אוניברסיטת חיפה
University of Haifa

Department of Geography and
Environmental Studies

SUPER RESOLUTION SUB-PIXEL CONVOLUTIONAL NEURAL NETWORK VERSUS DATA FUSION

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Basic terminology

- **Pan-sharpening** - merging of a monochrome image acquired by a broadband panchromatic (Pan) instrument with a multispectral (MS) image over the same area

- **Multi-temporal pan-sharpening** – the merged MS and Pan datasets are acquired from the same platform but at different times

- **Multi-platform pan-sharpening** - the merged MS and Pan datasets are acquired from different platforms and at different times

Data fusion – combination of spatial details resolved by the Pan instrument and the spectral diversity of the MS image into a unique product

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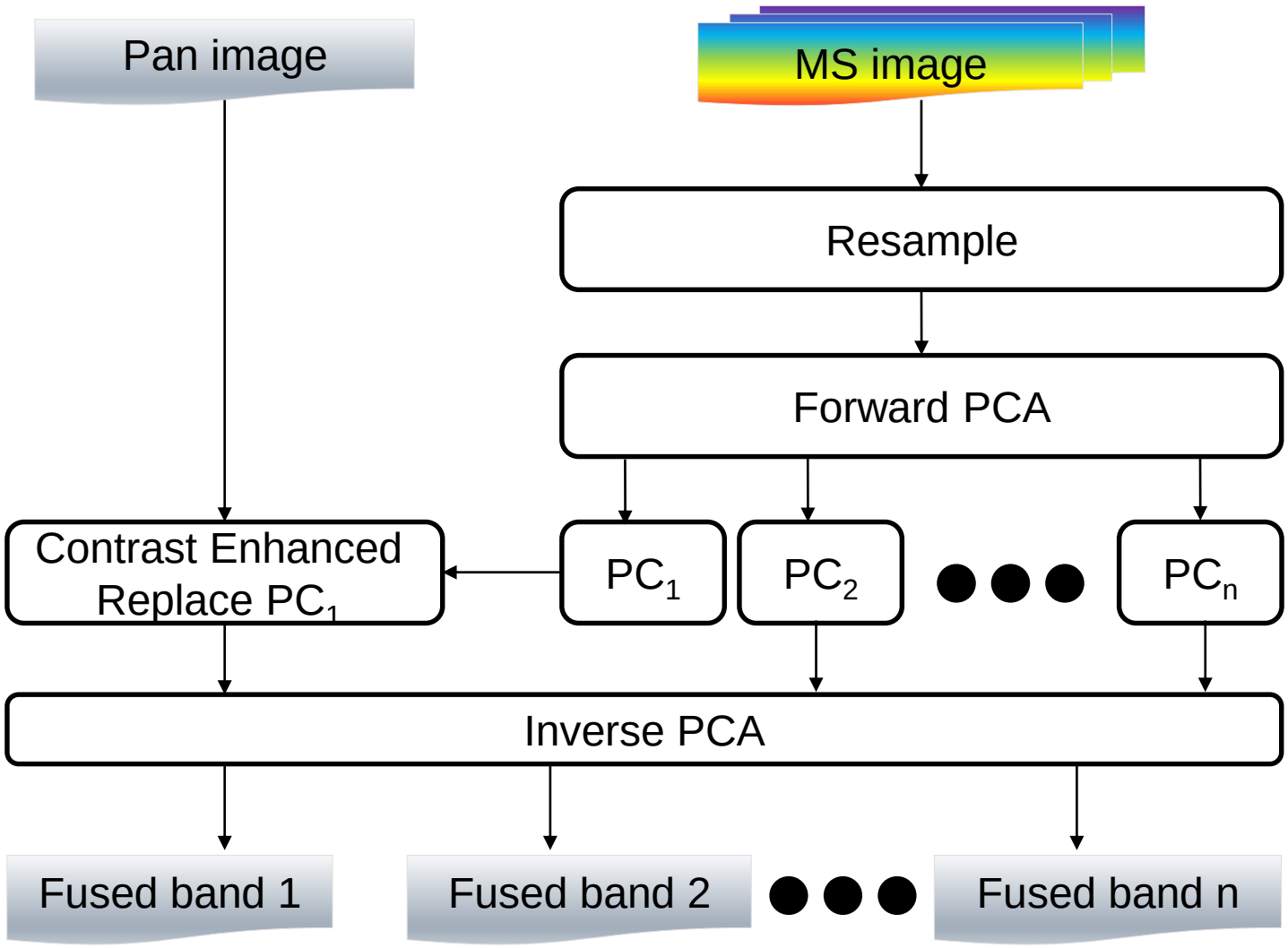
Basic terminology

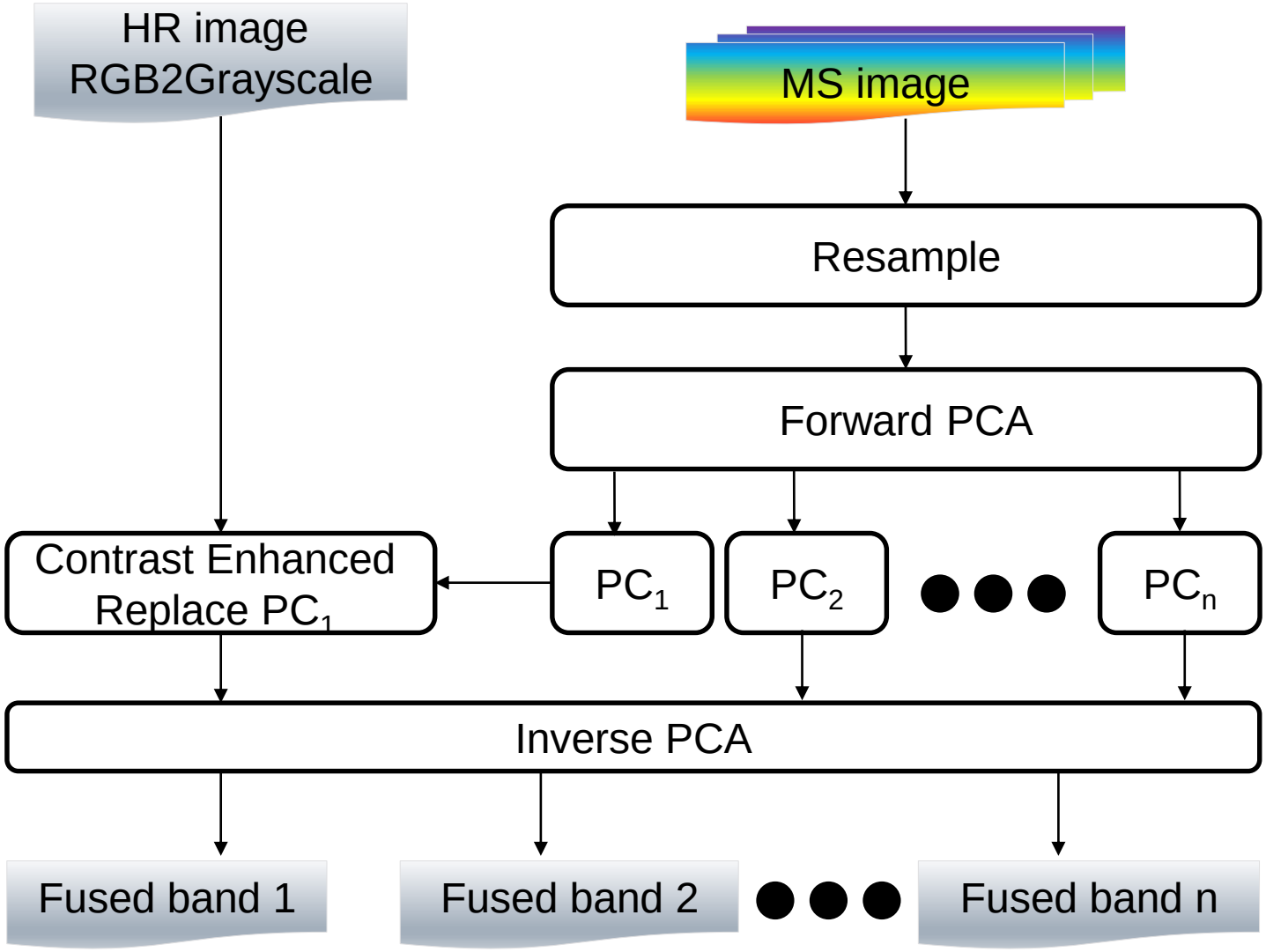
- **Super-resolution** - spectral-spatial (pan-sharpening) and spatio-temporal image resolution enhancement algorithm
  - Input: multiple spatial/spectral/temporal low-resolution images of the same scene
  - Process: fusion model that maps the high-resolution image into the low-resolution
  - Output: High-resolution reconstructed image

- **Image fusion as a restoration problem** - reconstruction of the original scene from a degraded observation = classical deconvolution problem

Pan-sharpening via PCA



Multi-platform pan-sharpening via PCA



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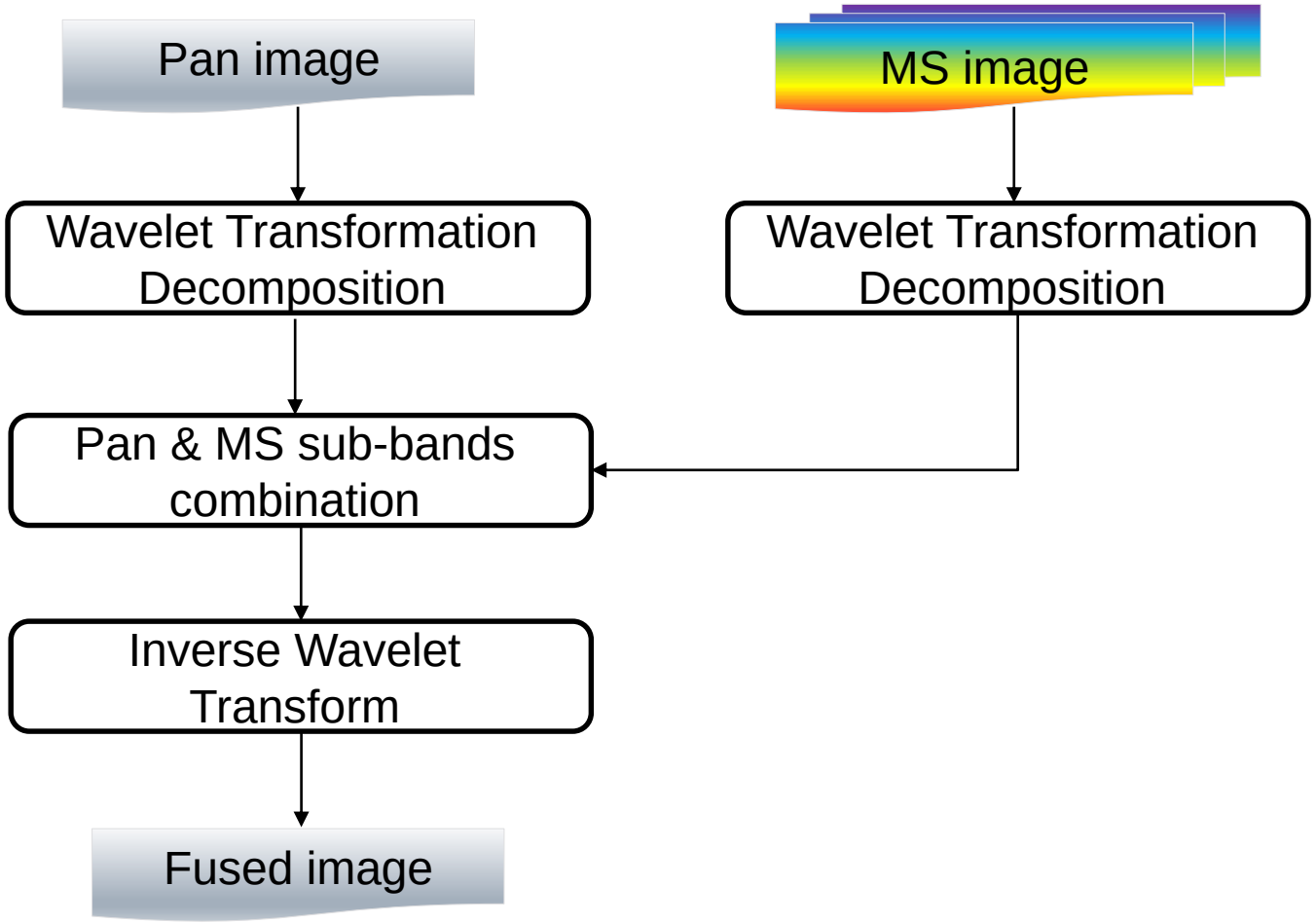
Pan-sharpening via DWT



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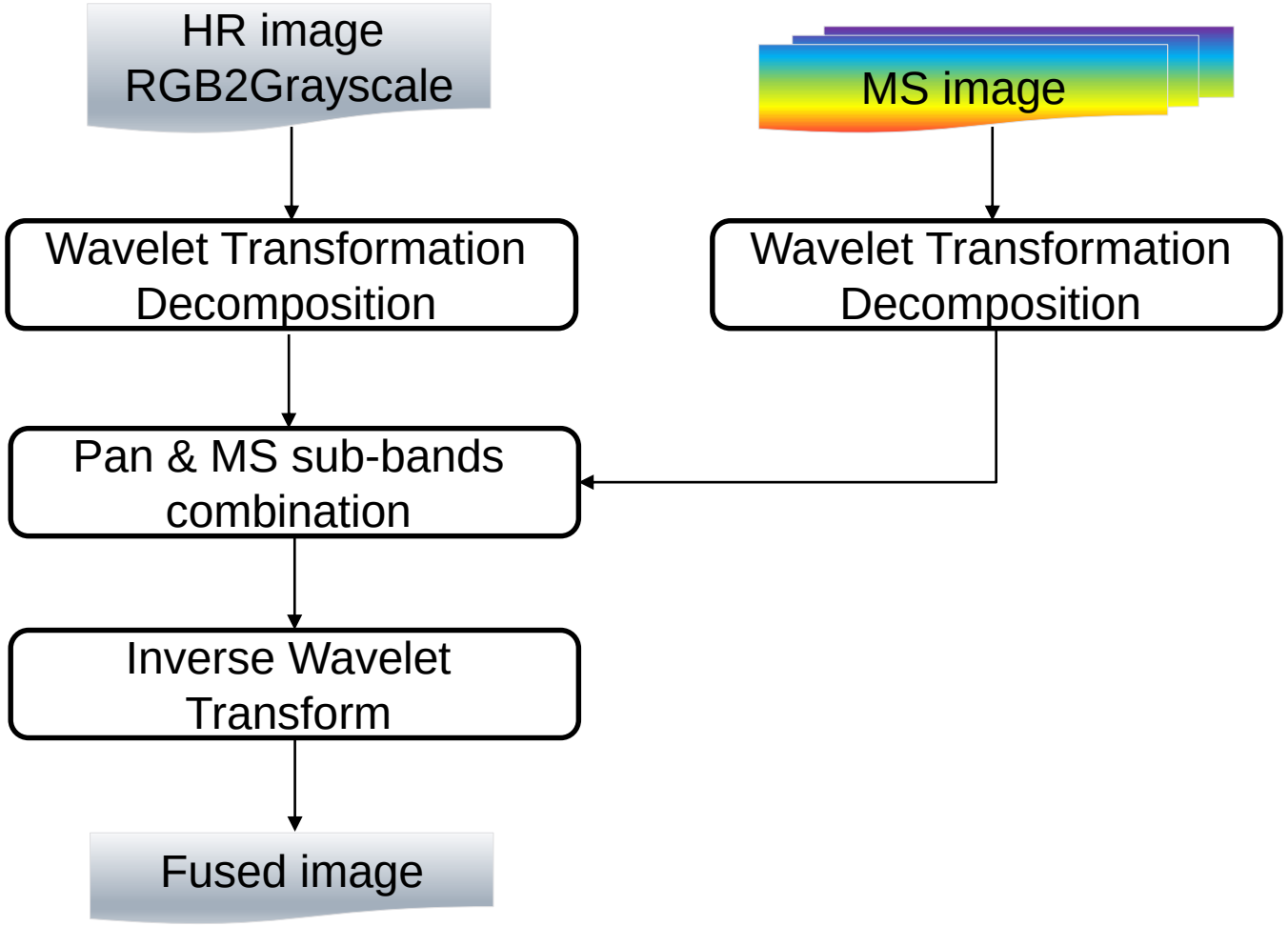
Multi-platform pan-sharpening via DWT



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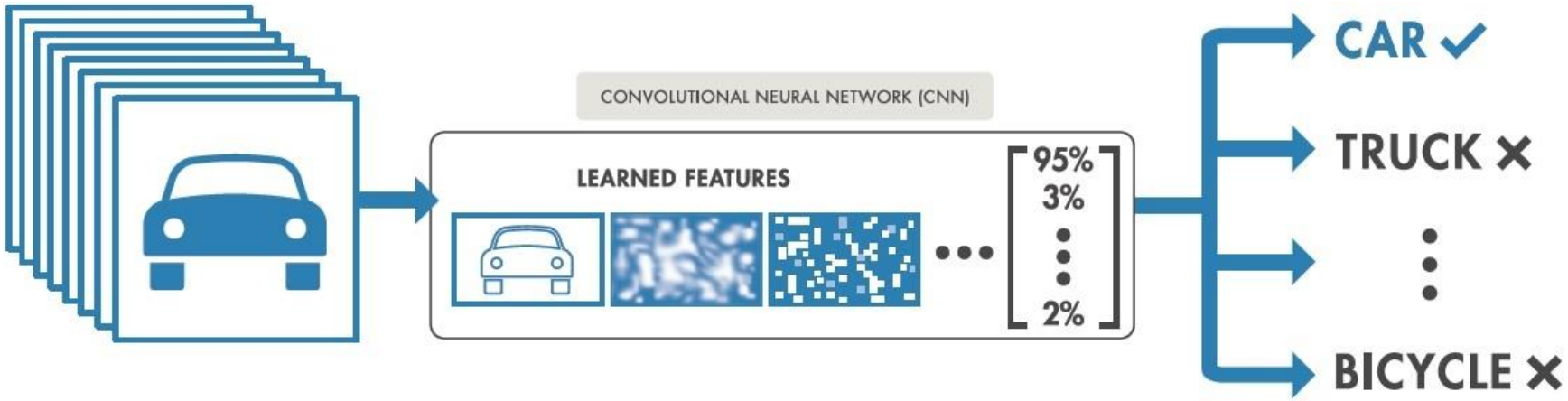
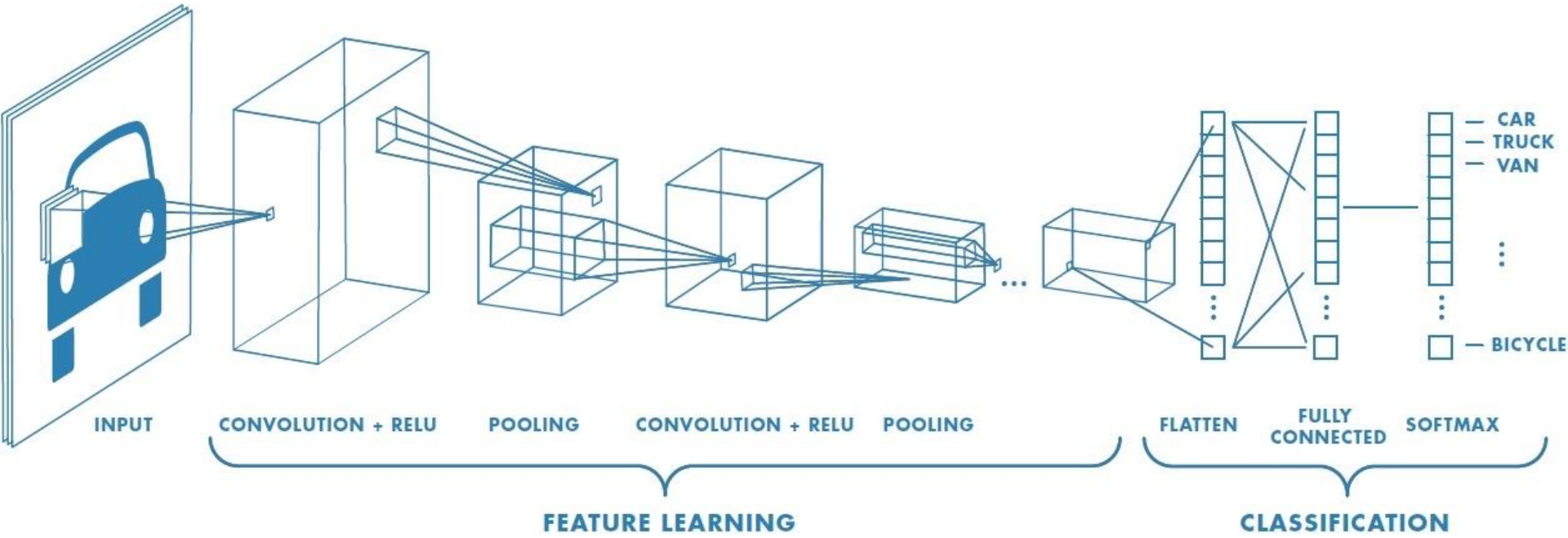
Convolutional Neural Network

- Deep learning technique
  - Learn directly from image data
  - Eliminating the need for manual feature extraction



Source: www.mathworks.com

How CNNs Work



- Filters are applied to each training image at different resolutions
- The output of each convolved image is used as the input to the next layer
- The filters start as very simple features and increase in complexity to features that uniquely define the object

Source: www.mathworks.com

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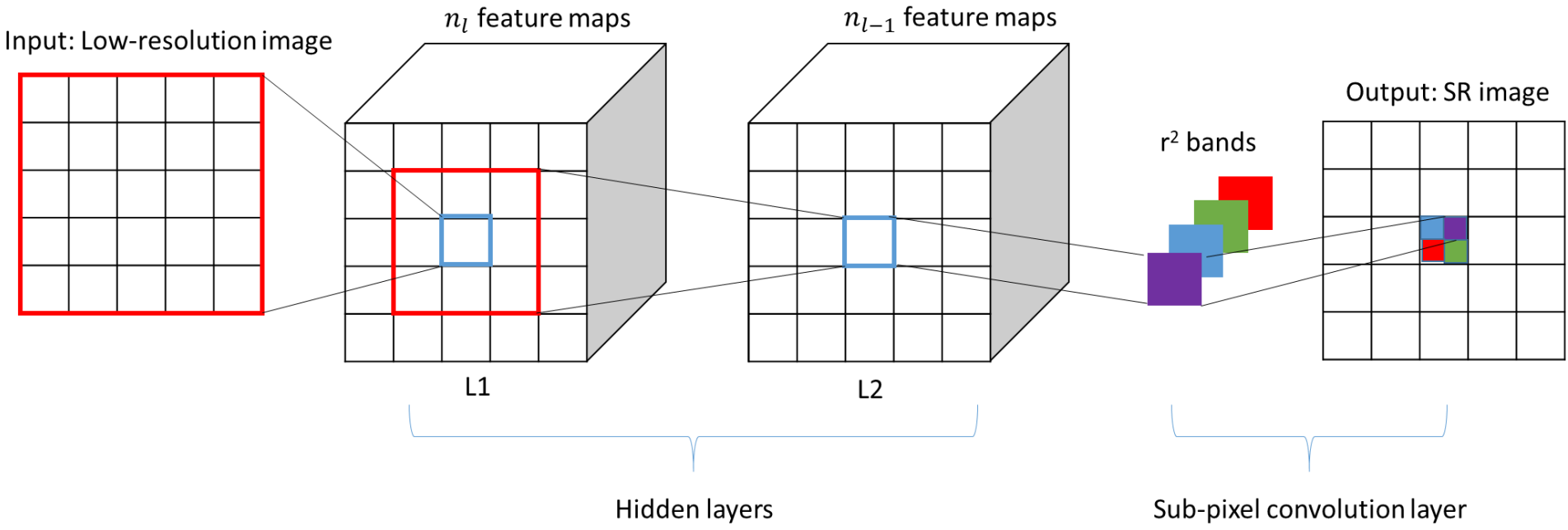
SR and CNN



- feature maps extraction feature learning
- feature maps aggregation from LR space

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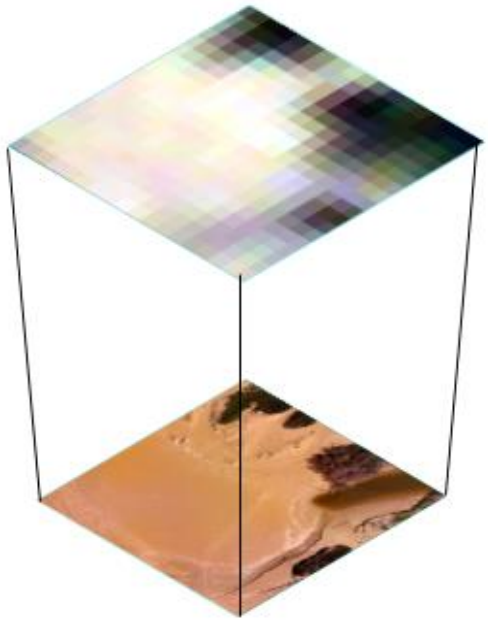
Case Study

- DJI PHANTOM-4 drone with a high-resolution RGB camera on a gimbal with three stabilization planes
- RapidEye - a full end-to-end commercial Earth Observation system comprising a constellation of five mini-satellites across 440 to 850 nm
- Sentinel-2 - multi-spectral imager with 12 spectral bands spreads over three levels of resolutions 10, 20 and 60 m
- Landsat 8 – pushbroom sensor with 7 bands across 440 to 2290 nm and 30m pixel size + pan image with 15 m



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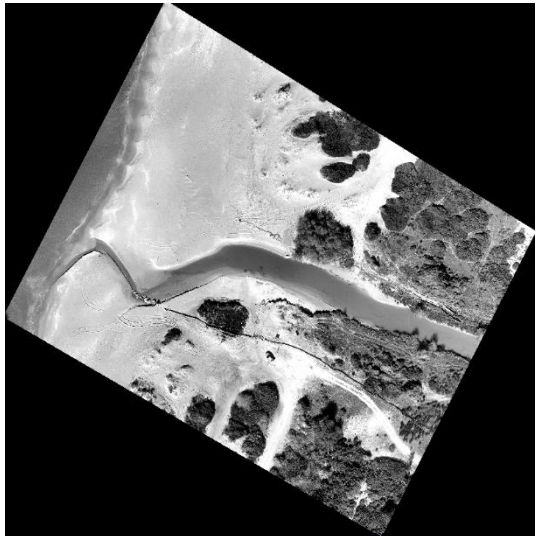
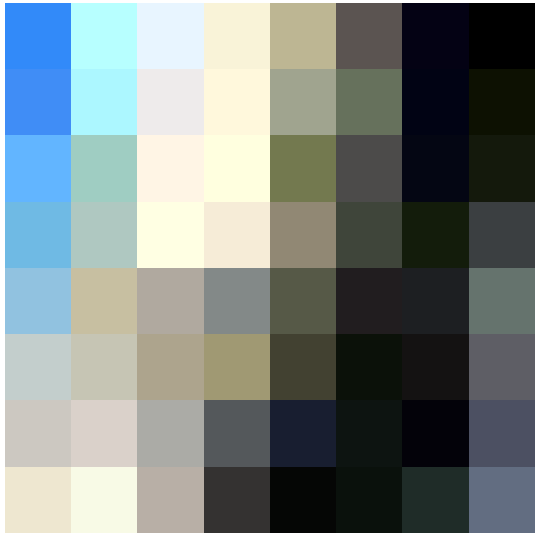
Results PCA

HR



L8



RapidEye

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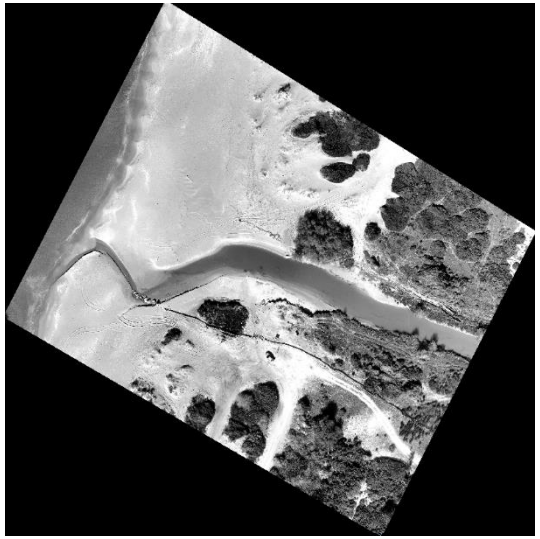
Results DWT

HR



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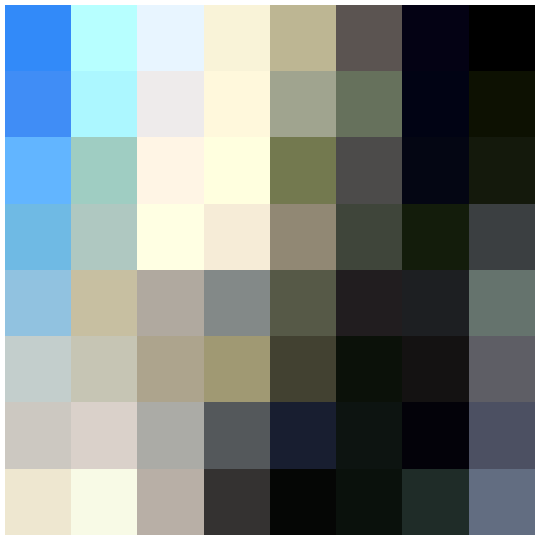
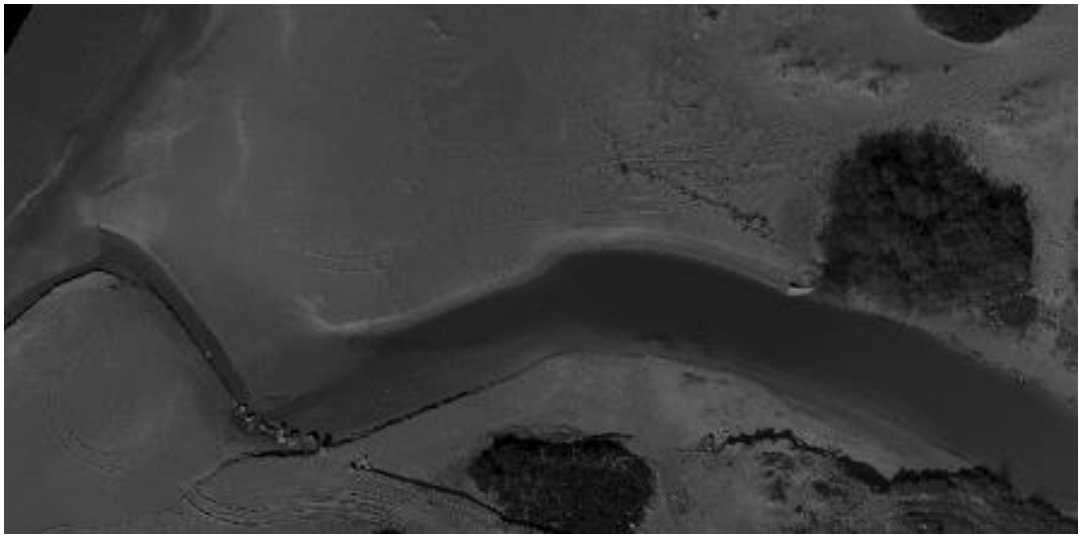


RapidEye



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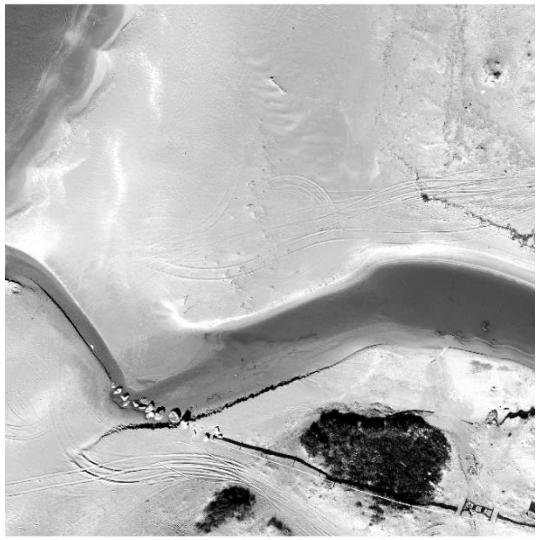
Results CNN

HR



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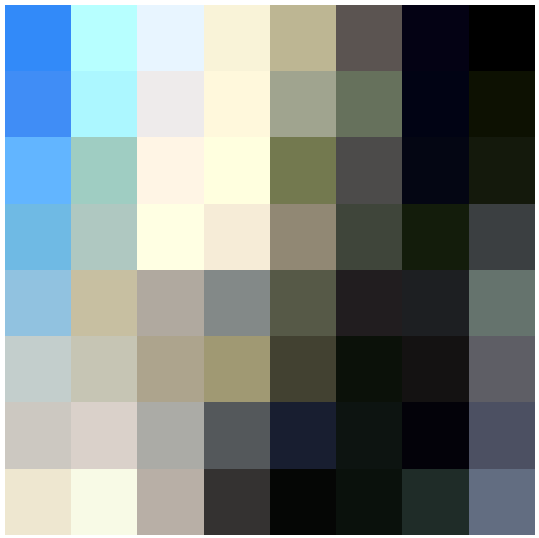
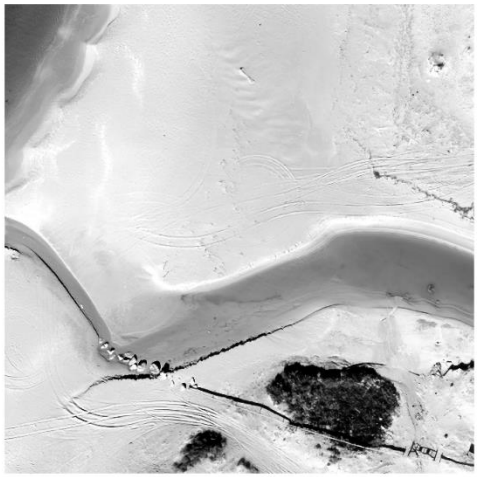


RapidEye

SRCNN image

B

G

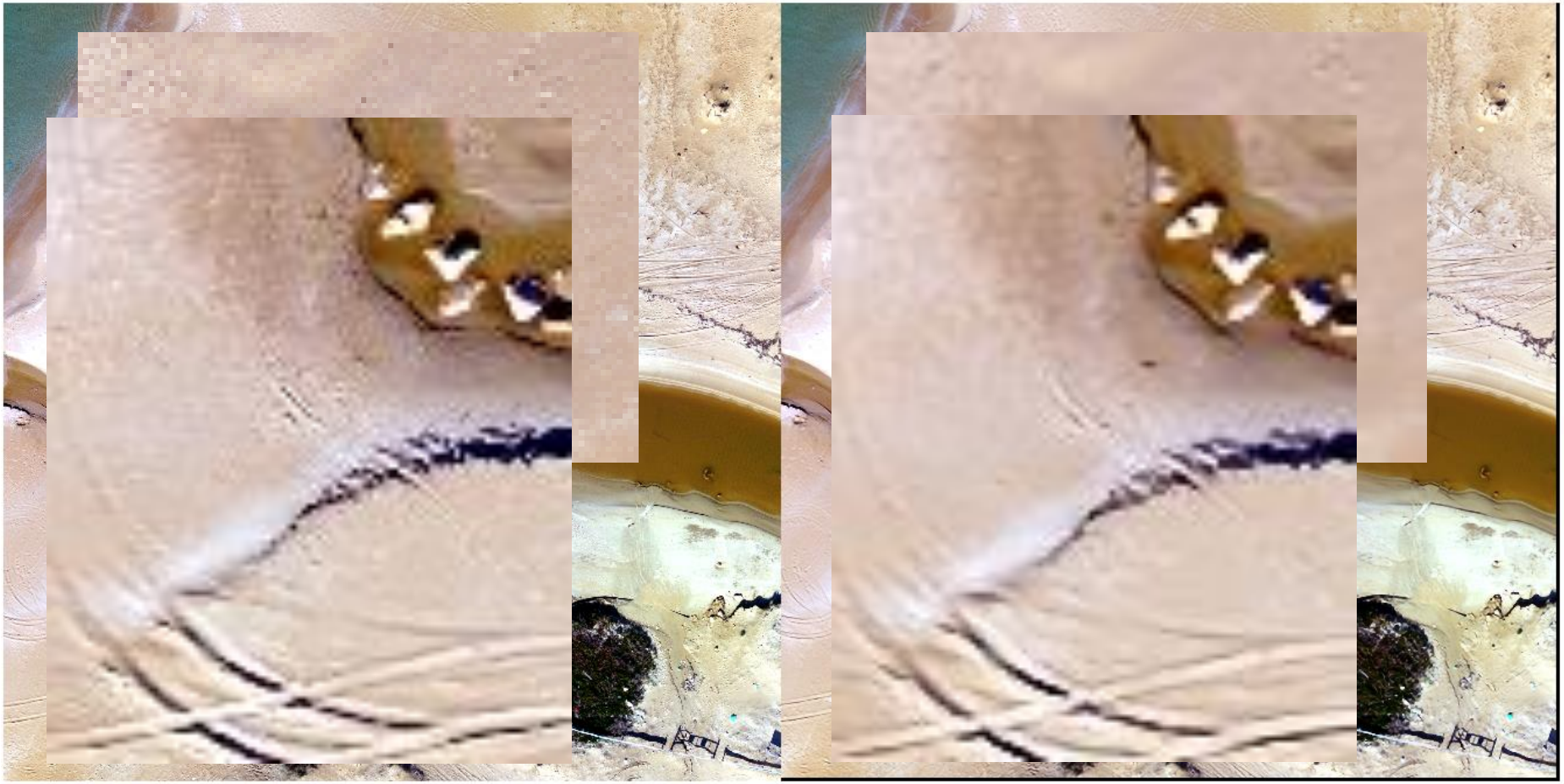


R

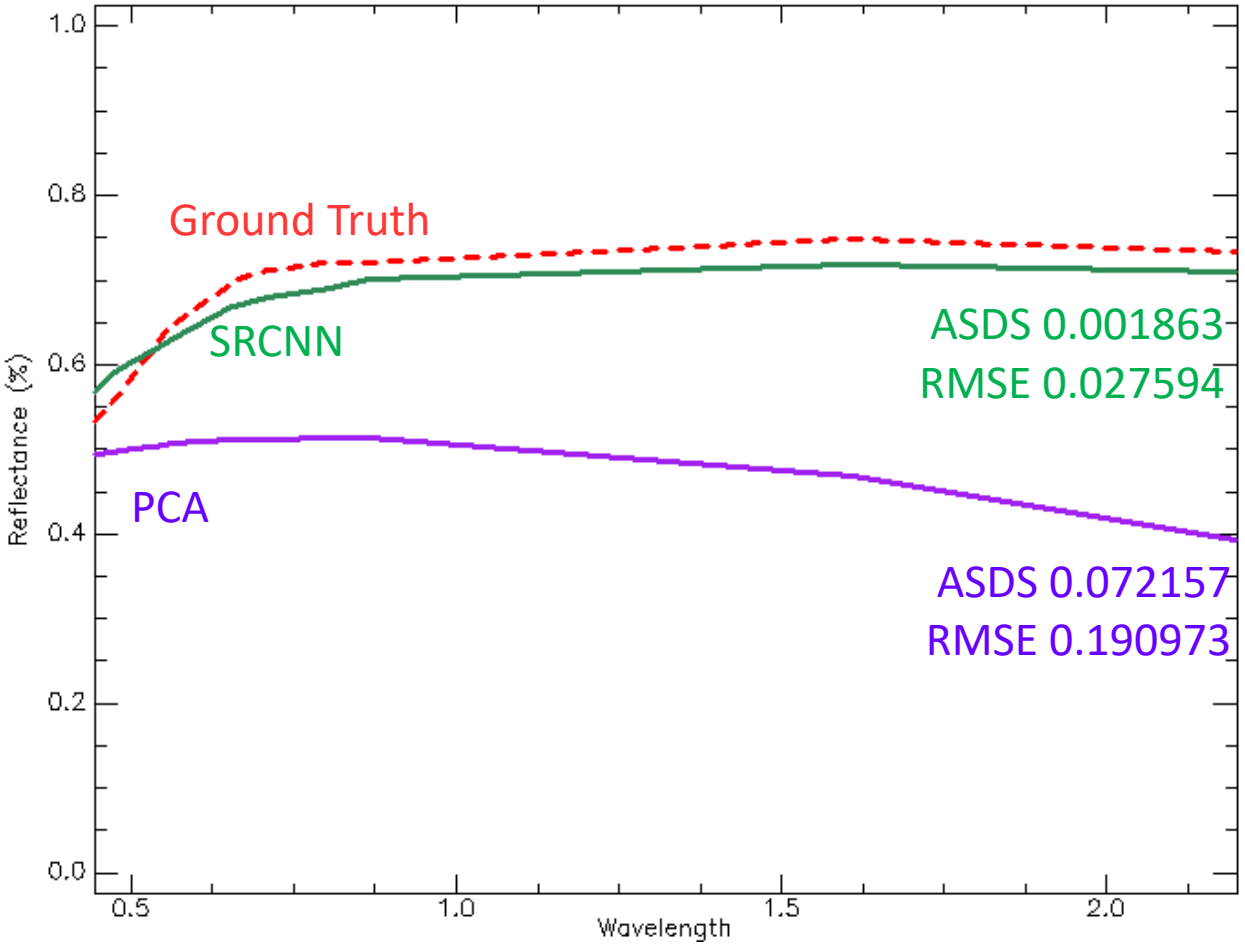
Results CNN

HR –RGB

SRCNN–RGB



Spectral Validation



ASDS = Average Sum of Deviation Square
(Ben-Dor et al., 2004)

$$ASDS = \frac{\sum_{\lambda=350}^{2500} \sigma\left(1 - \rho_\lambda / \rho^*_\lambda\right)^2}{2151}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

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Thank you for your attention!

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