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Deep Learning Based Sentinel-2 Super Resolution Methods for Supporting Climate Change Adaptation & Mitigation Applications

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Introduction

Europe's efforts towards the implementation of the Paris Agreement for Climate Change (CC) are substantial. The earth observation data from the Sentinel program provide the required information to support CC adaptation and mitigation policies. However, their uptake in the context of CC applications is often limited due to inherent spatial resolution constraints. To address this challenge, the EIFFEL Horizon2020 project provides tools to enhance the spatial resolution of earth observation data to address the needs of five different CC adaptation and mitigation applications.

One of the satellite missions that can support the envisioned CC-related applications is Sentinel 2, which provides environmental monitoring of aspects such land use change (Phiri et al., 2020), detailed forest health monitoring (Gupta and Pandey, 2021) and water availability (Bhangale et al., 2020). Sentinel 2 sensor acquires four bands at 10 m resolution, six bands at 20 m resolution, and three bands at 60 m resolution. When using Sentinel 2 data, it is always favorable to have all bands available at the highest spatial resolution, to support more detailed and accurate information extraction (Lanaras et al., 2018). Given the wide range of CC-related applications that Sentinel 2 data can support, it is mandatory to develop an efficient tool for **enhancing the 20 m and 60 m spatial resolution Sentinel 2 bands to 10 m**.

Deep-learning (DL) based super-resolution methods have demonstrated efficient performance in enhancing Sentinel 2 bands of 20 and 60 m spatial resolution. Most of the existing DL Sentinel 2 super-resolution methods are based on deep residual neural network architectures which can alleviate the vanishing gradient problem and can achieve a faster convergence speed during training (Lanaras et al., 2018; Palsson et al., 2018; Wu et al., 2020). The performance of deep residual networks can be sensitive to important training hyperparameters. **This study evaluates the performance of a deep residual network architecture for Sentinel 2 Super-Resolution when trained with a large training dataset and the effects of various training hyperparameters such as:**

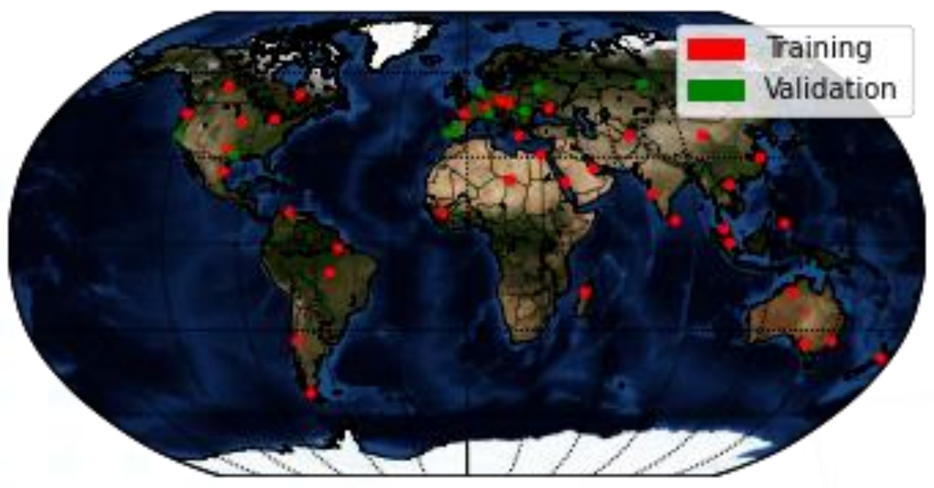
- **size of patches**
- **number of training epochs**
- **batch size**
- **number of residual blocks**
- **loss function**

The most efficient hyperparameter configuration is used for training the Sentinel-2 super-resolution network, which will provide Sentinel-2 data with enhanced spatial resolution bands. The enhanced data will support five different CC adaptation & mitigation applications under the frame of EU-funded project EIFFEL (grant agreement No. 101003518).

Methodology

Training Dataset Preparation

45 cloud-free Sentinel 2 Level 2A images from around the globe.



The images were split into training and validation datasets (80/20).

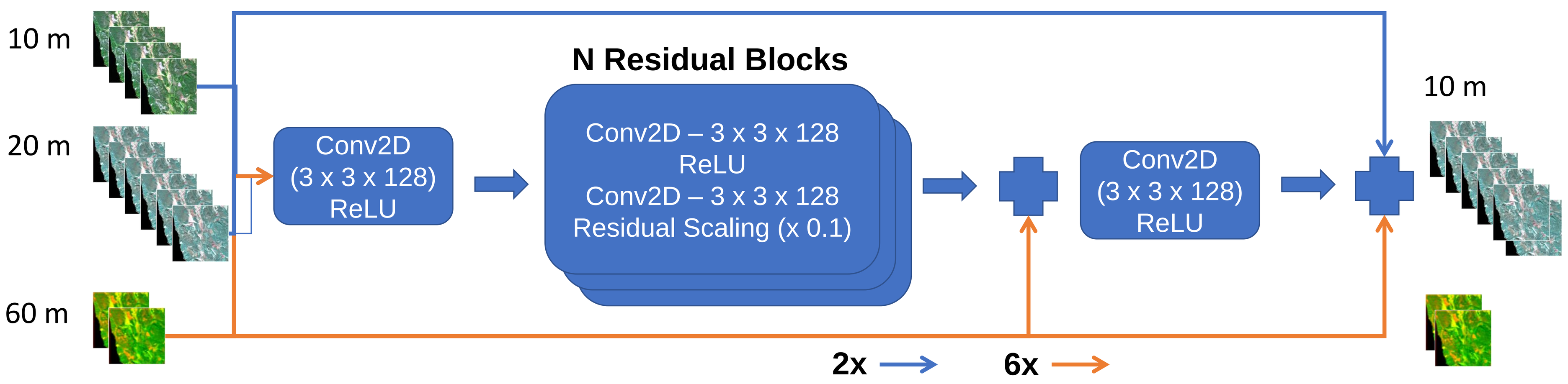
Due to the lack of high-resolution reference images, the images were downscaled with bilinear interpolation by a scale factor of 2 and 6 and recovered to their original spatial resolutions. The original coarse images were used as the reference and the downgraded-recovered as the input during training.

Three different training datasets were created by tiling each image into 1000 tiles of three different patch sizes (32x32, 64x64, 128x128).

Evaluation was performed on 5 test images covering 5 individual pilot areas.

Deep Residual Neural Network Architecture

The **Deep Sentinel-2 (DSen2)** is a well known ResNet architecture with verified performance on super-resolving Sentinel 2 data and fast convergence during training process (Lanaras et al., 2018).



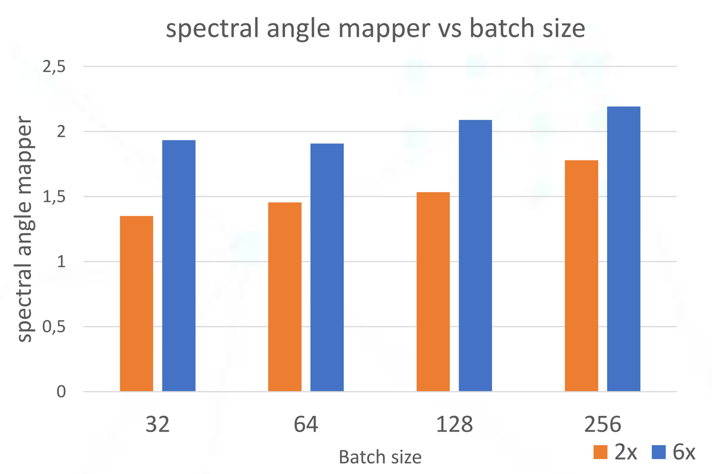
Training Settings

DEFAULT: Patch size = 32, Batch size = 128, Loss function = Mean Absolute Error (MAE), Residual blocks = 6, Optimizer = ADAM with Nesterov momentum, learning rate = 10^{-4} (reduced by a factor of 2 when stable for 5 epochs), Epochs = 50

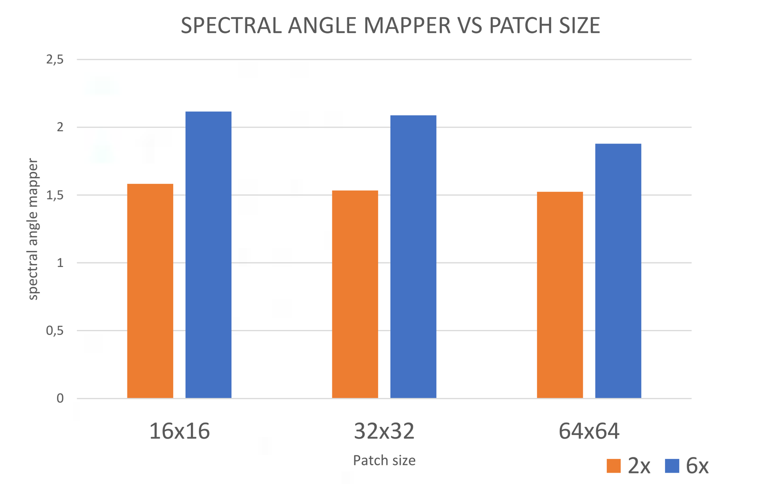
EVALUATED: Patch size = 16, 32, 64 - Batch size = 32, 64, 128, 256 - Loss function = MAE, MSE, Huber Loss, Relative Dimensional Global Error (ERGAS) – Number of Residual blocks = 1, 6, 12

Various quantitative evaluation metrics were computed during training at the end of each epoch and for the test images: **MAE**, **Peak Signal-Noise Ratio (PSNR), spectral angle mapper (SAM), ERGAS, universal image quality index (UIQ).**

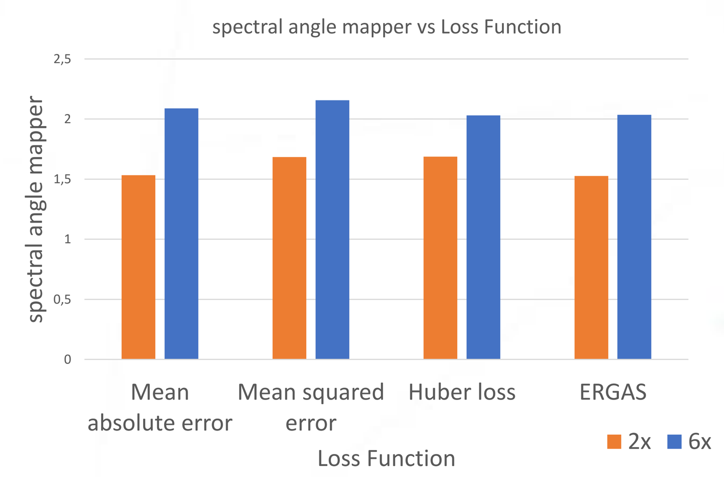
Results & Conclusions



Batch size 32 is better for both 2x and 6x



Larger scale factor (6x) requires larger patch size (64 x 64)



MAE and ERGAS have the best performance

	2X	6X
Batch size	32	32
Patch size	32	64
Num of residual blocks	6	
Loss function	Mean absolute error	

	MAE	PSNR	SAM	ERGAS	UIQ
2x	0.0121	34.7523	1.3308	1.4961	0.9991
6x	0.0159	32.2598	1.9371	2.4763	0.9986

Future Directions

- Super-resolved Sentinel-2 data will be used as input to five different CC related applications.
- The actual enhancement of the CC application results will be the evidence of the value of Sentinel-2 DL super-resolution techniques in supporting CC mitigation and adaptation applications.

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REVEALING THE ROLE OF GEOSS AS THE DEFAULT DIGITAL PORTAL FOR BUILDING CLIMATE CHANGE ADAPTATION & MITIGATION APPLICATIONS

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