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SIT.net: SAR Deforestation Classification of Amazon Forest for Land Use Land Cover Application

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Abstract

The process of turning forest area into land is known as deforestation or forest degradation. Reforestation as a fraction of deforestation is extremely low. For improved qualitative and quantitative classification, we used Sentinel-1 dataset of State of Para, Brazil to precisely and closely monitor deforestation between June 2019 and June 2023. This research aimed to find out suitable model for classification called Satellite Imaging analysis by Transpose deep neural transformation network (SIT-net) using mathematical model based on Band math approach to classify deforestation applying transpose deep neural network. The main advantage of proposed model is easy to handle SAR images. The study concludes that SAR satellite gives high-resolution images to improve deforestation monitoring and proposed model takes less computational time compared to other techniques.

Keywords

Brazilian Amazon, Sentinel-1, Band Math, Transpose CNN Transformation Network

1. Introduction

Forest monitoring is important part of healthy climate and useful for sustainable development. The world's largest ecological specifically carbon sinker and collector is the forest. Thus, precisely keeping track of variation in forest cover is reaching the entire world's climate neutrality plan. With the help of merging different band, use mathematical modelling and apply color thresholding with segmentation to find out more accurate deforest mitigation. Due to high mitigation of deforestation compared to reforestation affecting the climate changes [1] as well as human life including global development of society, greenhouse effect and many more problems arise.

Comprising the majority of terrestrial species worldwide, tropical forests are among the planet's most biodiverse ecosystems. Unpleasantly, the last several decades have seen an alarming acceleration of the use of both renewable and non-renewable natural resources in conjunction with industrial development. This has resulted in significant environmental changes, such as the loss and degradation of forests [2]. In the Brazilian Legal Amazon (BLA), the ongoing deforestation process is a particularly dire scenario. Approximately 5,200,000 km, or more than 59% of Brazil's total land area is comprised of this region [3].

In environmental research, remote sensing (RS) has proven highly valuable [4], most notably when it comes to tracking forest ecosystems. Due to cloud coverage and heavy rain, it is more difficult to monitor deforestation accurately. That's why, compared to optical satellite, SAR satellite is good for penetrating clouds and gives better resolution during heavy rainfall [5]. Using remote sensing imagery to track changes in the world's forests is a very successful approach, mostly because it is inexpensive and has a short duration of interval to revisit the same area for better observation [6].

SAR satellite is an active sensor which detects and measures their own illuminated energy for investigation purpose, good in both day and night time [7]. SAR satellite time series is good for observation due to high spatial resolution (20 m) and temporal resolution (6 days) for land monitoring [8]. Sentinel-1 has four types of data for different purposes like raw data level 0 for auxiliary information, SLC-Single Look Complex data level 1 for soil and vegetation monitoring, GRD-Ground Range Detection level-1 for land monitoring, Level-2 OCN for Floor and Ocean data monitoring [9]. Due to different acquisition mode, their polarization and resolution are difficult including range of coverage area. The surface characteristics and deforestation monitoring are revealed by the backscattering coefficient that SAR sensors record and the radar's incidence angle determine how the surface reacts to these elements [10].

Deforestation brought on by woodcutting, ranching, mining, oil extraction, building dams, and infrastructure projects together account for forest loss. Degradation of forests and climate related climate change shifts, wildfires, framing industrial plantations, and tree illnesses [11].

The deforestation analysis using Sentinel-1 requires pre-processing to remove speckle noise and need stabilization used for balancing the radar signals variation in different time series images [12]. Stabilization is useful if you are using Maximum Likelihood detection approach and U-net CNN approach but not useful with Adaptive linear threshold approach [13].

The ongoing research on deforestation, RDSTC-Reversed Depth wise Separable Transposed Convolution faces problem of segmenting and classifying mixed pixel and unable to identify early stage of fire detection [14].

Using deep learning model with U-net adding (residual block attenuation gate unit) RAU-Net and use dataset with merging different band of Sentinel-1,2, MODIS, to increase the accuracy for detecting fire [15].

Forest change detection is also important part of deforestation monitoring for LULC. The current scenario of research based on cloudless satellite images using deep learning CNN with attention mechanism for better analysis compared to standard U-net [16].

Forest biodiversity is an important for monitoring vegetation and helps towards sustainable development of world. Using Squeeze Excitation with Partial Convolution including transpose for forest mapping and structuring [17].

In SAR, backscattering defines the intensity of ground object which helps us for better understanding. Using the patch based CNN3D model gives better result compared to CNN2D as well as CNN1D with dual polarization SAR. The arising, if patch size is large creates more smoothing and neglect small objects which reduce accuracy and unnecessary computation is required [18].

Deforestation Expansion pattern observed by frontier which reflect important information about carbon, water, biodiversity for better understanding of regional forest loss. Using fine scale spatial temporal optimization techniques with Bayesian Deep learning methodology (DnCNN + BLUC) helps to improve accuracy of SAR satellite and reduce speckle noise problem but due to variation of wet season and dry season patch size and patch framing is different which reflect different variation [19].

Basically, Land Use Land Cover means land used by human which is directly related to human nature interrelationship for sustainable development. The remote sensing images have different spectral land which is used for different applications. For combining different spectral band on the basis of remote sensing indices like NDVI, NDBI, NDWI and apply Random Forest to monitor changes increase the accuracy and efficiency. In future Random Forest combine with Deep Learning to deal with mixed pixel problem and identifying complex boundaries as well [20].

As per the latest literature review, author is summarizing this paper with new ideas based on Transpose Deep neural network designing including the segmentation concept and mathematical pre-processing. The structure of paper is based on Motivation and associated contribution. The main motivation is SAR satellite that gives high resolution in both day and night and penetrates clouds even not effecting during heavy rain or other climate effects.

Use Multi Temporal Speckle Filtering and compare their results to find out the best filter to reduce speckle noise which is the big disadvantage of SAR satellite. Apply Band Math Merging Concept to create new bands for analysis and implement new methodology called SIT.net to classify time series satellite images for monitoring deforestation. For calculating area of deforestation, use Color Thresholding and compare their results for better analysis. Apply segmentation and compare their results to identity the best segmentation for creating mask to analyze deforestation. Use Multi Temporal Speckle filters like Boxcar, Lee Sigma, Frost, Median and Intensity Driven Adaptive Filter (IDAN) and compare their results.

- **Organization of paper**
  - Dataset Study
  - Methodology Modelling
  - Outcomes Exploration

2. Materials and Method

2.1. Dataset Study

In Brazil, the most responsible area of tree loss since 2010 to 2022 is Para. In Para, approximately the third most responsible region for tree loss is Novo Progresso since 2001 to 2022. In October 2023, Novo Progresso got many alert regarding deforestation and mainly due to fire [21]. Past 15 years, REDD Reducing Emission of Deforestation and Forest Degradation monitoring the Brazil and analyze that Para is the second largest area of Brazilian Amazon of deforestation [22] [23]. As per the above analysis, authors choose State of Para, Brazil dataset to analyze the proposed model for deforestation classification. Below "**Figure 1**"and "**Table 1**" visualize the study area using google earth pro.

The dataset used in this paper captured from NASA. For the analysis of proposed model, author use Sentinel-1 GRD images of year 2019 and year 2023. The Sentinel-1 has feature of Dual Pole Ground Range Detector to observe the Earth accurately in both day and night without any interruption of heavy rains or clouds. "**Table 2**" summarizes more about dataset used in this paper.

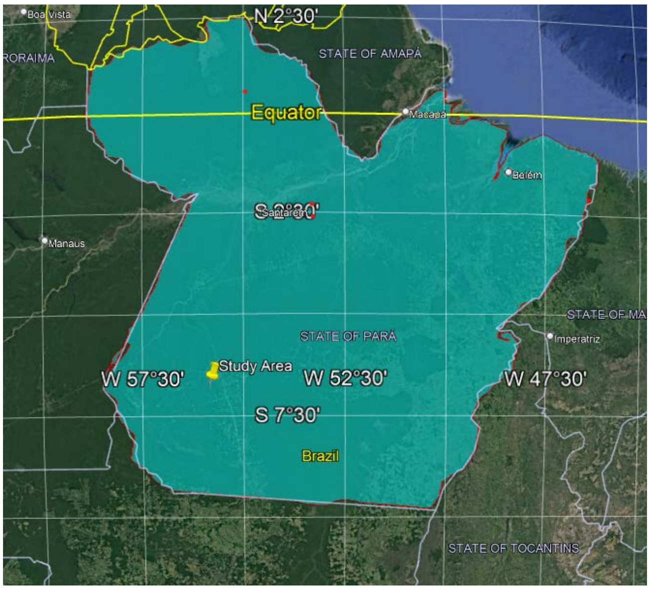


Figure 1. Geographical representation of study area.

Table 1. Study area geographical coordinates.

Year	Dataset Description				
	Study Area	Latitude	Longitude	Pixels	Size
2019-2023	State of Para	−7.849	−54.457	799,205,772 m	1680 MB

Table 2. Image acquisition description.

Year	Data Acquisition Description				
	Acquisition date and time	Acquisition mode	Polarization	Product type	Mission
2019	21 July, 09:15 utc	IW	VV, VH	GRD	Sentinel-1A
2023	24 July, 09:16 utc	IW	VV, VH	GRD	Sentinel-1A

2.2. Methodology Modelling

The modelling of complete methodology is based on five steps. With the help of workflow diagram the whole proposed concept visualize easily. Below "Figure 2" explains the number of steps used in this paper. The proposed model divide into three sections, but pre-processing and intermediate processing done by SNAP tool to prepare data for training and testing for our proposed model operated in MATLAB 2023b, to check the accuracy and loss for validation.

The Sentinel-1 data is a type of SAR (Synthetic Aperture Radar). SAR data need to pre-processed, author use SNAP-Sentinel Application Platform software developed by ESA (European Space Agency) Copernicus. This tool is suitable for earth observation analysis. The pre-processing steps used for SAR are described in "Table 3".

After pre-processing, need to apply filtering to reduce speckle noise. Speckle noise is the only challenge in SAR satellite images. Speckle noise is multiplicative in nature and due to this coherent of imagery is also affected. There are many Bayesian and Non-Bayesian methods are available to reduce speckle noise. In this paper, authors compare Bayesian filters to reduce noise [24] [25] [26] [27]. "Table 4" describes multi temporal speckle filters.

The next methodology is called BMM, Band Math Merging concept. Mathematical modelling based on arithmetic concept like addition, subtraction, multiplication, division. On the basis of filters analysis, apply band math in each filters for better results. With the help of multiple band math merging concept, get more understanding of which band math is perfect for deforestation analysis.

In this paper, the basic mathematical model is used called addition, subtraction, and multiplication. The dataset of 2019 and 2023 Sentinel-1 dual polarization (VV, VH) is used for Band Math merging to create new band called Add, Sub, Mul for analysis. The expression used here are as follows:

$$\text{Add}_{\text{band}} = \text{VV} + \text{VH}. \tag{1}$$

$$\text{Sub}_{\text{band}} = \text{VV} - \text{VH}. \tag{2}$$

$$\text{Mul}_{\text{band}} = \text{VV} * \text{VH}. \tag{3}$$

The next step based on deep neural networking concept. After applying Band Math in different filtered images and use that images for classification using proposed model called SIT.net. The proposed model is the combination of Transposed Convolutional neural network using Transformation methodology to analyze the accuracy of filtered images and Band Math filtered images. Below "Table 5" gives complete overview of proposed model with description.

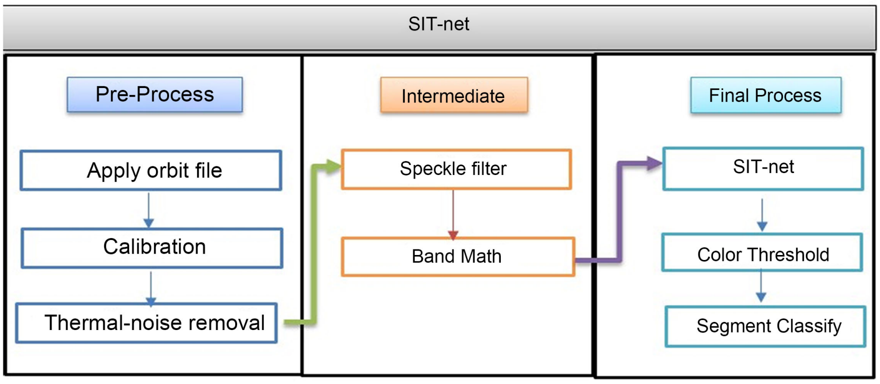


Figure 2. Workflow of methodology modeling.

Table 3. Sentinel-1 Pre-processing.

Steps	Pre-Processing Description		
	Description	Computational Time	
		2019	2023
Apply Orbit file	To provide accurate satellite position and velocity information	75 seconds	119 seconds
Calibration	Pixel value of SAR truly represented by RADAR backscattering of reflected surface	2.5166667 minutes	6.95 minutes
Thermal to Noise Removal	Remove thermal noise	19.5 minutes	18.95 minutes

Table 4. Multi temporal speckle filters analysis.

Filters	Multi Temporal Speckle Filters Description		
	Description	Computational Time	
		2019	2023
Boxcar	Filter size X: 3 Filter size Y: 3	57.416668 minutes	19.533333 minutes
Median	Filter size X: 3 Filter size Y: 3	59.383335 minutes	21.4 minutes
Frost	Filter size X: 3 Filter size Y: 3 Damping Factor	38.133335 minutes	20.65 minutes
Lee Sigma	Number of looks: 2 Window size: 5 × 5 Sigma: 0.9 Target Window size: 3 × 3	40.483334 minutes	30.116667 minutes
IDAN	Number of looks: 2 Adaptive Neighbour size: 30	50.116665 minutes	47.883335 minutes

Table 5. Proposed model description.

Layers	SIT.net model Description	
	Name	Description
Layer 1	Image Input Layer	define input image sizes 512 × 512
Layer 2	Transposed CNN	define filters size, number of filters, bias, strides for upsampling of image features to maintain the exact image information till the end of output images without any loss
Layer 3	Dropout Layer	Defines probability of dropping nodes to prevent overfitting
Layer 4	Batch Normalization Layer	Define mean and variance scale to make fast and stable analysis between layers
Layer 5	Flatten Layer	Helps neural network to learn more complex patterns and help te network for better prediction.
Layer 6	Gru Layer	Defines activation function and number of hidden units to check dependence between different time series data.
Layer 7	Fully Connected Layer	Define output size with the help of connection between every neurons of one layer to other layers to provide flexibility.
Layer 8	Softmax layer	Helps to convert scale of vector numbers into scale of vector probabilities for prediction
Layer 9	Classification Layer	To computer loss and accuracy using probability of above layer for analysis

"**Figure 2**" workflow diagram helps us to understand the complete overview between pre-processing, intermediate processing and final processing. The proposed model analyzed by their output results and images. In next section, we discussed about the outputs of pre-processed results of 2019 and 2023 dataset. And after applying different Multi temporal speckle filtering on pre-processed images for better visualization. The filtered images used for Band math merging concept to create new band for applying proposed model on it and compare the results between filtered images and band math filtered images using accuracy and loss.

For calculating the deforested area, we use Color Thresholding and Segmentation for identifying the deforested pixels using binary images. The gray scale value of each RGB channel is used to divide the foreground and background pixels in RGB color thresholding algorithm which means the intensity of the image pixels is not independent of color chromatics gives unreliable thresholding. That's why L*a*b or HSV is used, where the intensity parameters and chromatic characteristics are separated [28]. To convert the color thresholding images into binary and create mask for identifying the deforested area. To calculate the deforested area, binary mask is used. For the area calculation, authors convert number of pixels into kilometer per square.

$$\text{Area per km}^2 = \frac{\text{Km}}{\text{pixel}}. \tag{4}$$

2.3. Outcomes Exploration

The experimental analysis is based on four sections. The First section, discussed about pre-processed images as an input for further analysis based on "Table 3". The second section, discussed about the intermediate processing results based on "Table 4" and based on "Equation (1)", "Equation (2)", and "Equation (3)" Band Math merging of filtered images. And the third section, discussed about the proposed model results based on "Table 4" and the comparison between two different dataset. The final Forth section, based on "Equation (4)"discussed about deforested area calculation and their difference analysis.

The pre-processing of original image computation gives an overview that, due to deforestation in 2023 images takes less computation time compared to 2019 original image computation. Deforested pixel area and non-deforested pixel area have different pixel vales area computed easily and fast. With the help of "Table 6", it reflects the differences.

For better understanding of dataset, histogram and adjusted histogram of original images see in below "Figures 3(a)-(f)".

The next step is applying speckle filtering. The multi-temporal speckle filtering helps to understand which fitter gives better results and take less computational time see in below "Table 7" and compare it with "Table 4".

After applying the multi-temporal speckle filtering, band math concept based on "Equation (1)", "Equation (2)", and "Equation (3)"applied see in below "Table 8". The band math gives more visual images for analysing the deforestation and their computational time is seen in "Table 4". The new bands help to train proposed model to analyze and check the accuracy and loss between two different data.

Table 6. Pre-processed images.

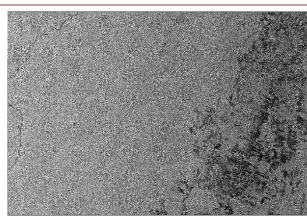
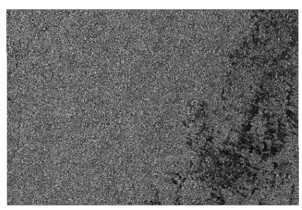
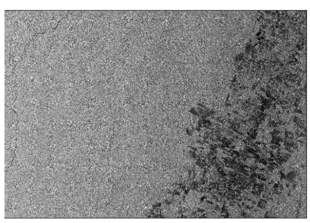
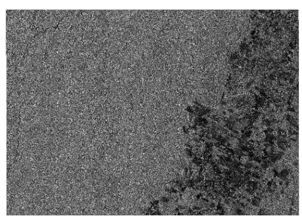
Year	Comparison	
	Original Image	Pre-Processed Image
2019		
2023		

Table 7. Multi-temporal speckle filtered images.

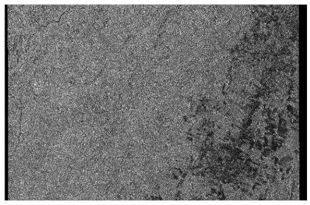
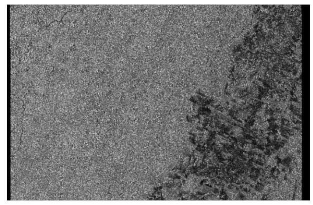
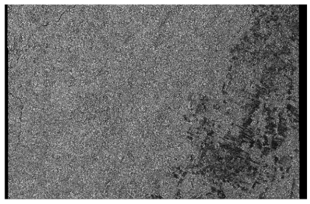
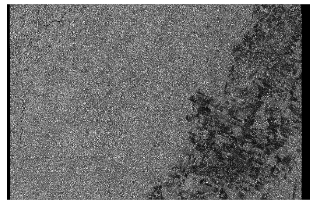
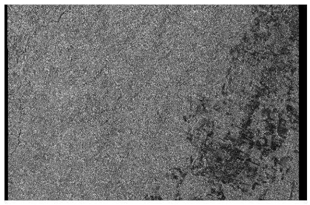
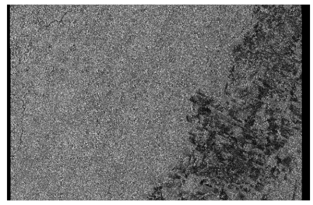
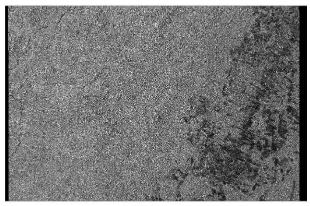
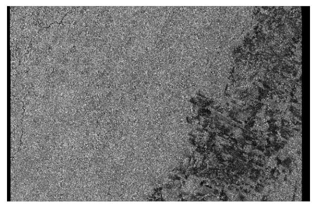
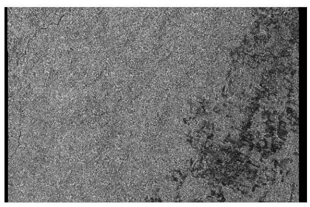
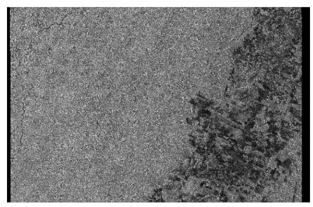
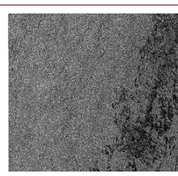
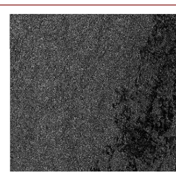
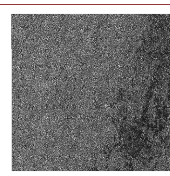
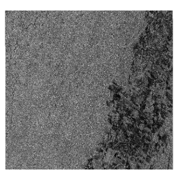
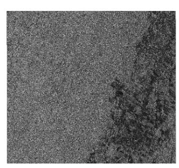
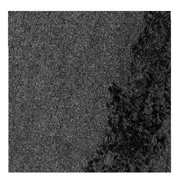
Filters	Comparison	
	2019	2023
Boxcar		
Median		
Frost		
Lee Sigma		
IDAN		

Table 8. Band math filtered image analysis.

Year	Band Math		
	VV + VH	VV − VH	VV * VH
2019			
2023			

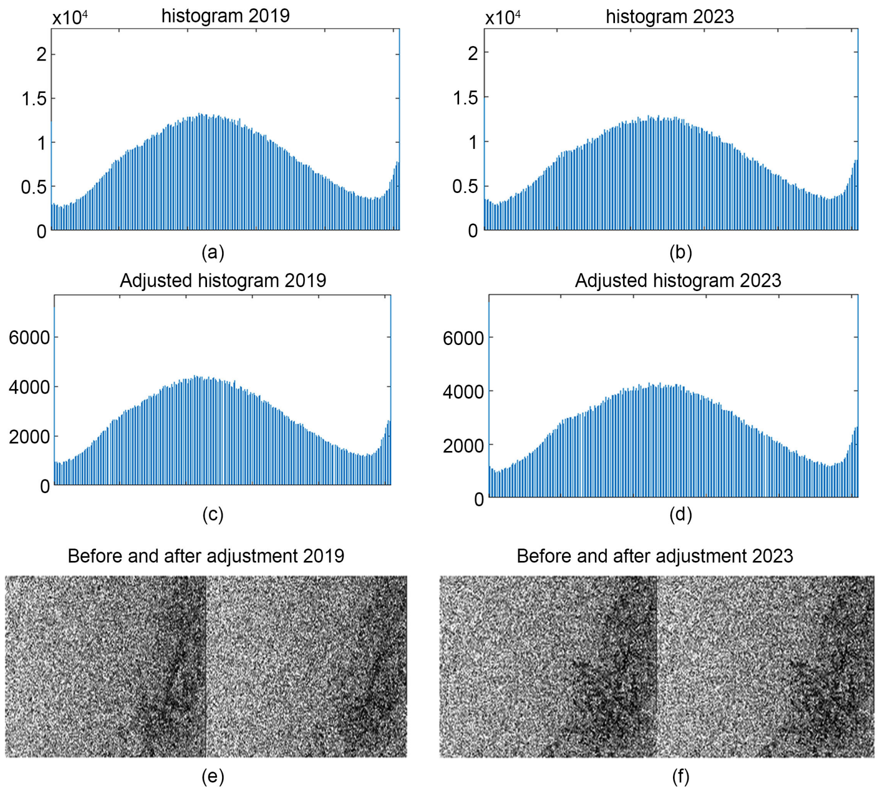


Figure 3. (a) Histogram of 2019; (b) Histogram of 2023; (c) Adjusted histogram of 2019; (d) Adjusted histogram of 2023; (e) Before and after image of 2019; (f) Before and after image of 2023.

The final processing based on three steps, first is applying proposed model in filtered images datast and band math images dataset, compare the accuracy and loss see in "**Table 9**".

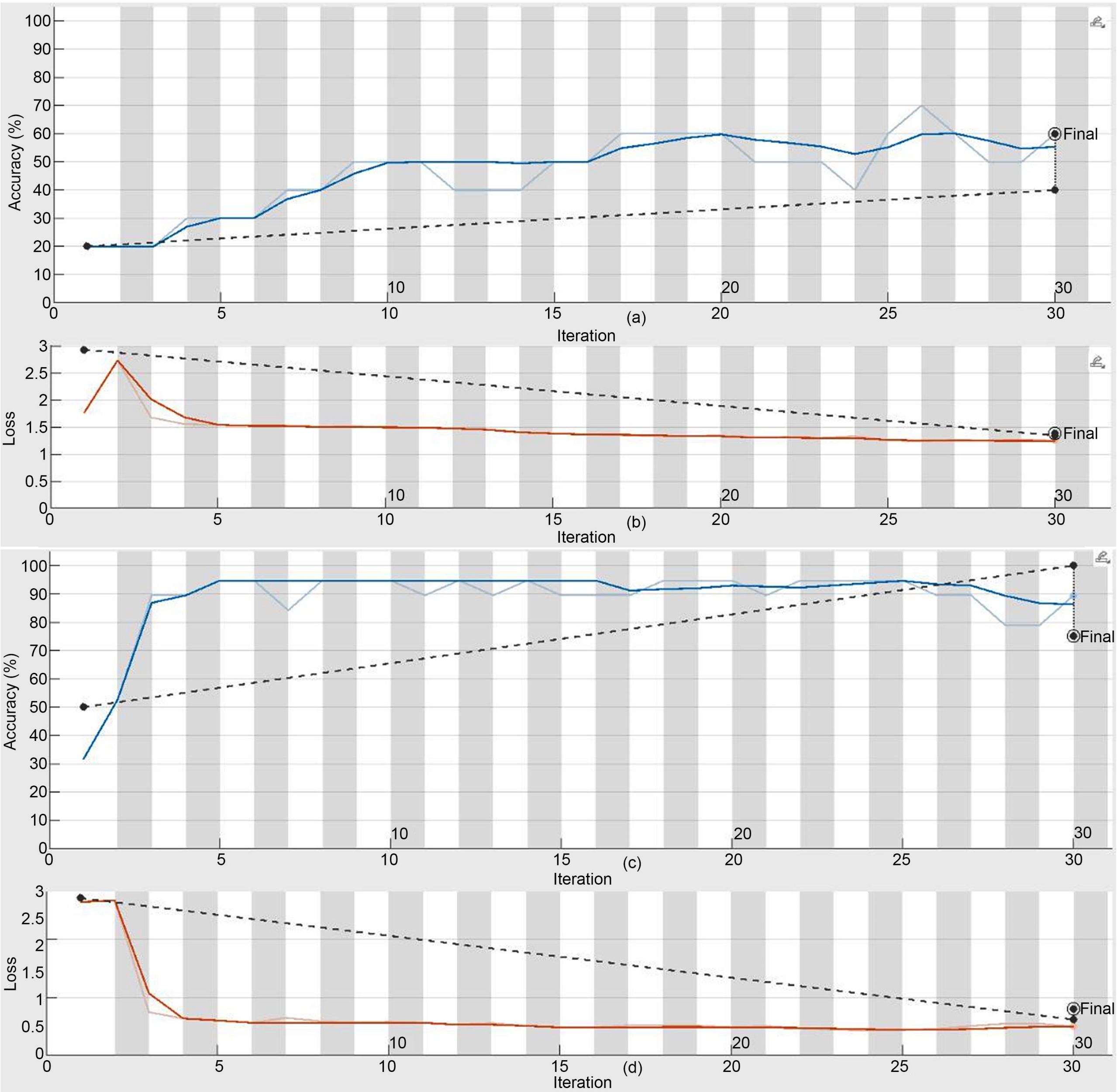
For justifying the proposed model functionality see in below **"Figures 4(a)-(d)**" accuracy and loss as per number of iteration of filtered images dataset and in "**Figures 4(e)-(h)**" is the accuracy and loss as per number of iteration of Band math images dataset. The dotted line explains the accuracy and loss and blue line and orange line explain the processing.

Once we analyze the accuracy and loss of both filtered images and band math images. The next step is to calculate deforested area. For identifying the deforested and non-deforested area, need segmentation and color thresholding. Using Color Thresholding, L*a*r gives better results compared to HSV and RGB to create mask see in below "**Figure 5(a)**" "**Figure 5(b)**".

We use Binary Masked and apply on Original Images, compare with segmentation using Thresholding (100) and apply Morphology using circle shape pixel of radius 1 with active contouring using region based till 100 iterations for better analysis between deforested and non-deforested area. To calculate deforested area per pixel using props function which helps to give lot of information about segmented region in the images. We use area per pixel information and add them to calculate area see in below "**Table 10**".

Table 9. Proposed model analysis.

Data types	Analysis					
	Year	Number of images	Epochs	Accuracy	Loss	Processing time
Filtered Images	2019	10	30	60%	1.5	15 minutes 7 seconds
	2023	10	30	20%	1.32	21 minutes 1 second
Band Math Filtered Images	2019	15	30	75%	0.35	13 minutes 39 seconds
	2023	15	30	87.05	0.26	15 minutes 4 seconds



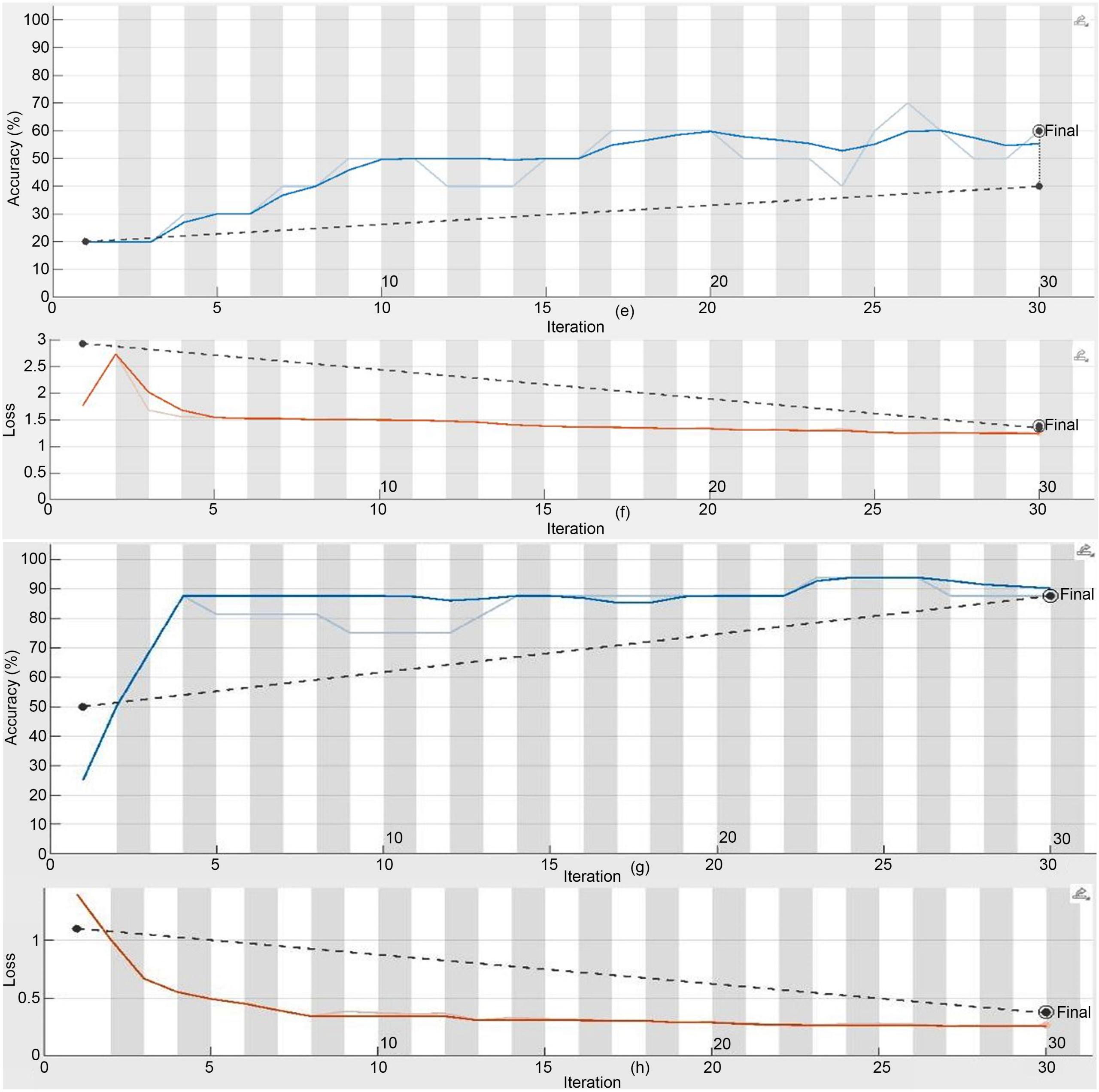


Figure 4. (a) Filtered images accuracy 2019; (b) Filtered images loss 2019; (c) Band math images accuracy 2019; (d) Band math images loss 2019; (e) Filtered images accuracy 2023; (f) Filtered images loss 2023; (g) Band math images accuracy 2023; (h) Band math images loss 2023.

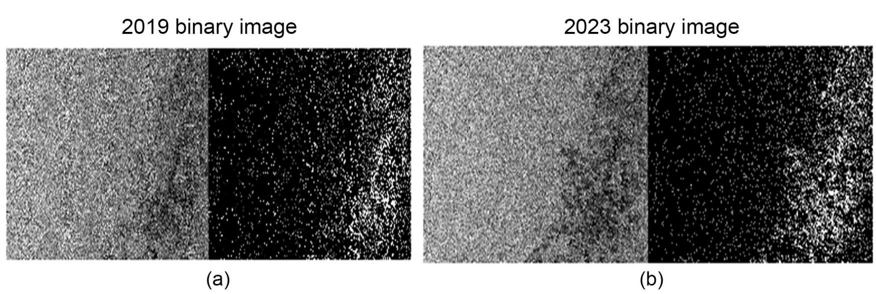


Figure 5. (a) Binary masked image 2019; (b) Binary masked image 2023.

Table 10. Deforested and non-deforested area analysis.

Area	Analysis			
	Original Images		Deforested Images	
Year	2019	2923	2019	2023
Area in pixels	2,123,772	2,110,929	75,566	78,222
Area in Km²	33,184	32,983	1181	1222

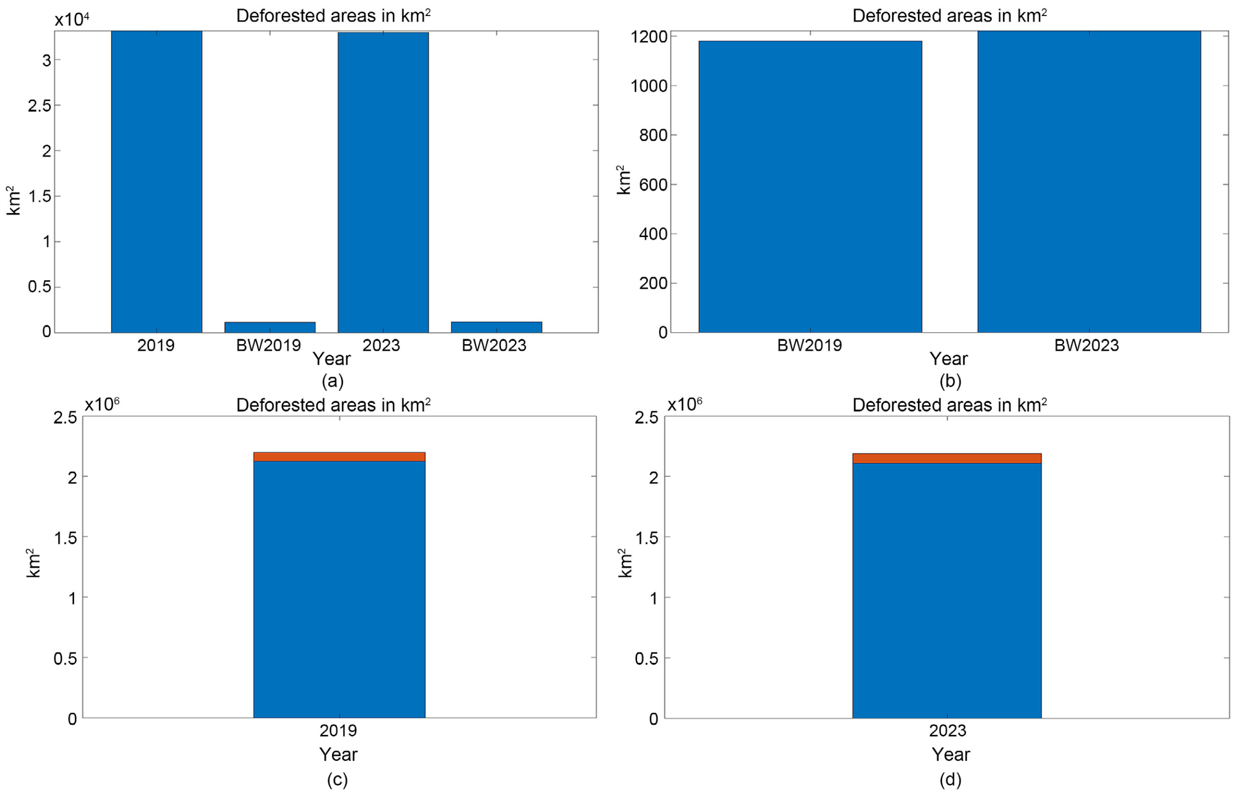


Figure 6. (a) Deforested and non-deforested; (b) Deforestation comparison; (c) 2019 deforestation; (d) 2023 deforestation.

For better analysis, bar graph of deforested and non-deforested area is seen in below "Figures 6(a)-(d)". In "Figure 6(a)" and "Figure 6(b)" helps to understand actual differences between non-deforested and deforested area using original images and segmented images of 2019 and 2023.

For better visualization, combine the segmented area with orange in color and non-deforested area with blue in color see in below "Figure 6(c)" "Figure 6(d)".

3. Conclusion

The forest monitoring is important for healthy environment. The proposed methodology helps to find out the deforested area using SAR satellite which helps to monitor in both day and night without any interruption of weather. For computational analysis of SAR satellite, imagery is the important key point of this paper due to large area covered. The Band Math concepts to create new band for dataset preparation take less time compared to multi-temporal speckle filtering and give better understanding of the images, also increase the accuracy and reduce the loss compared to filtered images. The proposed model takes less computational time for Band math image processing compared to filtered image processing. For calculating area, RGB and HSV do not give better results compared to L*a*b in color thresholding to create mask for analyzing deforestation and using segmentation with morphology and active contouring helps to eliminate unwanted mask to make more clear visualization of deforested area. In future, more images of different time series dataset are used for analyzing deforestation and applying proposed model in optical satellite to analyze deforestation.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Gomes, V.H., Vieira, I.C., Salomão, R.P. and Ter Steege, H. (2019) Amazonian Tree Species Threatened by Deforestation and Climate Change. *Nature Climate Change*, **9**, 547-553. https://doi.org/10.1038/s41558-019-0500-2

[2] Nobre, C.A., Sampaio, G., Borma, L.S., Castilla-Rubio, J.C., Silva, J.S. and Cardoso, M. (2016) Land-Use and Climate Change Risks in the Amazon and the Need of a Novel Sustainable Development Paradigm. *Proceedings of the National Academy of Sciences of the United States of America*, **113**, 10759-10768. https://doi.org/10.1073/pnas.1605516113

[3] Almeida, C.A.D., Coutinho, A.C., Esquerdo, J.C.D.M., Adami, M., Venturieri, A., Diniz, C.G., Gomes, A.R., *et al.* (2016) High Spatial Resolution Land Use and Land Cover Mapping of the Brazilian Legal Amazon in 2008 Using Landsat-5/TM and MODIS Data. *Acta Amazonica*, **46**, 291-302. https://doi.org/10.1590/1809-4392201505504

[4] Tarazona, Y., Zabala, A., Pons, X., Broquetas, A., Nowosad, J. and Zurqani, H.A. (2021) Fusing Landsat and SAR Data for Mapping Tropical Deforestation through Machine Learning Classification and the PVts-β Non-Seasonal Detection Approach. *Canadian Journal of Remote Sensing*, **47**, 677-696. https://doi.org/10.1080/07038992.2021.1941823

[5] Ban, Y., Zhang, P., Nascetti, A., Bevington, A.R. and Wulder, M.A. (2020) Near Real-Time Wildfire Progression Monitoring with Sentinel-1 SAR Time Series and Deep Learning. *Scientific Reports*, **10**, Article No. 1322. https://doi.org/10.1038/s41598-019-56967-x

[6] Wang, Z., Wang, Z., Yan, D., Mo, Z., Zhang, H. and Zhang, Q. (2023) RepDDNet: A Fast and Accurate Deforestation Detection Model with High-Resolution Remote Sensing Image. *International Journal of Digital Earth*, **16**, 2013-2033. https://doi.org/10.1080/17538947.2023.2220619

[7] Darbari, P. and Kumar, M. (2022) Satellite Image Enhancement Techniques: A Comprehensive Review. In: Goyal, V., Gupta, M., Mirjalili, S. and Trivedi, A., Eds., *Proceedings of International Conference on Communication and Artificial Intelligence*, Springer, Singapore, 431-447. https://doi.org/10.1007/978-981-19-0976-4_36

[8] Attema, E., *et al.* (2007) Sentinel-1: The Radar Mission for GMES Operational Land and Sea Services. *Bulletin*, **131**, 10-17.

[9] Filipponi, F. (2019) Sentinel-1 GRD Preprocessing Workflow. *Proceedings*, **18**, Article 11. https://doi.org/10.3390/ECRS-3-06201

[10] Singh, S.K., Prasad, R., Srivastava, P.K., Yadav, S.A., Yadav, V.P. and Sharma, J. (2023) Incorporation of First-Order Backscattered Power in Water Cloud Model for Improving the Leaf Area Index and Soil Moisture Retrieval Using Dual-Polarized Sentinel-1 SAR Data. *Remote Sensing of Environment*, **296**, Article ID: 113756. https://doi.org/10.1016/j.rse.2023.113756

[11] Jamshed, M.A., Theodorou, C., Kalsoom, T., Anjum, N., Abbasi, Q.H. and Ur-Rehman, M. (2022) Intelligent Computing Based Forecasting of Deforestation Using Fire Alerts: A Deep Learning Approach. *Physical Communication*, **55**, Article ID: 101941. https://doi.org/10.1016/j.phycom.2022.101941

[12] Ortega Adarme, M., Doblas Prieto, J., Queiroz Feitosa, R. and De Almeida, C.A. (2022) Improving Deforestation Detection on Tropical Rainforests Using Sentinel-1 Data and Convolutional Neural Networks. *Remote Sensing*, **14**, Article 3290. https://doi.org/10.3390/rs14143290

[13] Doblas, J., Shimabukuro, Y., Sant'Anna, S., Carneiro, A., Aragão, L. and Almeida, C. (2020) Optimizing Near Real-Time Detection of Deforestation on Tropical Rainforests Using Sentinel-1 Data. *Remote Sensing*, **12**, Article 3922. https://doi.org/10.3390/rs12233922

[14] Hossain, F.A. and Zhang, Y. (2023) MsFireD-Net: A Lightweight and Efficient Convolutional Neural Network for Flame and Smoke Segmentation. *Journal of Automation and Intelligence*, **2**, 130-138. https://doi.org/10.1016/j.jai.2023.08.003

[15] Ghali, R. and Akhloufi, M.A. (2023) Deep Learning Approaches for Wildland Fires Using Satellite Remote Sensing Data: Detection, Mapping, and Prediction. *Fire*, **6**, Article 192. https://doi.org/10.3390/fire6050192

[16] Kalinaki, K., Malik, O.A. and Lai, D.T.C. (2023) FCD-AttResU-Net: An Improved Forest Change Detection in Sentinel-2 Satellite Images Using Attention Residual U-Net. *International Journal of Applied Earth Observation and Geoinformation*, **122**, Article ID: 103453. https://doi.org/10.1016/j.jag.2023.103453

[17] Gazzea, M., Solheim, A. and Arghandeh, R. (2023) High-Resolution Mapping of Forest Structure from Integrated SAR and Optical Images Using an Enhanced U-Net Method. *Science of Remote Sensing*, **8**, Article ID: 100093. https://doi.org/10.1016/j.srs.2023.100093

[18] Liu, Y., Pu, X. and Shen, Z. (2023) Crop Type Mapping Based on Polarization Information of Time Series Sentinel-1 Images Using Patch-Based Neural Network. *Remote Sensing*, **15**, Article 3384. https://doi.org/10.3390/rs15133384

[19] Sun, R., Zhao, F., Huang, C., Huang, H., Lu, Z., Zhao, P., Meng, R., *et al.* (2023) Integration of Deep Learning Algorithms with a Bayesian Method for Improved Characterization of Tropical Deforestation Frontiers Using Sentinel-1 SAR Imagery. *Remote Sensing of Environment*, **298**, Article ID: 113821. https://doi.org/10.1016/j.rse.2023.113821

[20] Liang, J., Chen, C., Song, Y., Sun, W. and Yang, G. (2023) Long-Term Mapping of Land Use and Cover Changes Using Landsat Images on the Google Earth Engine

Cloud Platform in Bay Area—A Case Study of Hangzhou Bay, China. *Sustainable Horizons*, **7**, Article ID: 100061. https://doi.org/10.1016/j.horiz.2023.100061

[21] Ertel, J., Goldman, L., Spore, J. and Brandt, J. (2023) Tree Cover Data Sets on Global Forest Watch, Explained. https://www.globalforestwatch.org/blog/data-and-research/tree-cover-data-comparison/

[22] Ramsay, D. (2021) How One Brazilian State Is Tackling Deforestation within Its Border. https://forestsnews.cifor.org/70481/how-one-brazilian-state-is-tackling-deforestation-within-its-borders?fnl

[23] WRM Bulletin (2023) REDD and the Green Economy Exacerbate Oppression and Deforestation in Pará, Brazil. https://www.wrm.org.uy/bulletin-articles/redd-and-the-green-economy-exacerbate-oppression-and-deforestation-in-para-brazil

[24] Jain, V., Shitole, S. and Rahman, M. (2023) Performance Evaluation of DFT Based Speckle Reduction Framework for Synthetic Aperture Radar (SAR) Images at Different Frequencies and Image Regions. *Remote Sensing Applications*: *Society and Environment*, **31**, Article ID: 101001. https://doi.org/10.1016/j.rsase.2023.101001

[25] Baraha, S. and Sahoo, A.K. (2023) Synthetic Aperture Radar Image and Its Despeckling Using Variational Methods: A Review of Recent Trends. *Signal Processing*, **212**, Article ID: 109156. https://doi.org/10.1016/j.sigpro.2023.109156

[26] Shukla, A.K., Dwivedi, S.K., Chandra, G. and Shree, R. (2023) Deep Learning-Based Suppression of Speckle-Noise in Synthetic Aperture Radar (SAR) Images: A Comprehensive Review. In: Kumar, A., Ghinea, G., Merugu, S. and Hashimoto, T., Eds., *Proceedings of the International Conference on Cognitive and Intelligent Computing*, Springer, Singapore, 693-705. https://doi.org/10.1007/978-981-19-2358-6_62

[27] Sebastianelli, A., Del Rosso, M.P., Ullo, S.L. and Gamba, P. (2022) A Speckle Filter for Sentinel-1 SAR Ground Range Detected Data Based on Residual Convolutional Neural Networks. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **15**, 5086-5101. https://doi.org/10.1109/JSTARS.2022.3184355

[28] Pootheri, S., Ellam, D., Grübl, T. and Liu, Y. (2023) A Two-Stage Automatic Color Thresholding Technique. *Sensors*, **23**, Article 3361. https://doi.org/10.3390/s23063361