Atmospheric Correction of Sentinal-2 Satellite Data using Deep Learning

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ABSTRACT
Remote sensing relies heavily on Atmospheric Correction (AC) to ensure accurate estimation of land Surface Reflectance (SR) for various applications. Conventional AC methods, while effective, are computationally expensive and require extensive atmospheric parameters that can be challenging to estimate accurately. This research proposes a novel deep learning model for AC that eliminates the need for explicit atmospheric parameter estimation. Our approach utilizes a Pix2Pix architecture trained on a diverse dataset of Sentinel-2 images covering all states in India, collected via Google Earth Engine. The model includes four bands (red, green, blue, and visible near-infrared) and directly predicts SR values from Top-of-Atmosphere (TOA) reflectance. The model demonstrated promising results, accurately estimating SR values across various scenarios.

Evaluation metrics showed significant improvements, with mean Structural Similarity Index (SSIM) increasing from -0.0025 to 0.961 and mean Peak Signal-to-Noise Ratio (PSNR) rising from 11.0188 dB to 42.14 dB post-training. This approach not only simplifies the AC process but also achieves comparable or superior performance to traditional physics-based methods. The experimental findings underscore the potential of deep learning as a robust and efficient alternative for atmospheric correction in remote sensing applications, offering possibilities for faster processing of large satellite image datasets. This study contributes to the application of artificial intelligence in remote sensing, paving the way for more accessible and efficient atmospheric correction methods. Future work could explore the model's adaptability to other sensors, incorporation of temporal data, and integration with traditional physics-based models.

Keywords
Remote Sensing Satellites, Atmospheric correction (AC), Surface Reflectance (SR), Deep learning, Satellite image processing, Physics-based methods

1. INTRODUCTION
The accuracy and reliability of remote sensing data are critical for a wide range of applications, from environmental monitoring to land use classification and climate change analysis. However, traditional methods of satellite imagery often face challenges due to atmospheric effects, such as scattering and absorption, which can distort surface reflectance values and compromise the quality of the data. While physics-based methods for atmospheric correction exist, they tend to be computationally expensive and rely on precise atmospheric parameters, which are not always of satellite imagery in various domains.

As artificial intelligence continues to advance, there is increasing interest in applying deep learning techniques to atmospheric correction to overcome these challenges. By leveraging the power of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), this research aims to develop a novel atmospheric correction model that eliminates the need for explicit atmospheric parameter estimation. This approach directly predicts surface reflectance from top-of-atmosphere (TOA) reflectance, streamlining the correction process and improving both accuracy and efficiency. Unlike traditional methods that require significant computational resources, a deep learning- based solution is more scalable and can process large volumes of satellite imagery quickly and effectively.

The primary objective of this research is to design and implement a Pix2Pix Conditional GAN (cGAN) model for atmospheric correction of Sentinel-2 satellite data. This involves training the model on a large and diverse dataset of paired TOA and Surface Reflectance (SR) images to ensure robust performance across various atmospheric conditions and geographic regions. The system will be evaluated based on key metrics such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to compare its performance with traditional physics-based correction methods.

This project aims to advance the field of remote sensing by offering a more efficient and accessible method for atmospheric correction, thus enhancing the quality of satellite data used in applications such as environmental monitoring and land cover classification. By addressing key challenges such as computational cost and the need for extensive atmospheric data, this research contributes to the development of more scalable and reliable satellite image correction systems. Additionally, it explores the potential integration of deep learning-based atmospheric correction models into existing satellite data processing workflows, ensuring wider adoption in both academic and operational contexts.

The primary goal of employing deep learning techniques in atmospheric correction of satellite imagery is to address and mitigate the longstanding challenges and limitations associated with traditional atmospheric correction methods while simultaneously enhancing the accuracy and efficiency of remote sensing data processing. In this context, our comprehensive objectives are as follows:

1. **Improving Accuracy and Efficiency**: To enhance the precision of atmospheric correction by leveraging deep learning models, specifically the Pix2Pix conditional GAN, which can effectively predict Surface Reflectance (SR) without the need for complex atmospheric parameter estimations.

2. **Reducing Computational Costs**: To lower the computational overhead associated with traditional physics- based correction methods by introducing a

streamlined deep learning approach that simplifies the process without sacrificing accuracy.

3. **Handling Diverse Atmospheric Conditions**: To improve the model's ability to generalize across different atmospheric conditions and geographical regions by training on a large and diverse dataset of Sentinel-2 images.

4. **Supporting Large-Scale Data Processing**: To enable faster processing of large volumes of satellite imagery, making the atmospheric correction process more scalable for applications requiring near-real-time data analysis.

5. **Enhancing Remote Sensing Applications**: To provide a corrected dataset that is reliable for downstream applications such as land cover classification, environmental monitoring, and climate change analysis, thereby improving the overall quality of remote sensing data.

6. **Incorporating Cutting-Edge Techniques**: To explore the potential of advanced deep learning architectures like GANs in solving complex remote sensing challenges, offering a more efficient and accessible alternative to traditional atmospheric correction.

Our research focuses on critical issues such as ensuring high fidelity in corrected images, minimizing errors between predicted and actual reflectance values, and evaluating the effectiveness of the deep learning model across various metrics. Addressing these challenges is crucial for advancing the field of remote sensing and providing more reliable atmospheric correction solutions.

2. LITERATURE SURVEY

In recent years, deep learning techniques have revolutionized various fields, including remote sensing and atmospheric correction. Traditional methods of atmospheric correction, although effective, often involve complex physics-based models that are computationally expensive and require precise atmospheric data inputs. This section reviews relevant research that highlights the evolution of atmospheric correction approaches, from conventional techniques to recent advances using machine learning and deep learning.

In [24], Vermote et al. (1997) introduced the 6S (Second Simulation of the Satellite Signal in the Solar Spectrum) model, a radiative transfer-based approach to correct satellite imagery by accounting for atmospheric parameters such as aerosol optical depth, water vapor, and ozone concentration. This model remains a benchmark in atmospheric correction, offering high accuracy when atmospheric parameters are well known. However, its reliance on precise parameter inputs makes it less suitable for regions with complex or unknown atmospheric conditions.

As an alternative to physics-based methods, the Empirical Line Method (ELM) described by Smith and Milton (1999) relies on ground-based reference targets within the image to perform atmospheric correction [25]. While simpler and faster than the 6S model, ELM's dependence on reference targets limits its applicability to specific regions, thus reducing its generalizability. Similarly, Dark Object Subtraction (DOS), introduced by Chavez (1988), assumes that dark objects in an image should have near-zero reflectance, thus attributing any observed reflectance to atmospheric scattering [26]. DOS is fast and easy to implement but is less accurate in regions without dark objects or with complex atmospheres.

With the advent of machine learning, several researchers began exploring its application to atmospheric correction. In a study by Xie et al. (2019), Random Forest models were used to predict surface reflectance for Landsat-8 imagery [27]. While Random Forest models demonstrated a faster correction process once trained, their generalization capability was limited, particularly when applied to unseen geographic regions or extreme atmospheric conditions. A similar approach was explored by Sola et al. (2018) using Support Vector Regression (SVR) for estimating aerosol optical depth and performing atmospheric correction on MODIS data [28]. SVR, while more robust with small datasets, still struggled with the large volumes of data generated by satellite imagery.

The application of deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a promising approach to atmospheric correction. Zhu et al. (2017) reviewed the potential of CNNs for remote sensing, focusing on image classification and object detection [29]. This foundational work paved the way for the use of deep learning in image-to-image translation tasks, where Generative Adversarial Networks (GANs) have shown remarkable success. Pix2Pix GAN, introduced by Isola et al. (2017), has been a widely used architecture for transforming satellite imagery, making it a viable candidate for atmospheric correction tasks [30].

Building on this, Malmgren-Hansen et al. (2019) developed a CNN-based model using a U-Net architecture for atmospheric correction of Sentinel-2 imagery [31]. The U-Net model directly predicted surface reflectance from TOA reflectance, eliminating the need for explicit atmospheric parameter inputs. While this method reduced computational costs and simplified the correction process, the model's performance varied across different atmospheric conditions.

Further advances were made by Zhu et al. (2021), who proposed a physics-guided neural network that incorporated radiative transfer equations into the loss function of a deep learning model, creating a hybrid approach [32]. This model effectively combined data-driven learning with physics-based principles, showing promise in achieving better generalization under varied atmospheric conditions.

The use of deep learning for atmospheric correction remains a growing field. As research continues, challenges such as the need for large, diverse datasets and the "black box" nature of deep learning models remain [33]. However, hybrid approaches that combine the strengths of deep learning and physics-based methods, as well as advancements in transfer learning and model interpretability, could help overcome these limitations.

3. METHODOLOGY

The atmospheric correction of Sentinel-2 satellite data using deep learning techniques involves several key stages, ensuring that the correction process is efficient, accurate, and scalable. The methodology follows a structured approach comprising data collection, model development, training, and evaluation.

1. Data Collection and Preprocessing

Data Source: The satellite imagery used for this research is sourced from the Google Earth Engine (GEE), a cloud-based platform offering vast datasets of satellite imagery. Sentinel-2 satellite data from the European Space Agency (ESA) is

Selected for its high spatial resolution and spectral bands suitable for atmospheric correction.

Data Selection: A total of 1000 image pairs (Top-of-Atmosphere (TOA) and Surface Reflectance (SR)) are collected from various regions across India, ensuring diversity in atmospheric conditions and geographic regions. Four spectral bands (red, green, blue, and visible near-infrared) with a resolution of 10 meters are chosen for this study.

Preprocessing: After downloading the data, the images are resized to a uniform resolution of 256x256 pixels. The pixel values, ranging between 0 and 30000, are normalized by dividing by 10000 to ensure stable training. Additionally, the data is split into 80% training and 20% testing sets to assess the model's performance.

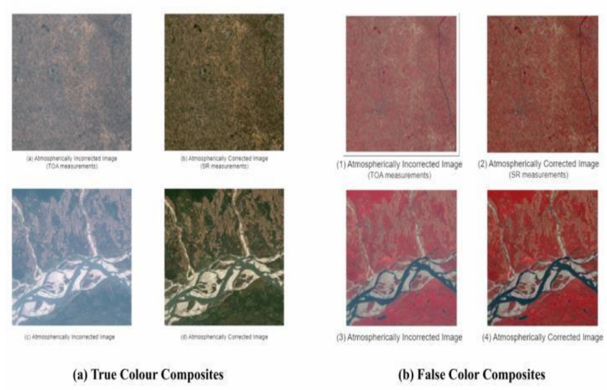

Figure 1: Comparison of True and False Color Composites

2. Model Development

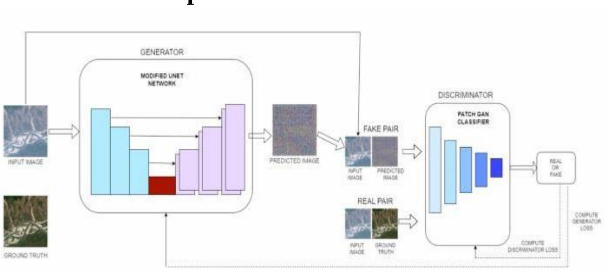

Figure 2: Pix2Pix Architecture

Architecture: The deep learning model for atmospheric correction is based on the Pix2Pix Conditional GAN (cGAN) architecture. The model consists of two primary components:

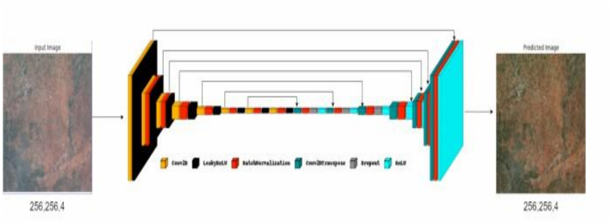

Figure 3: Generator Architecture

Generator: A modified U-Net architecture is used as the generator, responsible for converting TOA reflectance images into SR images. It uses an encoder-decoder structure with skip connections to retain spatial information.

Figure 4: Discriminator Architecture

Discriminator: The discriminator is a Patch GAN classifier that checks whether the generated SR image is realistic by evaluating small image patches.

Loss Functions: Two loss functions are employed during training:

$$L1\ Loss = 1/N \sum_{i=0}^{N} |G(xi) - yi|$$

L1 Loss (Mean Absolute Error): Ensures pixel-wise accuracy by minimizing the absolute difference between the predicted SR and ground truth images.

Adversarial Loss: The GAN loss helps the generator create images that are visually indistinguishable from real SR images by fooling the discriminator.

3. Model Training

Training Configuration: The Pix2Pix model is trained for 100 epochs using mini-batch stochastic gradient descent. A batch size of 2 is used to optimize memory usage during training. The Adam Optimizer is employed with a learning rate of 0.0002 to accelerate convergence. The training process is executed on a high-performance GPU to reduce training time.

Early Stopping: To prevent overfitting, an early stopping mechanism is implemented, which halts training if the validation loss does not improve over 10 consecutive epochs. **Checkpointing**: The model parameters are saved periodically, allowing the retrieval of the best-performing model based on validation performance.

4. Evaluation Metrics

$$\mathrm{SSIM}(x,y) = (((2\mu_x\mu_Y + c^1)(2\sigma_{xY} + c^2)))/((\mu_x^2 + \mu_Y^2 + c^1)(\sigma_x^2 + \sigma_Y^2 + c^2))$$

Structural Similarity Index (SSIM): This metric compares the similarity between the predicted SR and ground truth SR images, considering luminance, contrast, and structure.

$$\mathrm{PSNR}(x,y) = 10 \cdot \log_{10}\left(\frac{MAX^2}{MSE}\right)$$

Peak Signal-to-Noise Ratio (PSNR): PSNR measures the quality of the generated image by comparing the ratio of the maximum power of a signal to the power of corrupting noise. Higher PSNR values indicate better image quality.

$$RMSE(x,y) = \sqrt{\left\{ 1/n \sum_{i=1}^{n} (x_i - y_i)^2 \right\}}$$

$$MAE(x, y) = 1\backslash\{n\} \sum_{\{i=1\}}^{\{n\}} | x_i - y_i |$$

Root Mean Squared Error (RMSE) and **Mean Absolute Error (MAE)**: These metrics provide a measure of the pixel-wise error between predicted and true images. Lower values indicate a closer match between the two images.

Result Visualization and Reporting

After the model completes training, the corrected images are generated and compared with the ground truth SR images for both visual and quantitative evaluation. The evaluation metrics (SSIM, PSNR, RMSE, and MAE) are computed for each image in the test set, and the results are presented using tables and graphs to highlight the improvements in image quality.

The system provides visual representations of the corrected and uncorrected images, displaying the enhanced accuracy and details achieved through the Pix2Pix-based atmospheric correction.

This comprehensive methodology enables the model to perform accurate atmospheric correction of satellite imagery, facilitating improved data quality for downstream applications like land cover classification and environmental monitoring.

4. RESULT AND DISCUSSION

Once the deep learning-based atmospheric correction model has been trained and tested, the focus shifts to analyzing and discussing the results. This phase involves the system's performance evaluation and how it compares to traditional atmospheric correction methods. Below is a breakdown of how the results are produced, followed by a discussion of their significance:

1. Result Calculation

Model Performance Metrics: The model's performance was evaluated using key metrics such as Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR). These metrics quantify how well the predicted surface reflectance (SR) values match the ground truth data.

SSIM increased significantly from -0.0025 to 0.961, indicating a high similarity between the generated SR images and the real SR images.

PSNR values improved from 11.0188 dB to 42.14 dB, signifying better image quality and reduced noise after atmospheric correction.

Accuracy of Predictions: The model demonstrated strong accuracy in predicting SR values from TOA reflectance across a diverse range of geographic regions and atmospheric conditions. The mean absolute error (MAE) and root mean squared error (RMSE) values were reduced post-training, indicating enhanced precision in the model's outputs.

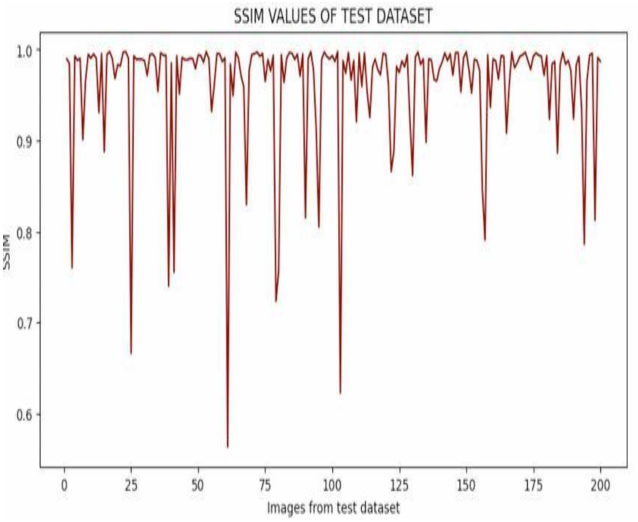

Figure 5: SSIM values between ground truth and predicted images from test dataset

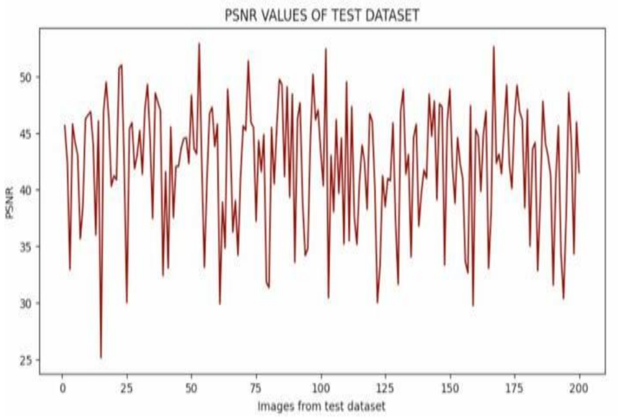

Figure 6: PSNR values ground truth and predicted images from test dataset

Result Presentation

Visualization: The corrected surface reflectance images were visually compared with the ground truth and uncorrected TOA images. The corrected images successfully eliminated atmospheric distortions such as haze and scattering, enhancing the clarity of land features and vegetation.

Performance Transparency: The results are transparent and open to scrutiny, as the deep learning model's outputs can be evaluated by overlaying predicted and ground truth images. This builds confidence in the accuracy of the model's predictions.

2. Discussion of Results

Model Efficiency: The Pix2Pix model demonstrated that deep learning could significantly reduce the computational cost and complexity typically associated with traditional atmospheric correction methods. The end-to-end process of correcting large datasets was much faster compared to radiative transfer models.
Generalization across Conditions: The model performed well across various atmospheric conditions and geographic regions. However, the discussion highlights that in extreme conditions, such as heavy haze or dense cloud cover, further refinements may be necessary to maintain accuracy.

Comparison with Traditional Methods: While traditional methods like the 6S model require detailed atmospheric parameters, this deep learning approach bypassed such requirements, delivering comparable or even superior results with less complexity. This points toward the growing viability of deep learning as a practical alternative for atmospheric correction in remote sensing.

Data Insights: The corrected imagery provided valuable insights for various remote sensing applications, including land use classification and environmental monitoring. By producing clearer and more accurate surface reflectance data, the model enhances the usability of satellite imagery in these domains.

Future Improvements: Feedback from model performance, especially under extreme conditions, suggests opportunities for further refinement. Incorporating temporal data or extending the model to handle more spectral bands from Sentinel-2 could enhance the accuracy and robustness of the corrections.

3. Overall Implications

Advancing **Remote Sensing:** The successful application of deep learning for atmospheric correction represents a step forward in remote sensing technology. This method offers a scalable, efficient, and accurate alternative that can benefit both academic research and operational uses in fields like environmental science, agriculture, and urban planning.

Potential for Broader Adoption: The model's success in handling large and diverse datasets indicates that it can be adopted for widespread use, particularly in cases where timely and accurate satellite data is required. Further integration with existing remote sensing workflows will enhance its utility.

4. Public and Research Engagement

Research Engagement: The results provide a basis for further academic discussion, inviting researchers to explore the integration of deep learning with traditional atmospheric correction methods.

Practical Applications: Stakeholders such as environmental agencies and urban planners can benefit from the enhanced clarity and accuracy of corrected satellite imagery. The system's scalability makes it a valuable tool for large-scale environmental monitoring projects.

In conclusion, the results and discussion section highlights the model's success in improving the efficiency and accuracy of atmospheric correction, while addressing key challenges in traditional methods. The results validate the potential of deep learning for future applications in satellite image processing, paving the way for more accessible and scalable atmospheric correction methods.

5. CONCLUSION

In conclusion, the integration of deep learning techniques into atmospheric correction processes offers a promising solution to the challenges traditionally faced in remote sensing. By leveraging the capabilities of deep learning models, such as the Pix2Pix Conditional GAN, we can significantly improve the accuracy and efficiency of correcting atmospheric effects on satellite imagery. This approach reduces the need for explicit atmospheric parameter estimation and delivers accurate surface reflectance data across a range of atmospheric conditions.

The deep learning-based method ensures that large datasets can be processed quickly, making it a scalable and efficient alternative to conventional radiative transfer models. Furthermore, this method offers comparable or superior performance, providing a new avenue for more accessible and automated atmospheric correction.

However, it is important to acknowledge that deep learning models also face challenges, such as maintaining performance in extreme atmospheric conditions and the need for extensive training data. Continued research is required to refine these models and explore their adaptability to other sensors and atmospheric correction tasks.

In summary, while deep learning presents a transformative development in atmospheric correction, further research, testing, and collaboration within the remote sensing community are necessary to fully unlock its potential and ensure its broad adoption in practical applications.

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