - H_{i(Ref)})^2}} X\ 100 \quad (5)$$

Where $\boldsymbol{H}_{\boldsymbol{i}_{(\boldsymbol{Input})}}$ is the elevation values of input DEMs, $\boldsymbol{H}_{\boldsymbol{i}(\boldsymbol{Ref})}$ is the reference elevation values, $\boldsymbol{H}_{\boldsymbol{i}(\boldsymbol{fused})}$ is the Fused output DEM elevation values and n denotes the number of observations in (3), (4) and (5).

V. RESULTS

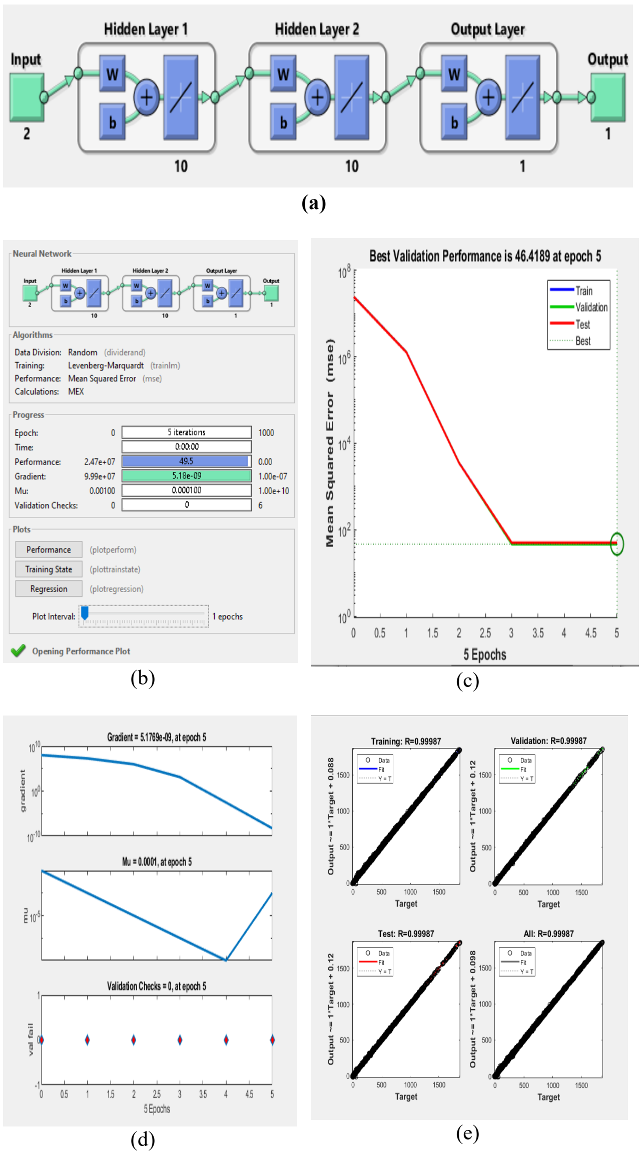


Fig. 5. ANN Model for Meghalaya and Assam (Plain) region (a). Model Architecture; (b). Model parameters; (c). Best performance while training; (d). Training state of the model; (e). Regression plot between target and output data.

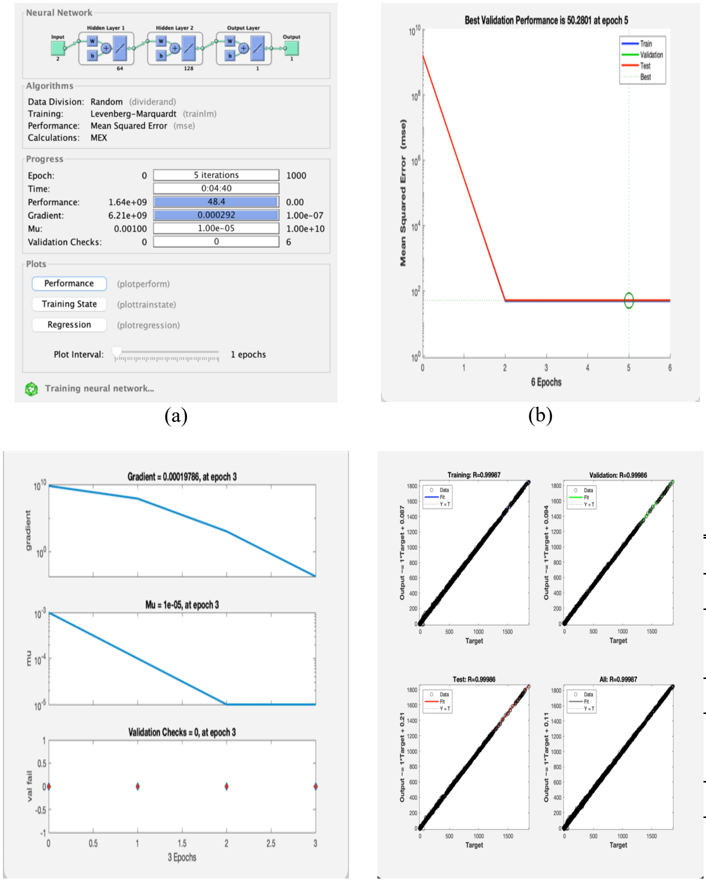


Fig. 6. ANN Model for Meghalaya and Assam (Hilly) region (a). Model Architecture and Model parameters; (b). Best performance while training; (c). Training state of the model; (d). Regression plot between target and output data.

The framework of DEM fusion and DEM improvement is developed using the adaptive learning capability of neural networks. Different architectures of the models are designed as suitable for modeling the complex terrain of the complete region and in plain and mountainous portions separately. A simple model with two hidden layers having 10 units in each layer is used to model the fusion framework for the complete study area (Fig. 5).

The Linear transfer function (PURELIN) models the terrain appropriately. A total of 22767 data samples distributed across the study region are prepared for training the model. The total data samples are divided into training, validation and testing samples by the 'dividerand' function in the ratio of 70:15:15 randomly. The loss parameter selected for checking the training performance is Mean Squared Error (MSE). The neural network model architecture, model parameters, training performance and regression plot between the target and output data are shown in Fig. 5. The relationship between the training and target samples from the ICESat-2 photon data is modelled and fused output DEMs are obtained using this model for the complete and plain portion of the study area.

Similarly, in the Meghalaya plateau region which is having a complex undulating mountainous terrain the model architecture designed is having two hidden layers with a comparatively large number of neurons (64 and 128 neurons in the first and second hidden layer respectively). The purelin that is the Linear transfer function is useful in this type of terrain modelling. The model structure used along with model parameters, performance while training and the regression plot is shown in Fig. 6.

The fused output DEMs obtained from the developed fusion framework are assessed in terms of ME and RMSE for accuracy using the ICESat-2 altimetry data in a point-based assessment (TABLE II). The RMSE of Fused output DEMs has reduced significantly to 7 m as compared to the 11 m of RMSE of input DEMs for the complete study site. While fused DEMs are improved over the plain portion around the Assam Valley region with an RMSE of 3.82 m in contrast to the 5.14 m RMSE of the input DEM. The value of RMSE has also reduced in the mountainous portion of the Meghalaya plateau region with an RMSE of 8.18 m for the fused DEM in contrast to 15.35 m RMSE of the input DEMs.

TABLE II: RESULTS FOR FUSED DEMS FROM THE ANN MODEL PREDICTIONS USING ICESAT-2 DATA IN MEGHALAYA AND ASSAM REGION

	Input DEM 1	Input DEM 2	Fused DEM
Total ICESat-2 footprints (22767 sample points)			
ME (m)	7.72	7.74	0.03
RMSE (m)	11.12	11.11	7.00
Plain Area (12175 sample points)			
ME (m)	3.21	3.20	-0.03
RMSE (m)	5.14	5.12	3.82
Mountainous Area (10591 sample points)			
ME (m)	12.91	12.95	-0.01
RMSE (m)	15.35	15.34	8.18

Further, the area-based accuracy assessment is performed over a test subset area in plain and hilly regions separately and evaluating the results with TanDEM-X 90 m DEM. The plain test area attained an RMSE of 2.21 m for fused DEM in contrast to 2.5 m of input DEMs. The fused output DEM produced in the plain region using the ANN-based fusion framework is represented in Fig. 7. The values of elevation in the fused DEM are within the correct range of elevations as checked from the toposheets of this area. Similarly, the complex terrain around the Meghalaya plateau region is also modelled using the fusion framework. This being a very highly undulating terrain having large variations in elevation from 900 to 1800 meters (approx.), the fused DEM obtained in this region contains some artefacts/voids, which are attempted to remove by estimating focal statistics such as mean and removing the no data values (Fig. 8). However, a more suitable interpolation technique can be used for removing these artefacts/defects in the output completely.

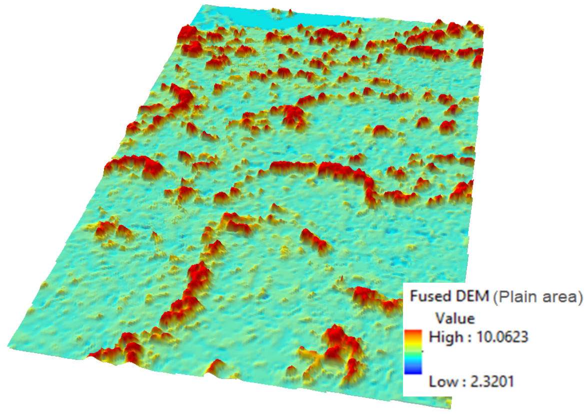


Fig. 7. Fused Output DEM (3D view) from ANN-based fusion approach in the plain portion of Meghalaya and Assam region

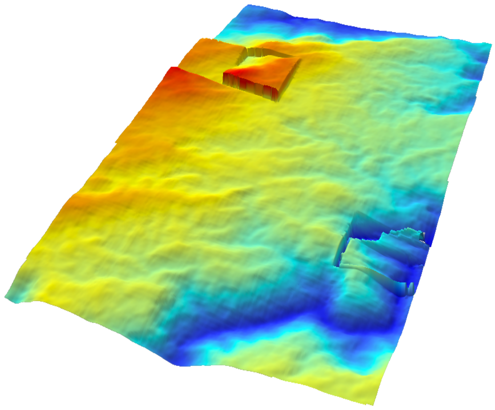
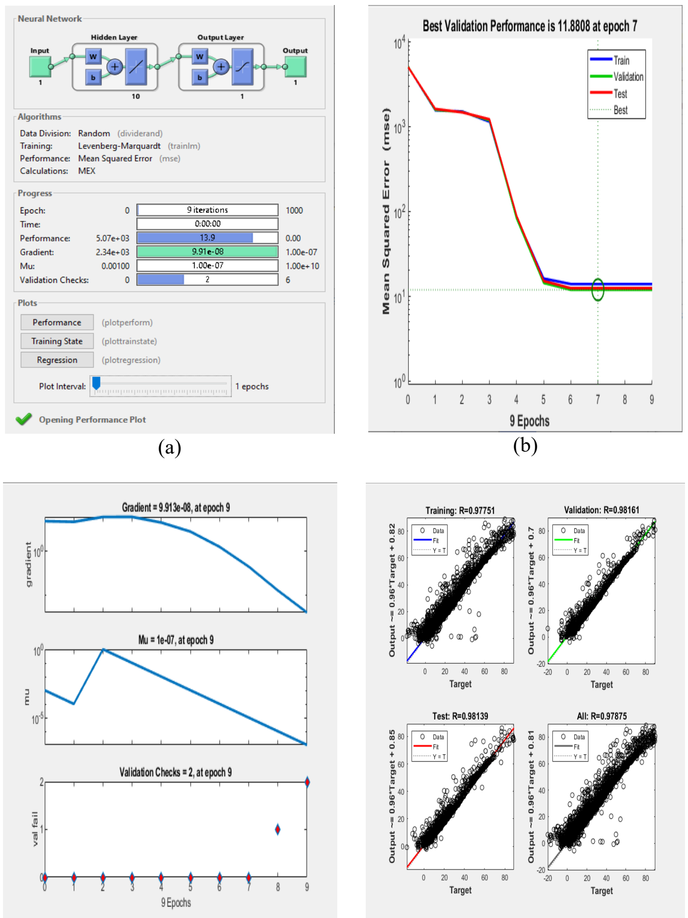


Fig. 8. Fused Output DEM (3D view) from ANN-based fusion approach in the mountainous portion of Meghalaya and Assam region.

The global openly available SAR-based TanDEM-X 90 m DEM is improved using the neural network models. The training data includes a total of 22994 points with the TanDEM-X DEM elevations as input data and the target data samples have the reference elevation of ICESat-2 ATL08 data. The underlying terrain is modelled using a single hidden layer structure with 10 units and using a linear activation function with TRAINLM algorithm (Fig. 9). The model parameters and performance while training are depicted in Fig. 9. Further, the plain and mountainous portion sample points are separated and assessed for accuracy.



(a) (b)

(d) (e)

Fig. 9. ANN Model for Meghalaya and Assam region for improvement of TanDEM-X 90 m DEM (a). Model Architecture and Model parameters; (b). Best performance while training; (c). Training state of the model; (d). Regression plot between target and output data.

The near-ground points are also assessed for checking the accuracy and improvement of the existing DEM (Table III). The point-based accuracy assessment infers that in terms of RMSE the improved DEM has obtained a value of 7.42 m in contrast to 11.2 m showing a percentage improvement of 34% over the input DEM. The percentage improvement in plain and mountain regions separately is around 21.57% and 37.13% respectively. The accuracy assessment on the near-ground points has shown a remarkable improvement of 46.76% in the plain portion of the study area and 54.59% in the mountain portion of the study area.

TABLE III: RESULTS ON THE IMPROVEMENT OF TANDEM-X 90 M DEM IN THE MEGHALAYA AND ASSAM AREA

Total ICESat-2 footprints (22994 points):			
	Input TDM	ANN Prediction	% IF
RMSE (m)	11.21	7.42	33.83
Plain Area Points:			
RMSE (m)	4.64	3.64	21.57
Mountainous Area Points			
RMSE (m)	14.07	8.85	37.13
Near Ground Points (having 0 to 0.5 m height error)			
Plain Area Points			
RMSE (m)	0.26	0.14	46.76
Mountainous Area Points			
RMSE (m)	0.29	0.13	54.59

VI. CONCLUSIONS

The artificial neural network (ANN) based fusion framework is developed for DEM fusion and DEM improvement in the North-eastern Himalayan region of India. The MATLAB NN-toolbox is an efficient platform for designing and implementing DEM fusion frameworks. The neural network structures designed for the modeling of such hybrid terrain having one part as plain topography and the other as mountainous type topography are implemented successfully. The results obtained for the complex and diverse terrain of the Meghalaya and Assam region with the developed models have shown a significant improvement in terms of RMSE and percentage improvement factor. The specialty of ANN models in handling non-linear data with universal approximation and adaptive learning has proven to be an efficient and effective tool for DEM fusion and DEM improvement in the north-eastern Himalayan region of India.

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Conflict of Interest

The authors of this study declare no conflict of interest.

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