

# Surface water fraction estimation CNN

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## 1 Architecture of the proposed CNN

Table 1 Architecture of surface water fraction estimating CNN

Layer type	Filters	Kernel size	Strides	Output shape
Input				9×9×8
Convolutional layer	32	(1,1)	1	9×9×32
Convolutional layer	64	(2,2)	1	9×9×64
Convolutional layer	128	(2,2)	1	9×9×128
Convolutional layer	256	(2,2)	1	9×9×256
Convolutional layer	256	(2,2)	1	9×9×256
Max pooling layer	-	(2,2)	1	4×4×256
Convolutional layer	256	(2,2)	1	4×4×256
Convolutional layer	256	(2,2)	1	4×4×256
Max pooling layer	-	(2,2)	1	2×2×256
Dropout	Dropout fraction = 0.5			1×1×256
Fully connected layer	-	-	-	1×1×64
Fully connected layer	-	-	-	1×1×1

## 2 Training

Training the proposed CNN consists of three steps: (1) In order to generate reliable surface

water fraction samples for training and validating the proposed model, 46 Landsat TM, ETM+ and OLI images were classified into binary water maps using a supervised classification method, random forest, and manually selected ‘water’ and ‘non-water’ samples. The binary water maps were then aggregated to the scale of MODIS pixels; (2) Then, the surface water fraction estimation convolutional neural network was constructed and trained using the surface reflectance of MODIS bands and Topographic Wetness Index (TWI) as input and the surface water fraction of MODIS grid cells as the target output; (3) In the end, the proposed model was evaluated using statistical metrics and auxiliary data.

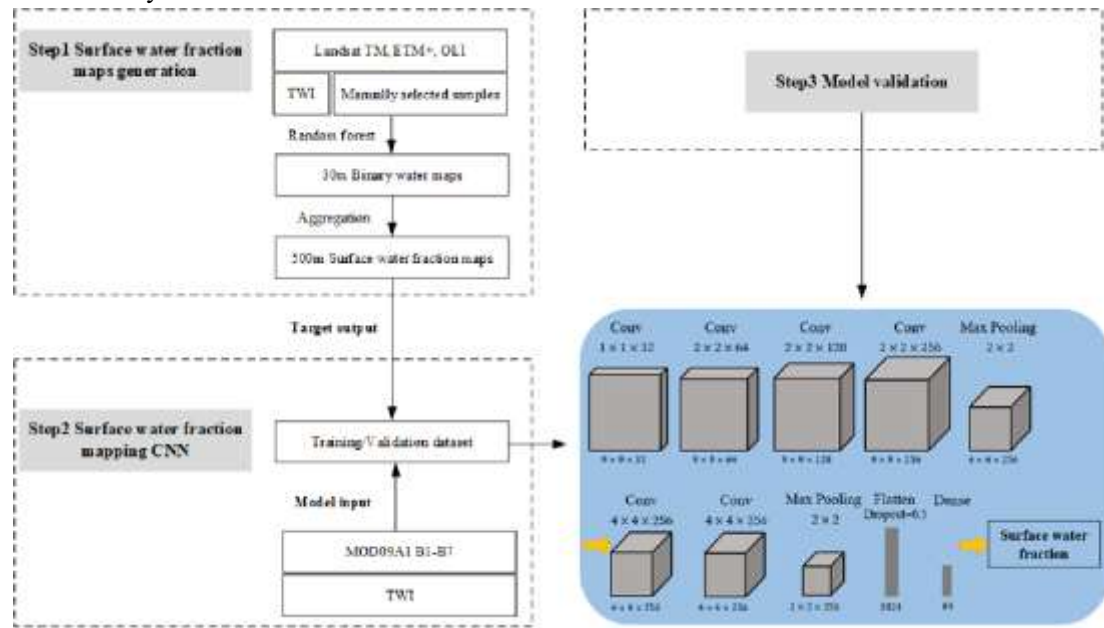


Fig.1. Training the surface water fraction estimation CNN

### 3 Accuracy assessment

Table 2 Overall performance. Bracketed numbers represent is the performance of ‘water’ samples.

Training sets			Validation sets		
R <sup>2</sup>	RMSE (%)	MAE (%)	R <sup>2</sup>	RMSE (%)	MAE (%)
0.975 (0.973)	5.938 (10.441)	1.810 (5.609)	0.967 (0.960)	6.925 (12.706)	2.081 (6.721)

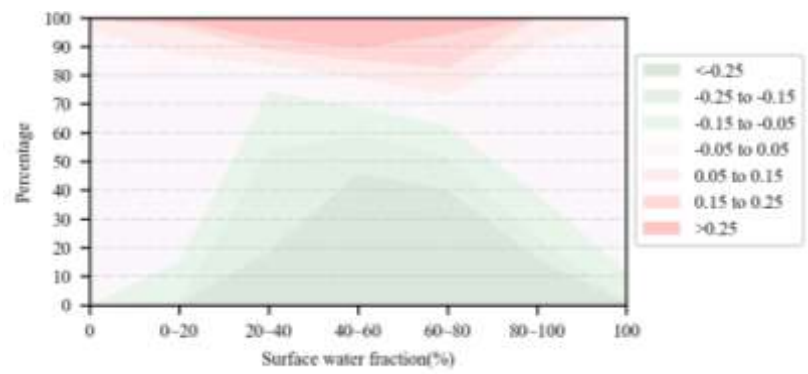


Fig.2. Stacked line plot illustrating signed deviations of each surface water fraction category in the validation data.