Deep Learning techniques for Satellite data: Atmospheric Corrections

Daniel García Díaz, Ignacio Heredia Cachá
garciad@ifca.unican.es, iheredia@ifca.unican.es
Instituto de Física de Cantabria (IFCA) (CSIC-UC)

Introduction

Remote sensing is a technique that allows obtaining information about an object through the analysis of data acquired by sensors that are not in contact with it, and the detection of changes from a multi-temporal sequence of satellite data is one of its most important applications.

As is well known, this process requires the application of atmospheric corrections to the images, so that the changes detected are only attributable to real landscape modifications. One of the techniques often recommended for applications of classification and detection of changes is the Dark Object Subtraction (DOS).

The technological advances in the sensors and the spatial and temporal resolutions now available open the door to new ways of monitoring the Earth by applying the latest techniques in machine learning or deep learning to these data.

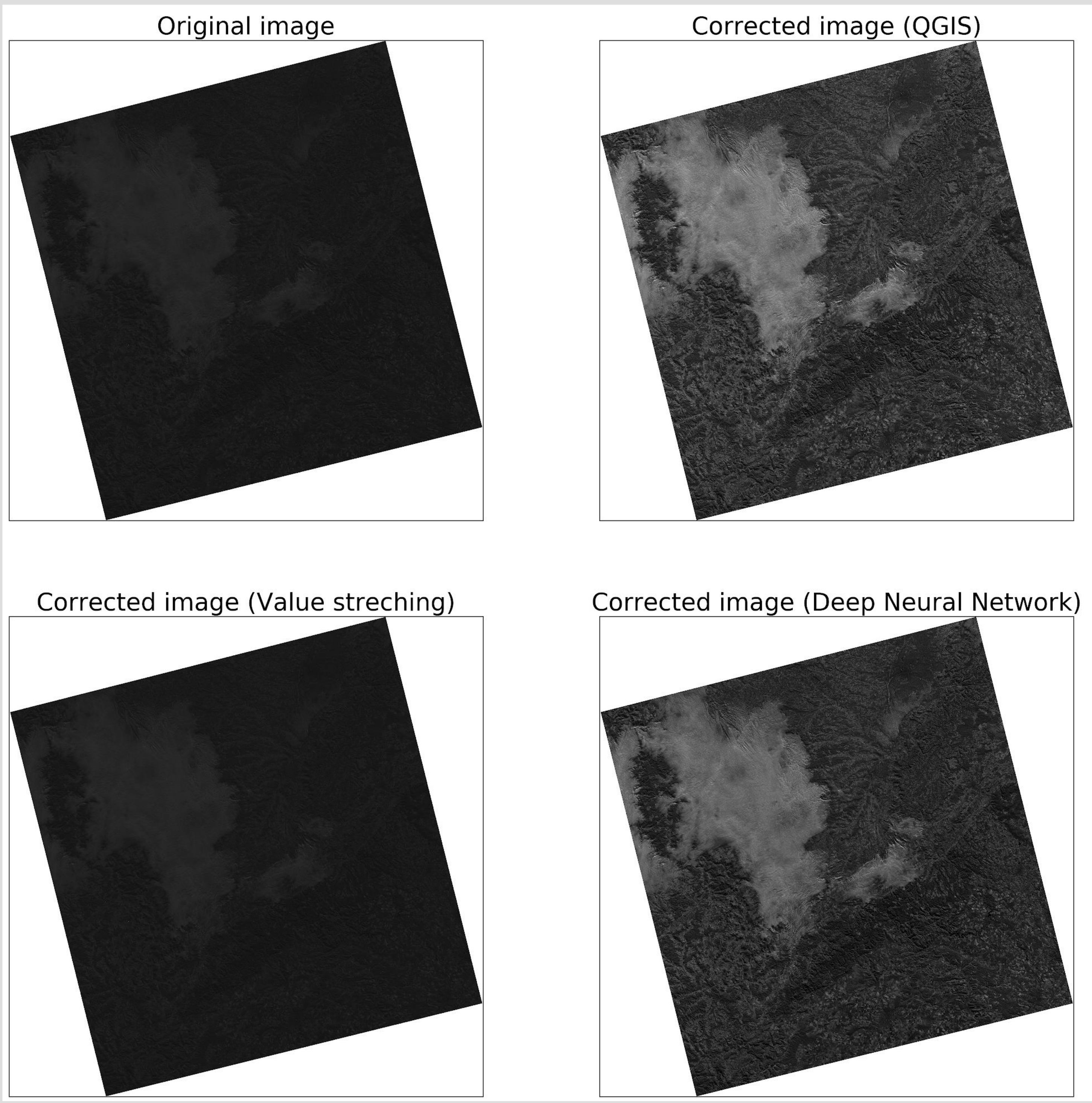

Fig 1: Image of the band 5 (λ = 0.851 - 0.897 µm) of Germany of the Landsat 8 satellite (NASA.)

Methods

The DOS atmospheric correction assumes that if there are areas in an image with very low reflectance values, any apparent reflectance in these areas should be the product of atmospheric scattering, and this information can be used to calibrate the rest of the image.

Data processing

Our approach to apply atmospheric correction consists of training the convolutional neural network to learn the correlation between the original image and the corrected image, like in the figure below.

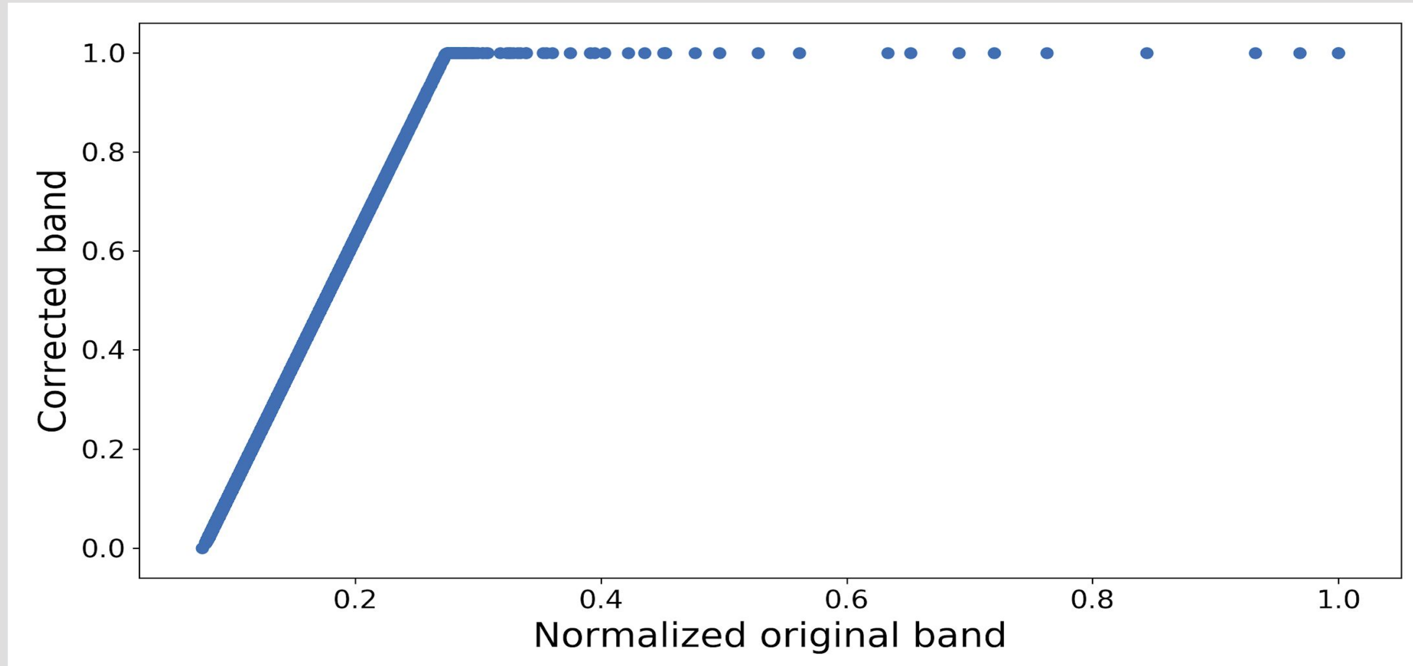

Fig 2: Correlation between the original band and the corrected band by DOS method

Convolutional Neural Network

Instead of using images to feed the convolutional neural network, we use the histograms of the pixel values images as inputs. As output values to predict we will use two points defining the linear fit of the correlation plot.

Using a small vector (the histogram values) instead of a full image allows us to use a small and simple neural network, which can be trained very fast (~20 min). The architecture of the network consists of a 5-layers deep fully connected network with Dropout. This architecture remains very simple, leaving us with a huge margin to improve these results.

Results

After training the convolutional neural network with tiles from six different countries that cover all types of landscape (including water, snow, ...). The results of applying the atmospheric corrections with the neural network can be seen in Figure 1 and 3.

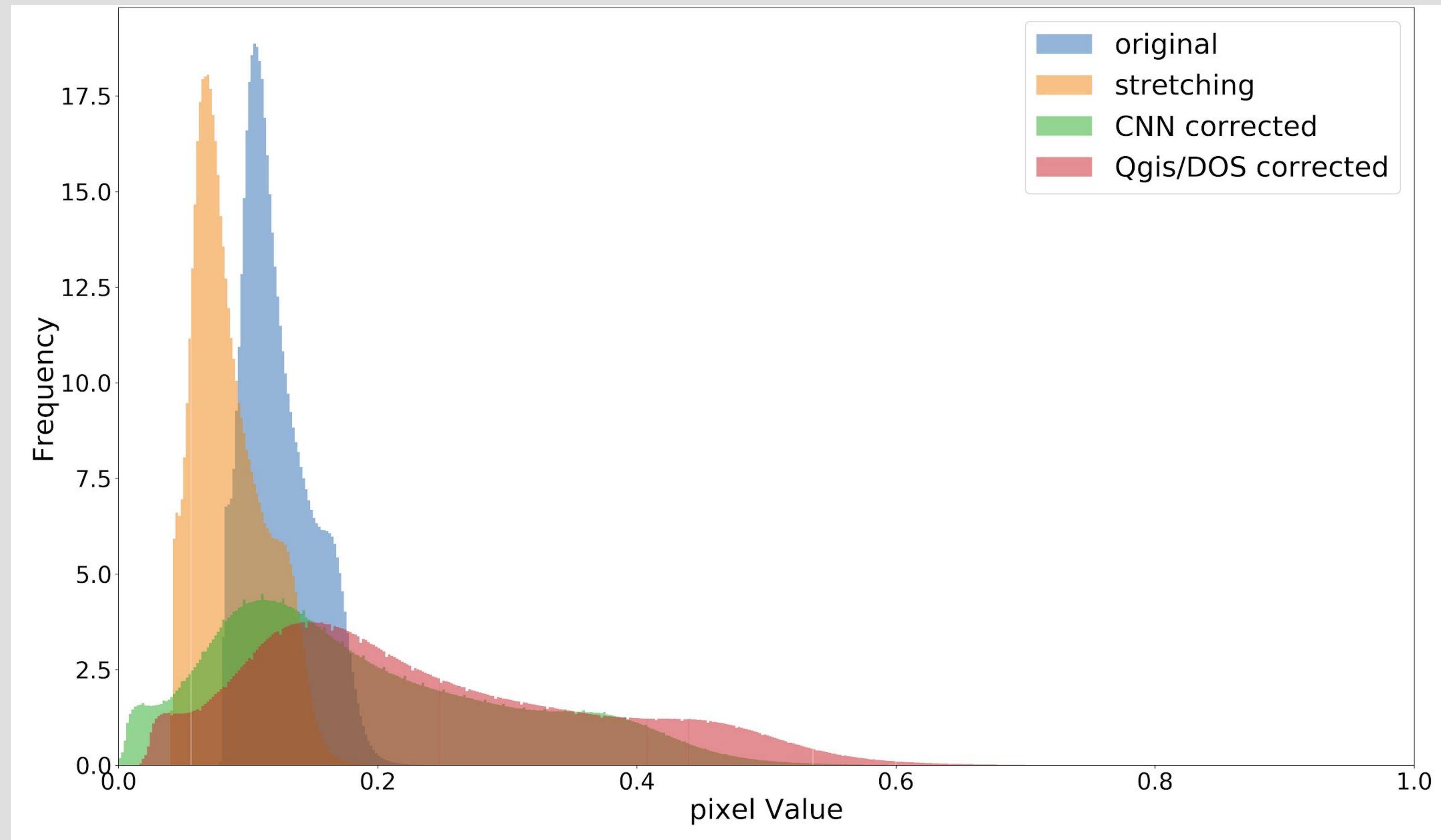

Fig 3: Image of the histograms calculated for the different images. The streching histogram is the original histogram equalized so that the contrast in the image is enhanced.

Conclusions

- Taking as reference the stretching (equalization) of the original histogram, the atmospheric corrections applied by the neural network greatly improve the quality of the image, being similar to the corrections applied by traditional methods.
- Once trained, the neural network applies atmospheric corrections three times faster than traditional methods (like DOS), going from 1 minute per band using programs such as Qgis to 20 seconds in the case of the neural network.
- This method is not only applicable to simple atmospheric corrections such as the DOS method, it can also be used for more developed radiative transfer models like LOWTRAN, MODTRAN or 6S.

XDC - eXtreme DataCloud is co-funded by the Horizon2020 Framework Program – Grant Agreement 777367
DEEP-Hybrid-DataCloud is funded by the Horizon 2020 Framework Programm Grant agreement number 777435