Deep learning Based Cloud And Shadows Detection on Satellite images

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HL 2017

HighLoad++

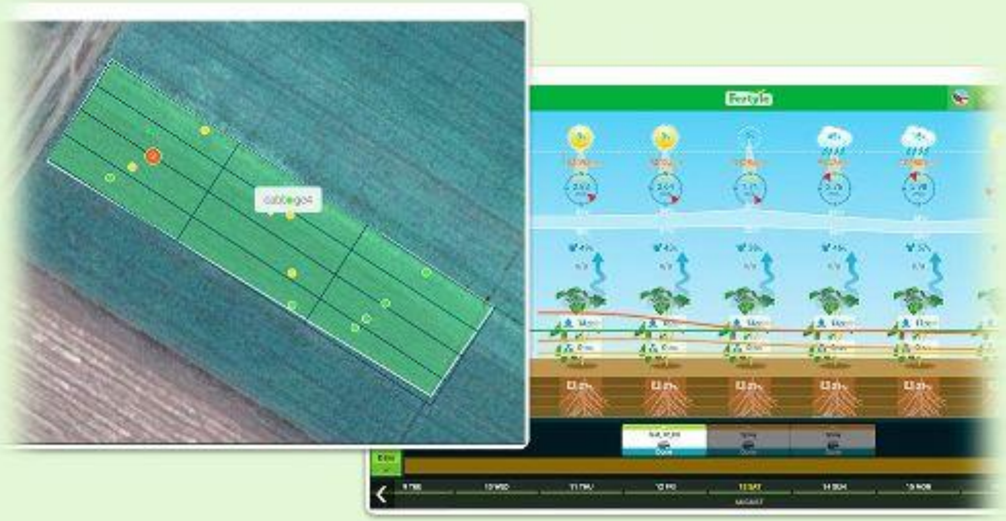
Профессиональная конференция разработчиков высоконагруженных систем

SCOUT

Fertyle's app provides step-by-step guidance to ensure scouts collect quality data every time. Better scouting, better results and better savings.

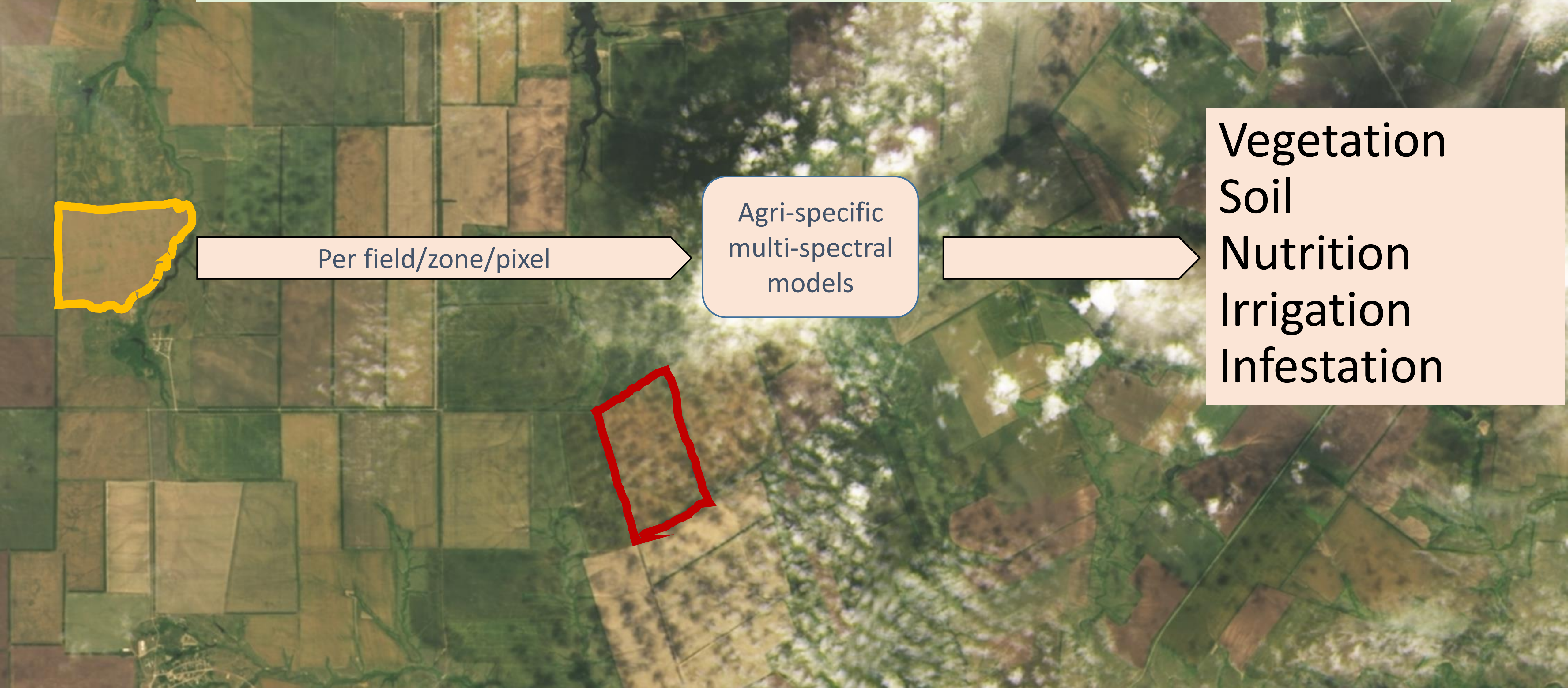
PLAN

Improve your forecasting. App runs biological models to provide partial spraying strategies for your crops against pests, disease and weeds.



Importance of cloud detection

why does it matter?

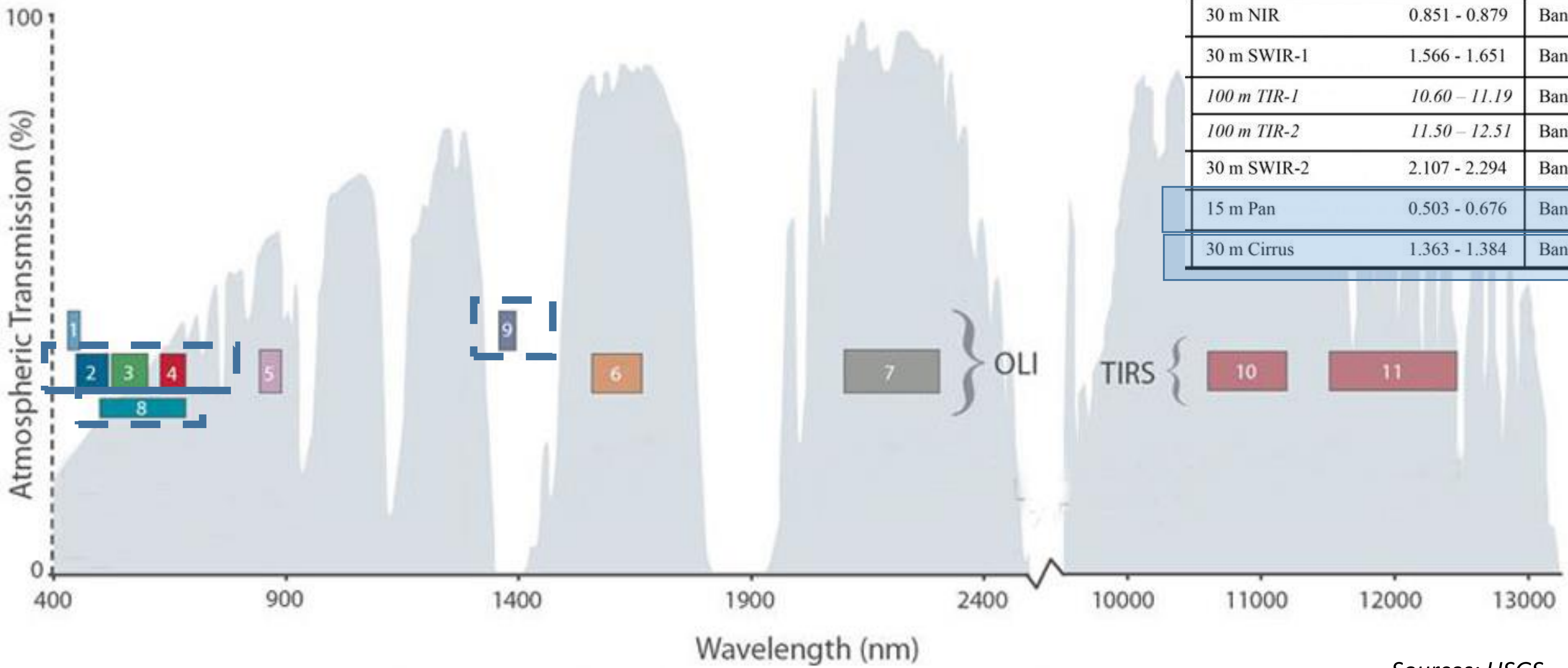


Landsat 8


Earth-View Baffle
Solar-View Baffle
Tertiary Mirror
Solar Diffuser Assembly
Shutter Wheel Assembly
Instrument Support Electronics
Focal Plane Electronics

Landsat 8 bands

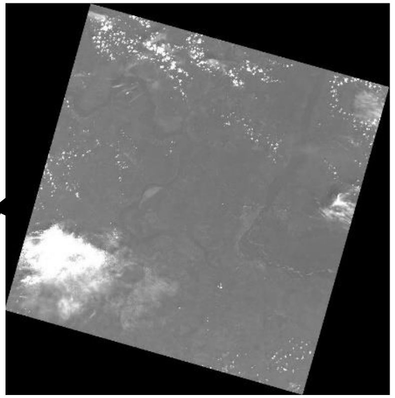
Landsat-8 OLI and *TIRS* Bands (µm)		
30 m Coastal/Aerosol	0.435 - 0.451	Band 1
30 m Blue	0.452 - 0.512	Band 2
30 m Green	0.533 - 0.590	Band 3
30 m Red	0.636 - 0.673	Band 4
30 m NIR	0.851 - 0.879	Band 5
30 m SWIR-1	1.566 - 1.651	Band 6
100 m TIR-1	*10.60 – 11.19*	Band 10
100 m TIR-2	*11.50 – 12.51*	Band 11
30 m SWIR-2	2.107 - 2.294	Band 7
15 m Pan	0.503 - 0.676	Band 8
30 m Cirrus	1.363 - 1.384	Band 9



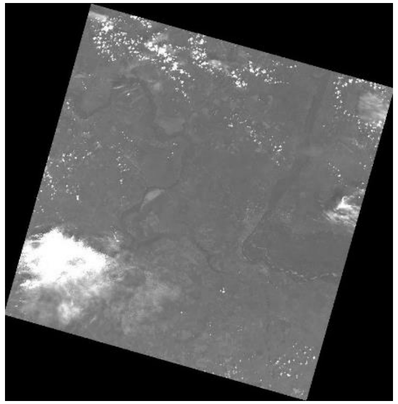
Sources: USGS

Satellite Scenes - bands

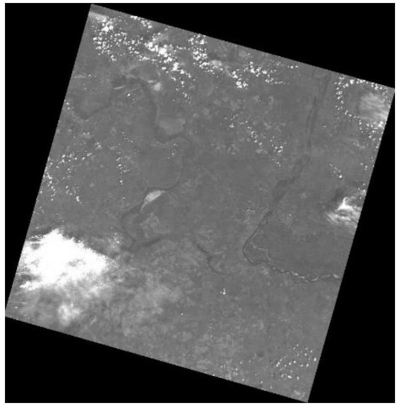
Volgograd



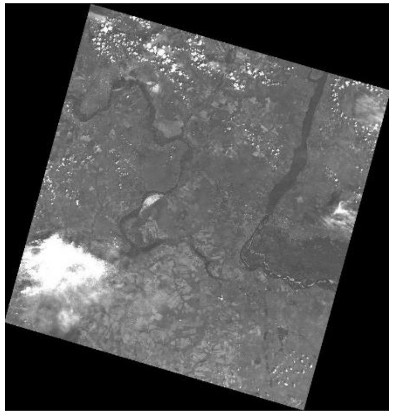
Band 1: Coastal/Deep Blue



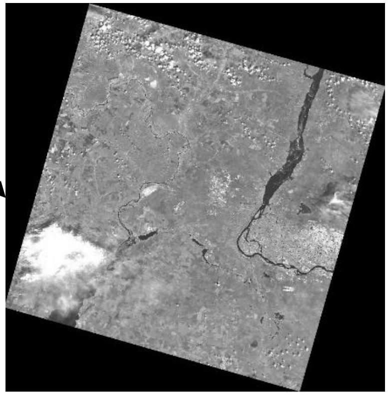
Band 2: Blue



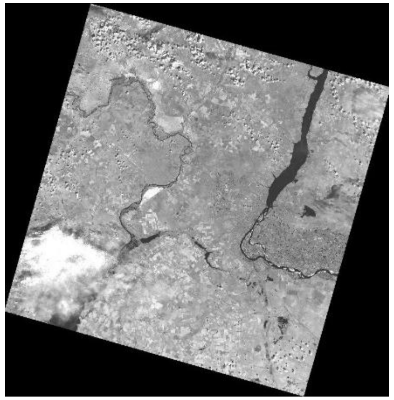
Band 3: Green



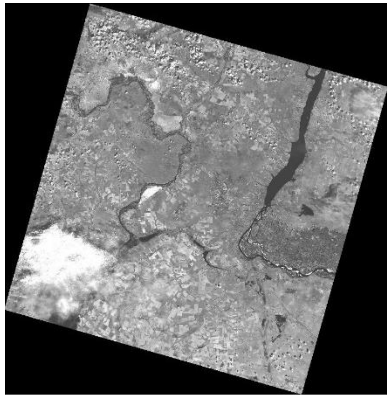
Band 4: Red



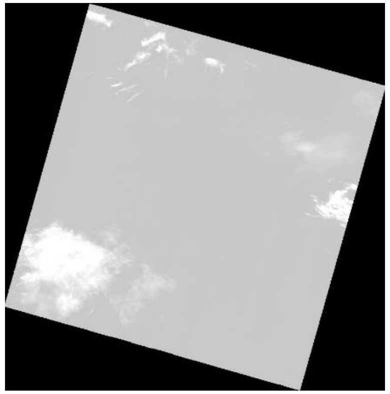
Band 5: Near Infrared



Band 6: Short Wave Infrared (1.6 um)

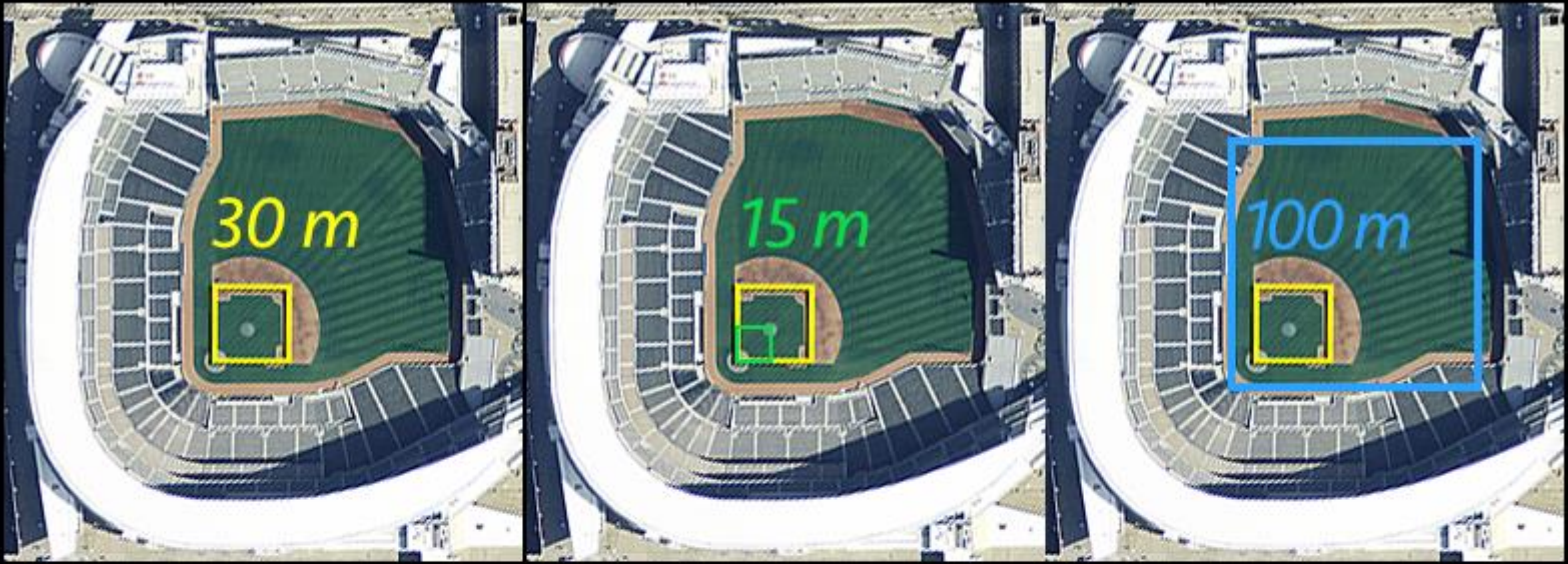


Band 7: Short Wave Infrared (2.2 um)



Band 9: Cirrus (1.36 um)

Landsat 8's Spatial Resolution



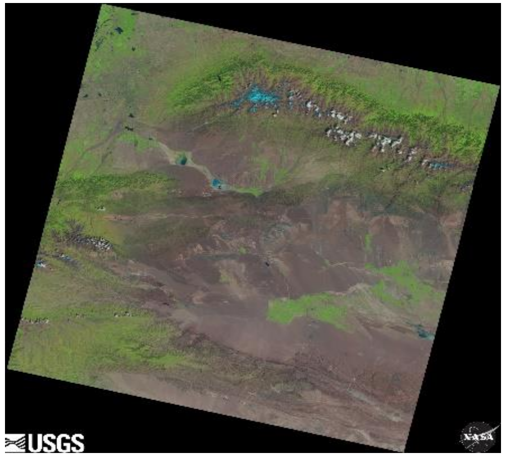
Vis-NIR-SWIR = 30 m

Panchromatic = 15 m

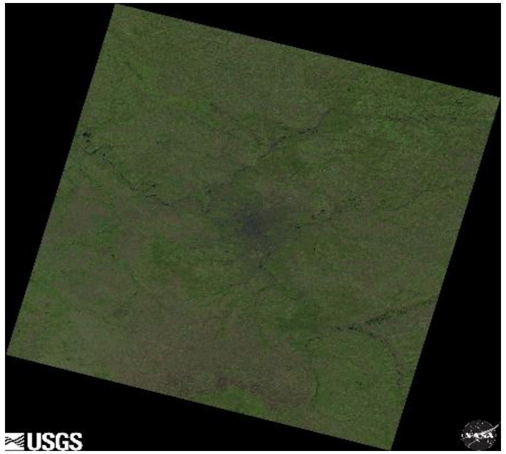
Thermal IR = 100 m
(Resampled to 30 m)

Satellite scenes – Cloud contamination

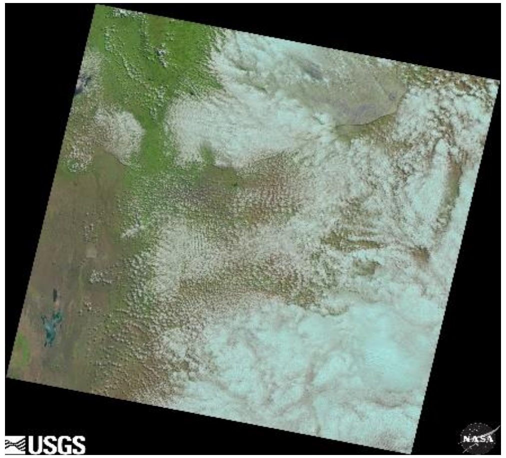
Volgograd



Urumqi, China



Paris, France

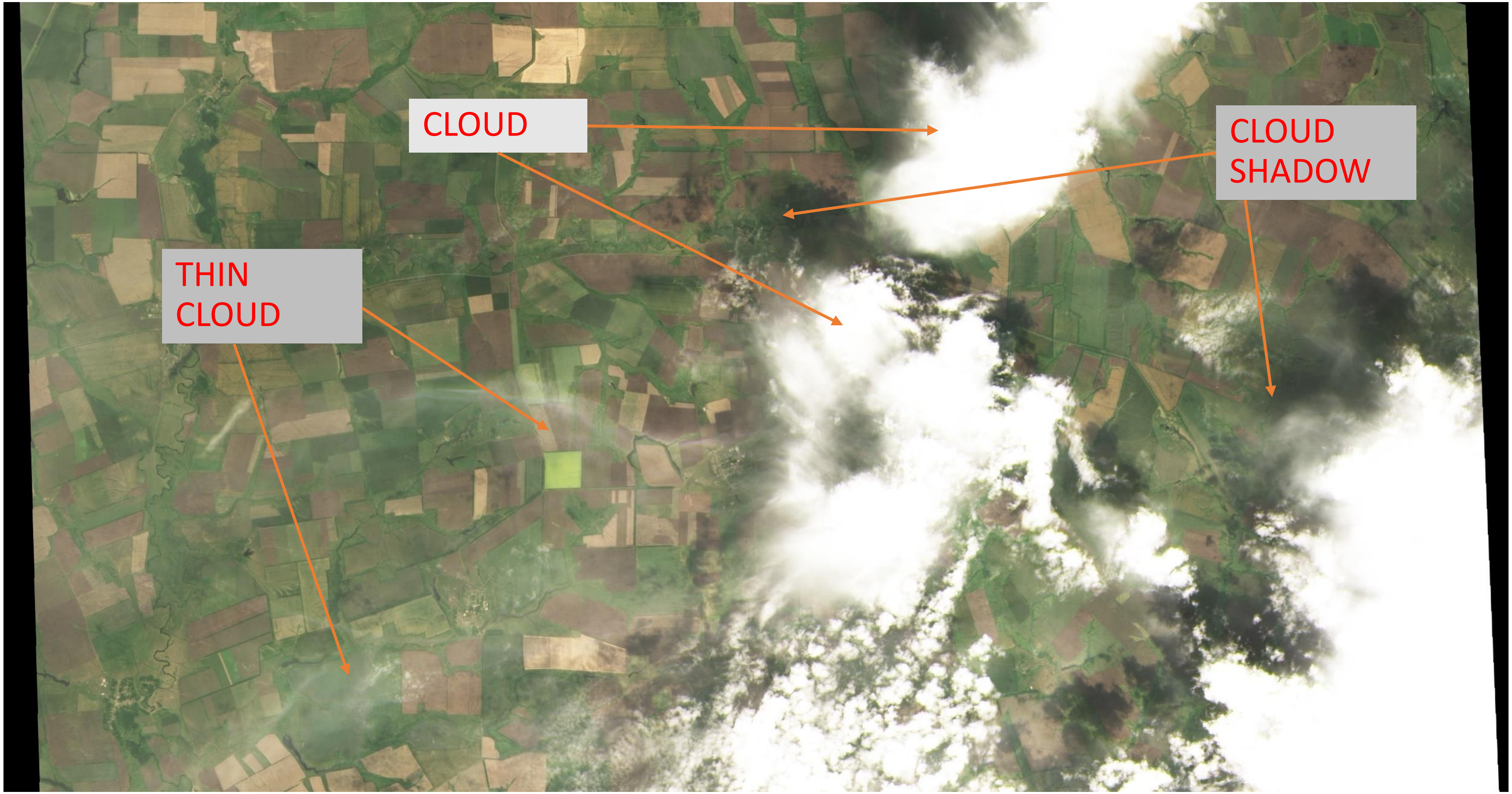


Nairobi,Kenya

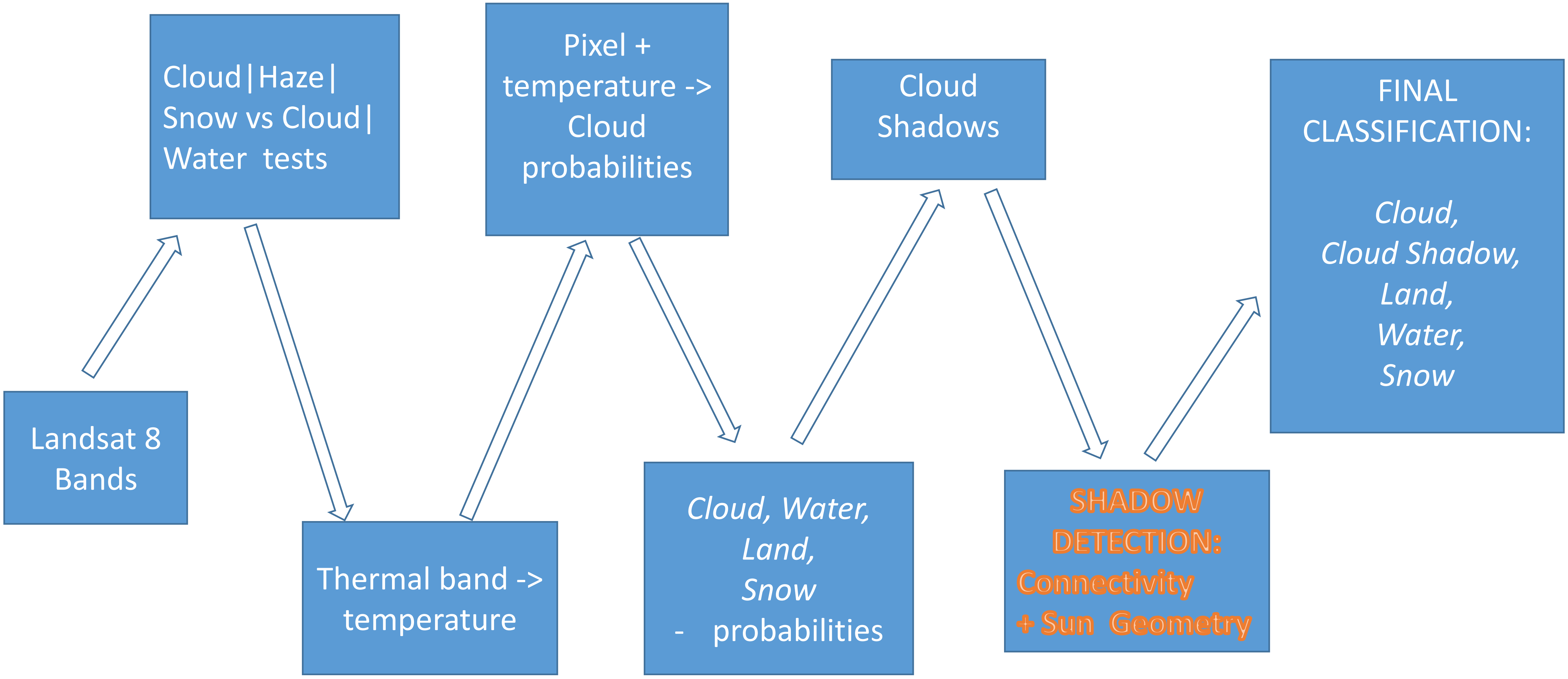
Amazon Forest

Las Vegas,US

CLassification

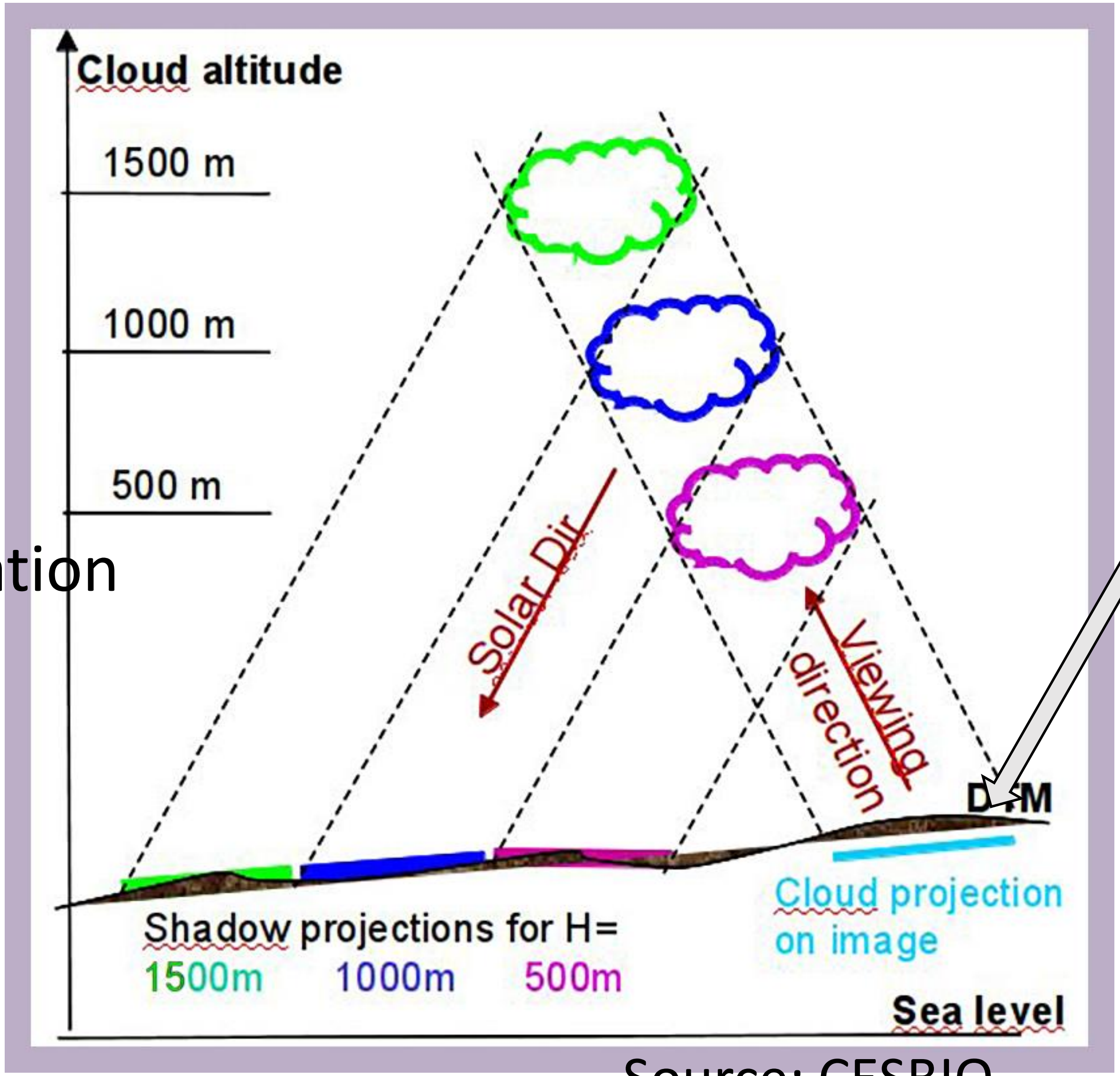


FMASK Flowchart



Traditional Algorithms - FMASK

Find related *cloud shadow* pixels using
- solar geometry
- connectivity information



Identify cloud pixels using thresholds

Source: CESBIO

Problems with FMASK

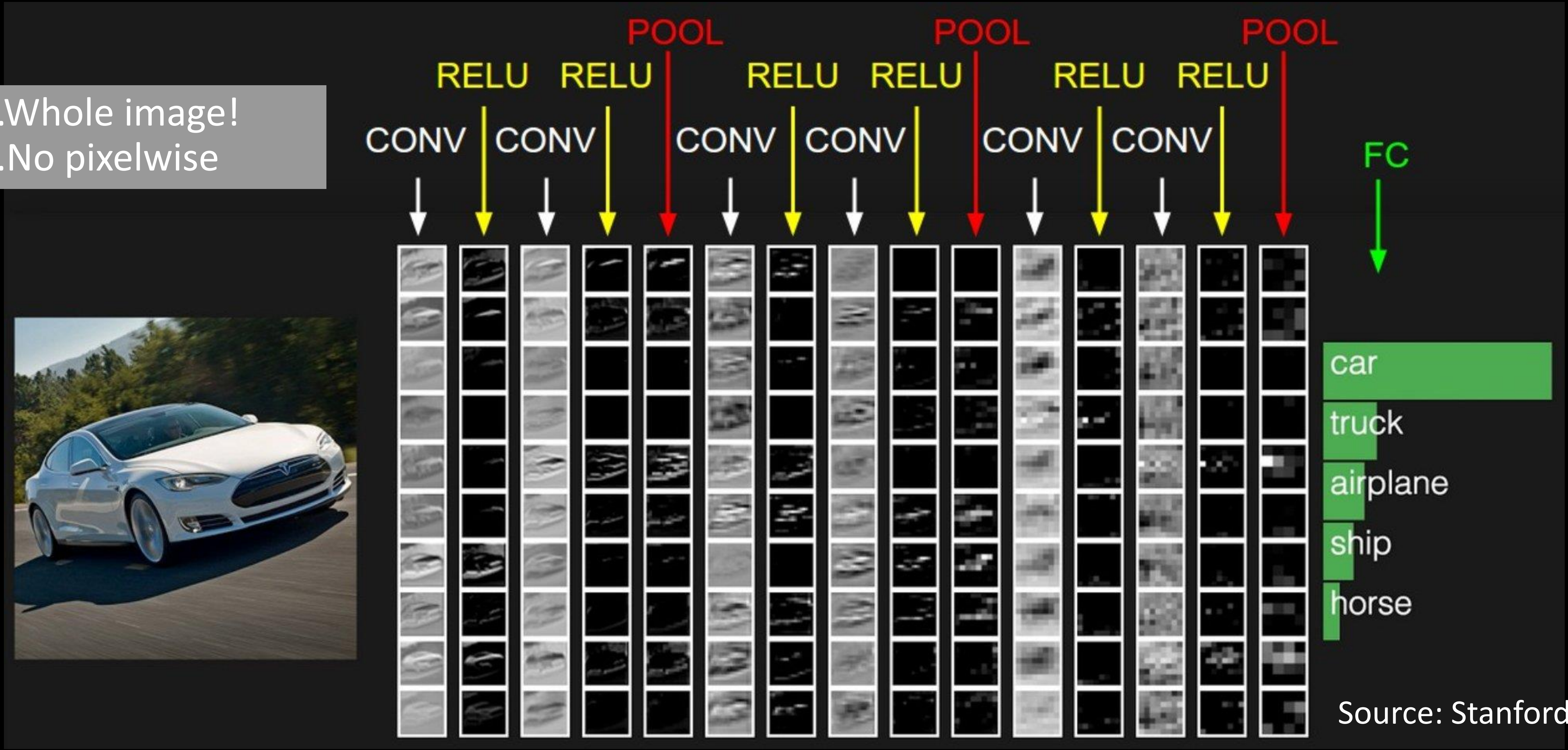
- Complicated algorithm -> have to tune for each satellite
- Connectivity and spatial relationships only used for cloud shadow determination. They should also be used for cloud detection!
- Very sensitive to threshold values
- Real implementation often crash on some non standard situations
- No way to detect thin clouds!

FMASK baseline results

	Mean accuracy	Standard deviation	Lowest accuracy /scene	Highest accuracy/scene
Overall	87.4%	13.5%	26.2%	100%
Grass/Cropland	90.1%	11.9%	61.4%	98.3%

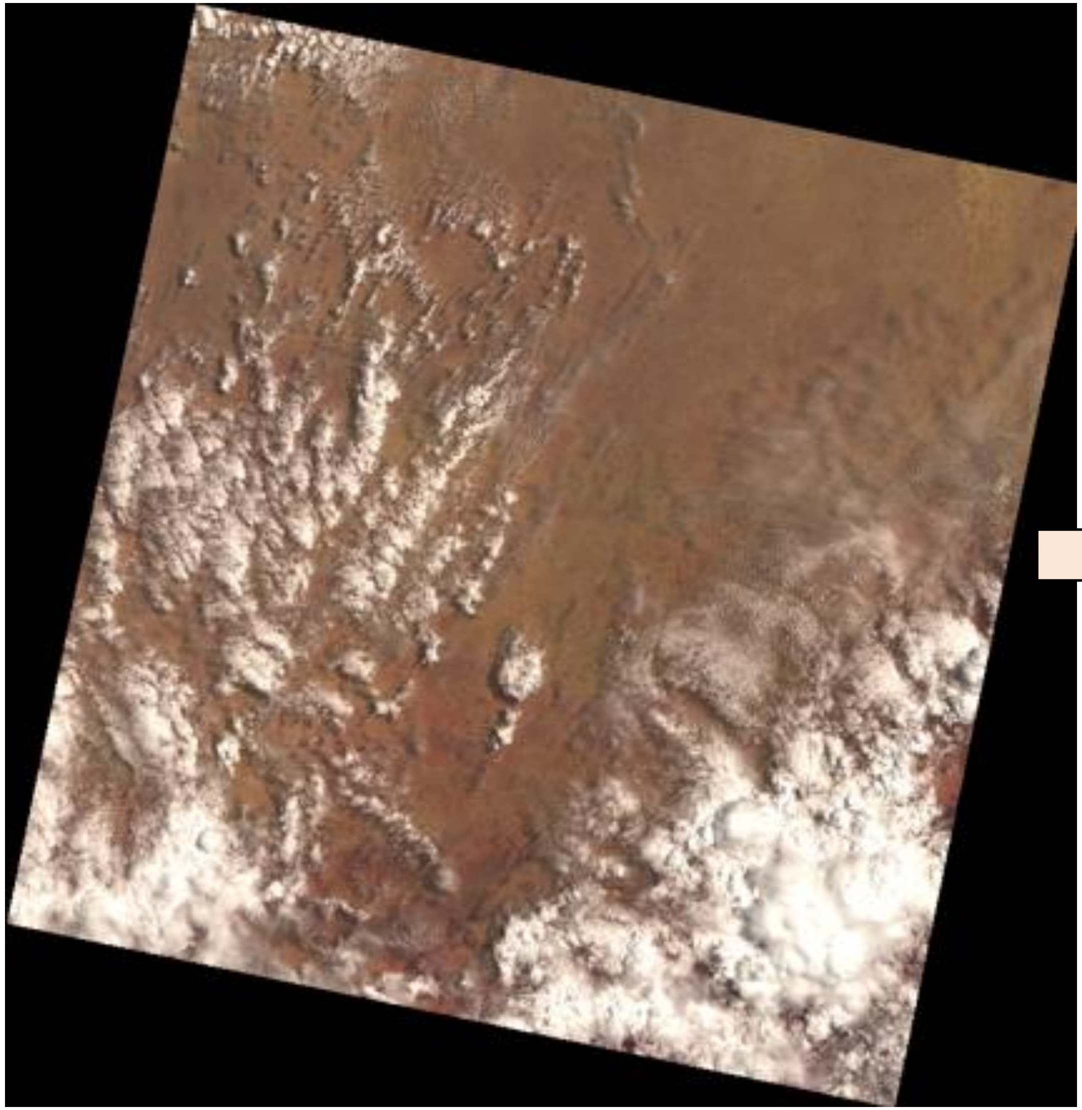
«Classical» CNN for visual recognition

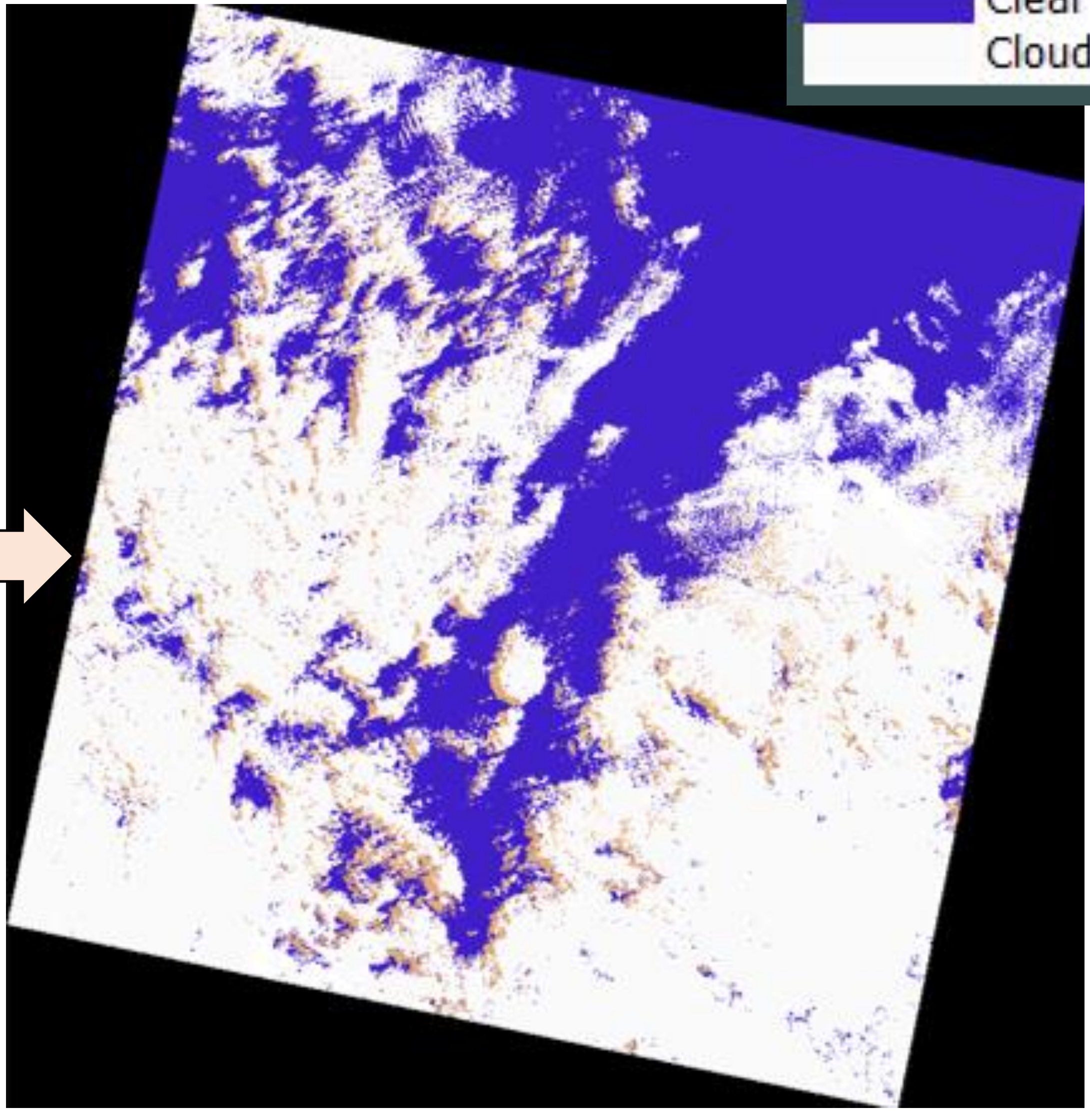
1.Whole image!
2.No pixelwise



Source: Stanford

Pixelwise classification





Color	Label
	Shadow
	Clear
	Cloud

Landsat 8 Cloud Cover Assessment Validation Data

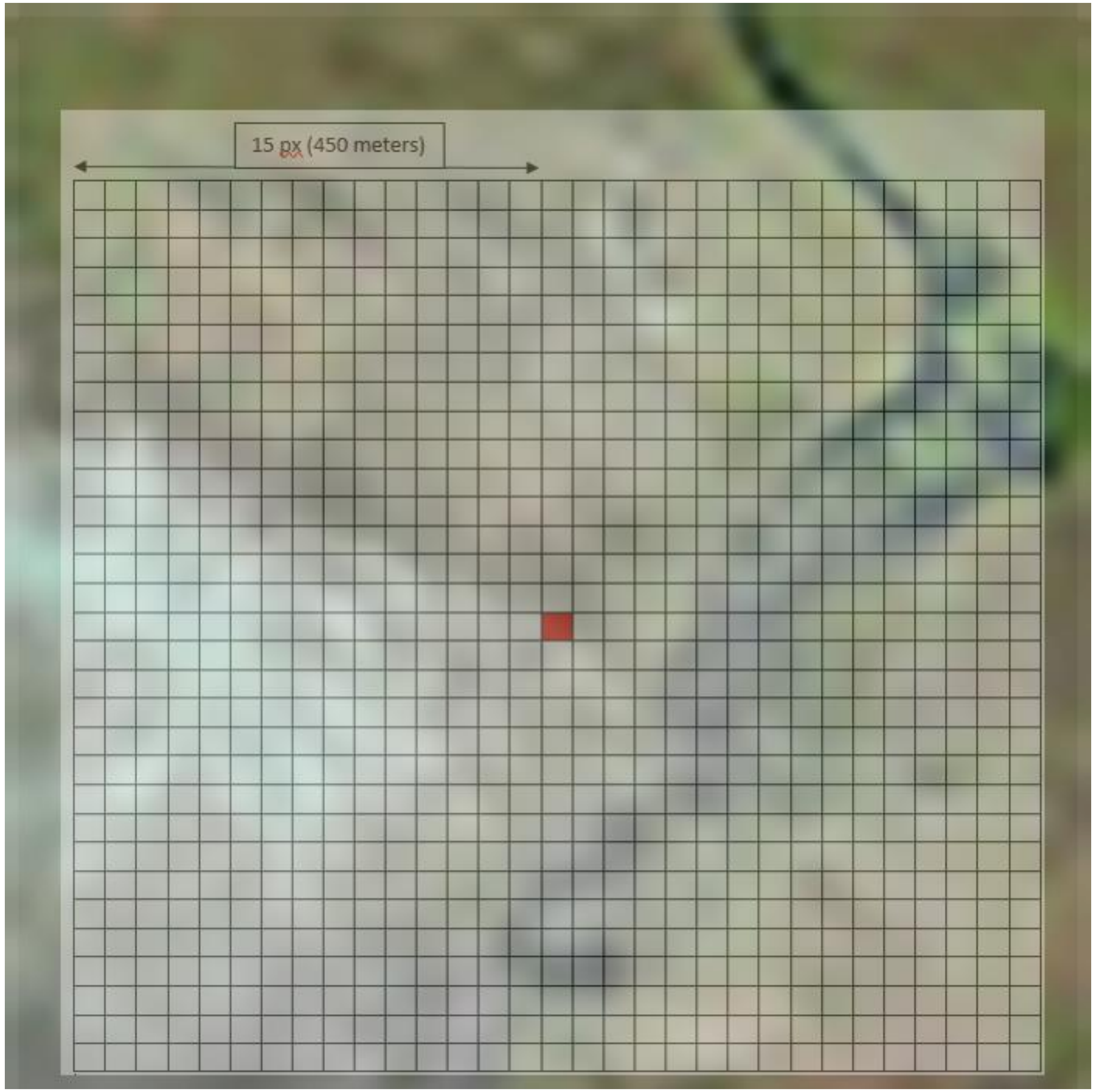
This collection contains 96 Landsat 8 Operational Land Imager (OLI) Thermal Infrared Sensor (TIRS) terrain-corrected (Level-1T) scenes, displayed in the biomes listed below. Manually generated cloud masks are used to validate cloud cover assessment algorithms, which

The interpretation for the bits in each manual mask is as follows:

Value	Interpretation
0	Fill
64	Cloud Shadow
128	Clear
192	Thin Cloud
255	Cloud

Grass/Crops	Scene ID (Level-1T)	Path	Row	Acquisition Date	Approximate Cloud Status
	LC80290292014132LGN00	29	29	5/12/2014	Cloudy
	LC80290372013257LGN00	29	37	9/14/2013	MidClouds
	LC80980712014024LGN00	98	71	1/24/2014	MidClouds
	LC81220312014208LGN00	122	31	7/27/2014	Clear
	LC81220422014096LGN00	122	42	4/6/2014	Cloudy
	LC81320352013243LGN00	132	35	8/31/2013	MidClouds
	LC81440462014250LGN00	144	46	9/7/2014	Cloudy
	LC81490432014141LGN00	149	43	5/21/2014	Clear
	LC81510262014139LGN00	151	26	5/19/2014	Cloudy

Our approach: patch extraction

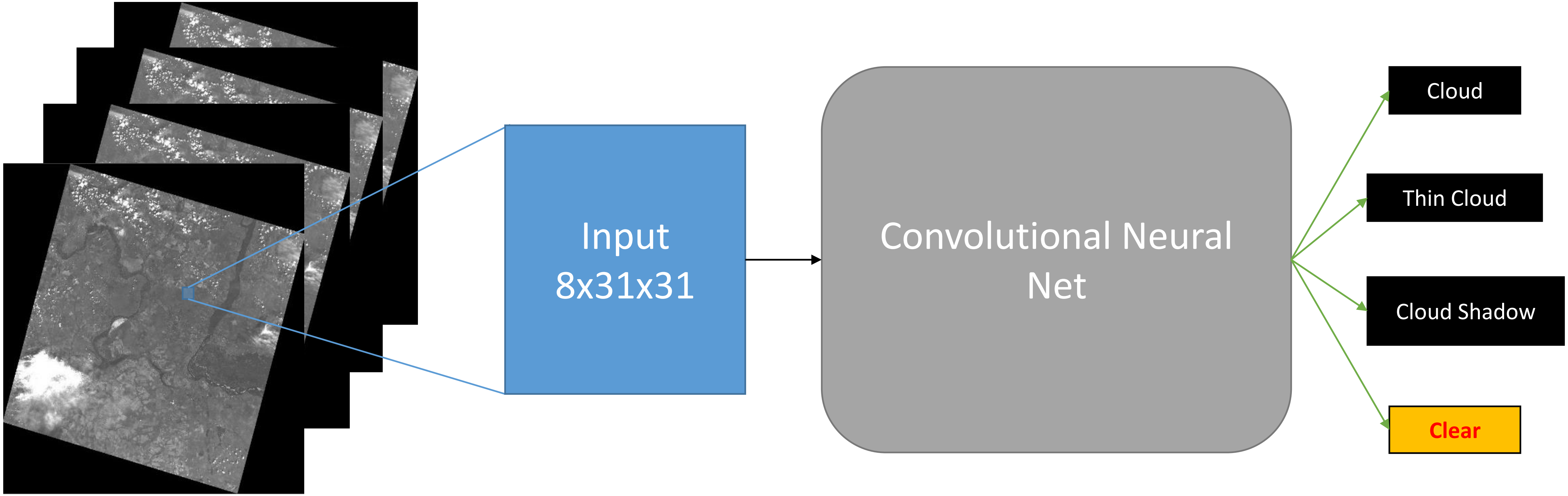


- The red pixel represents the center pixel of a 31x31 patch

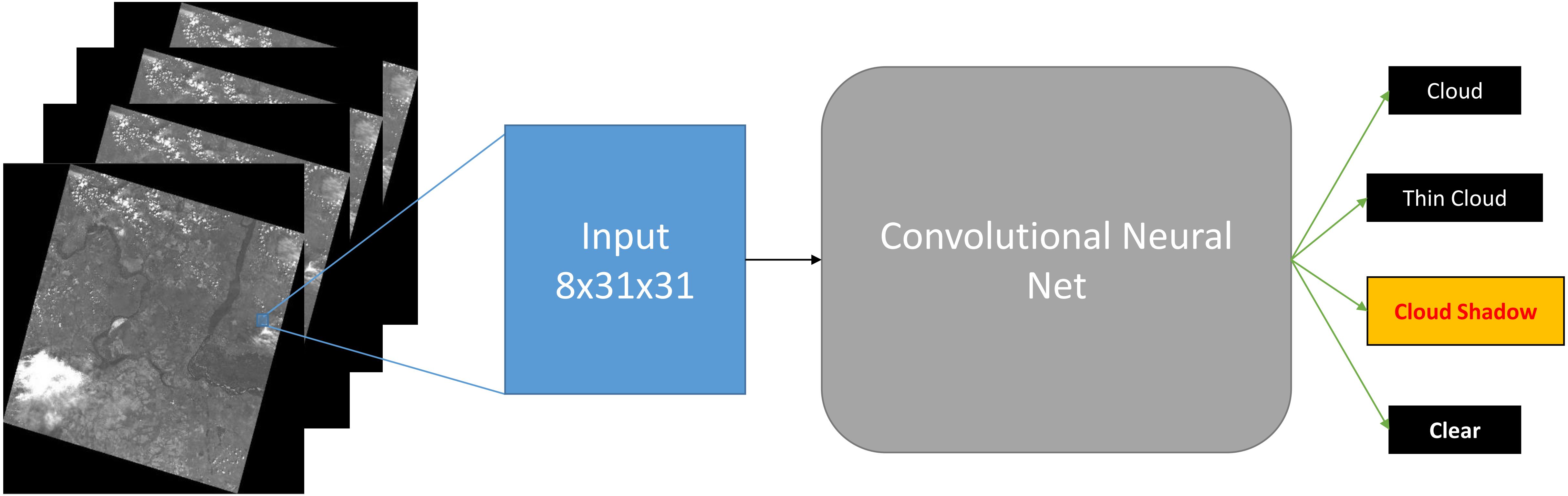
- Center Pixel -> Class

- Extract patches for every pixel in a scene and classify

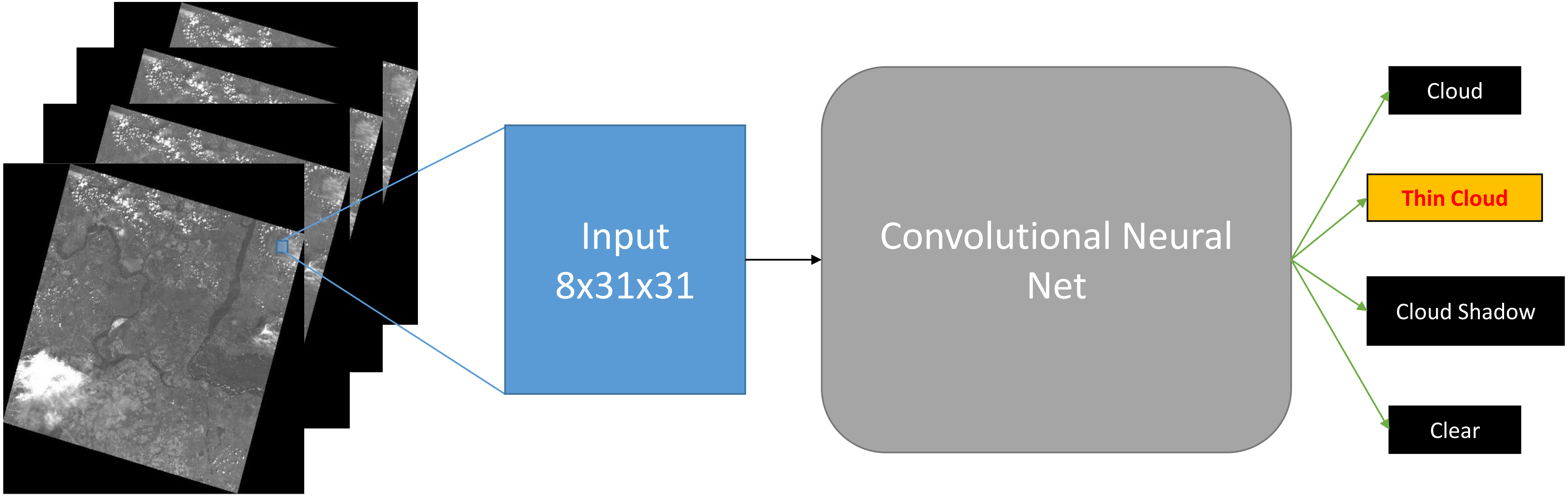
Clear Pixel


Input
8x31x31
Convolutional Neural
Net
Cloud
Thin Cloud
Cloud Shadow
Clear

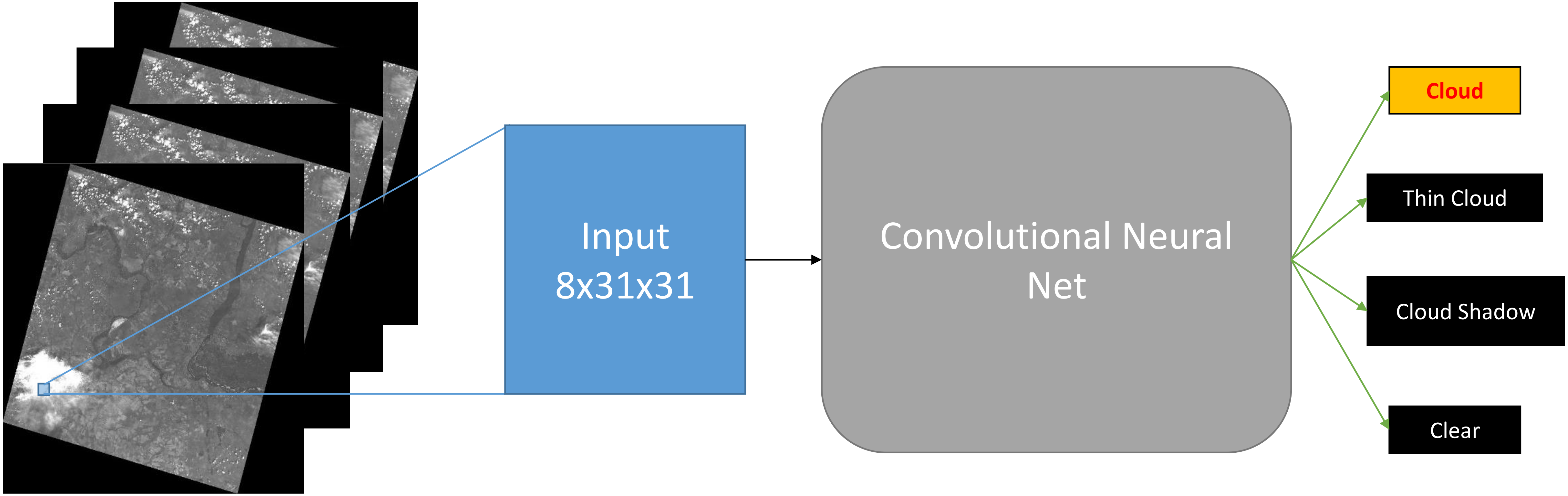
Cloud Shadow



Thin Cloud Pixel



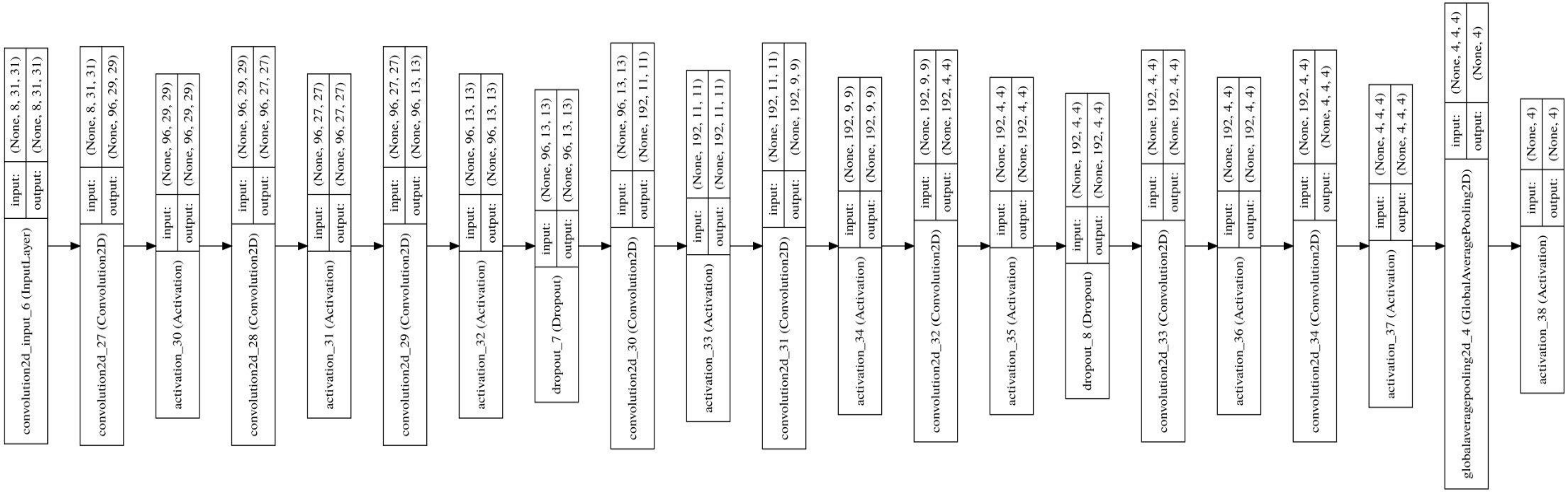
Cloud Pixel



Input
8x31x31
Convolutional Neural Net
Cloud
Thin Cloud
Cloud Shadow
Clear

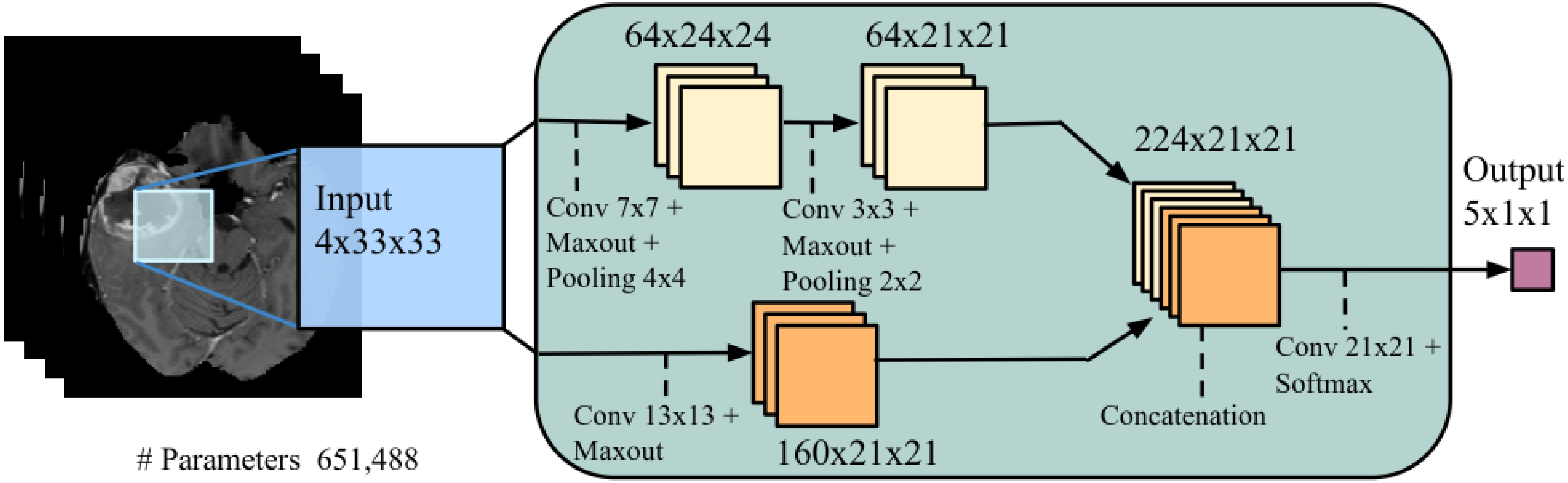
Singlepath CNN

All-CNN: only consists of convolutional layers

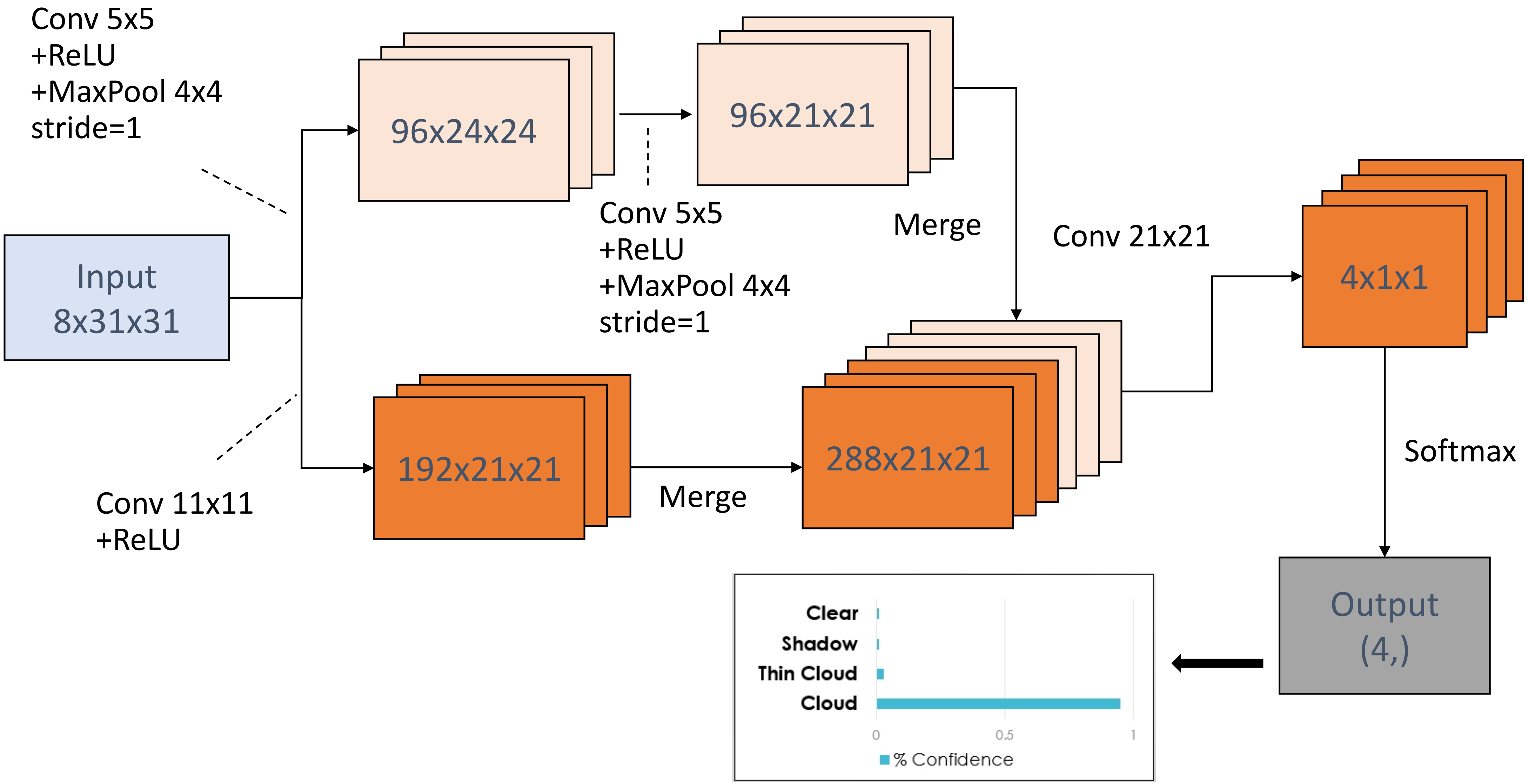


Multipath CNN

Inspired from neuroscience literature used to classify brain tumors.



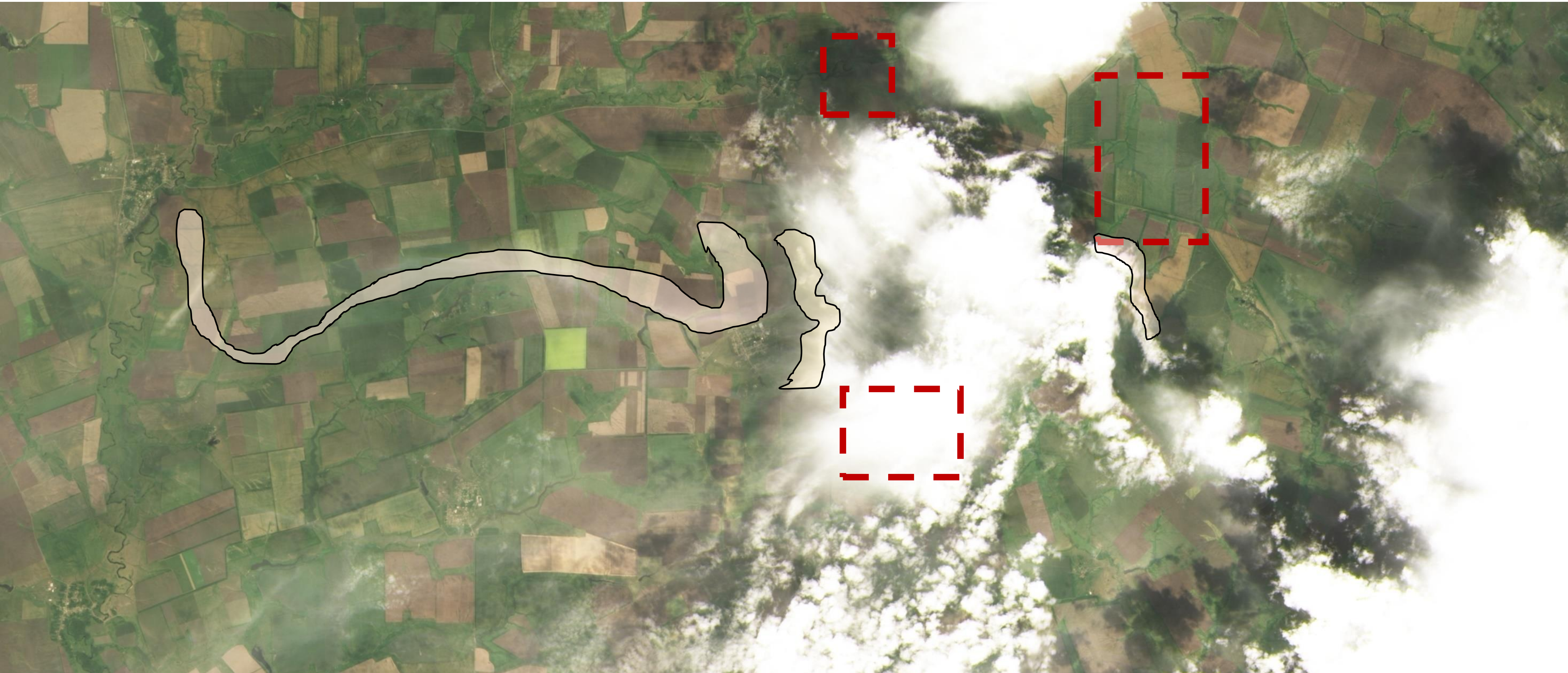
Our network: FertyleNet



Training approach

- Concentrate on Grass/Cropland Scenes For a Total of 12 Images
- Randomly extract (almost) equal amount of 31x31 patches per class per scene
- Force at least **25%** of all patches extracted per class to contain “mixed” categories of pixels i.e, at least **20%** of patch pixels will be of a different category than the target pixel

Homogeneous Patches



Training approach – cont.

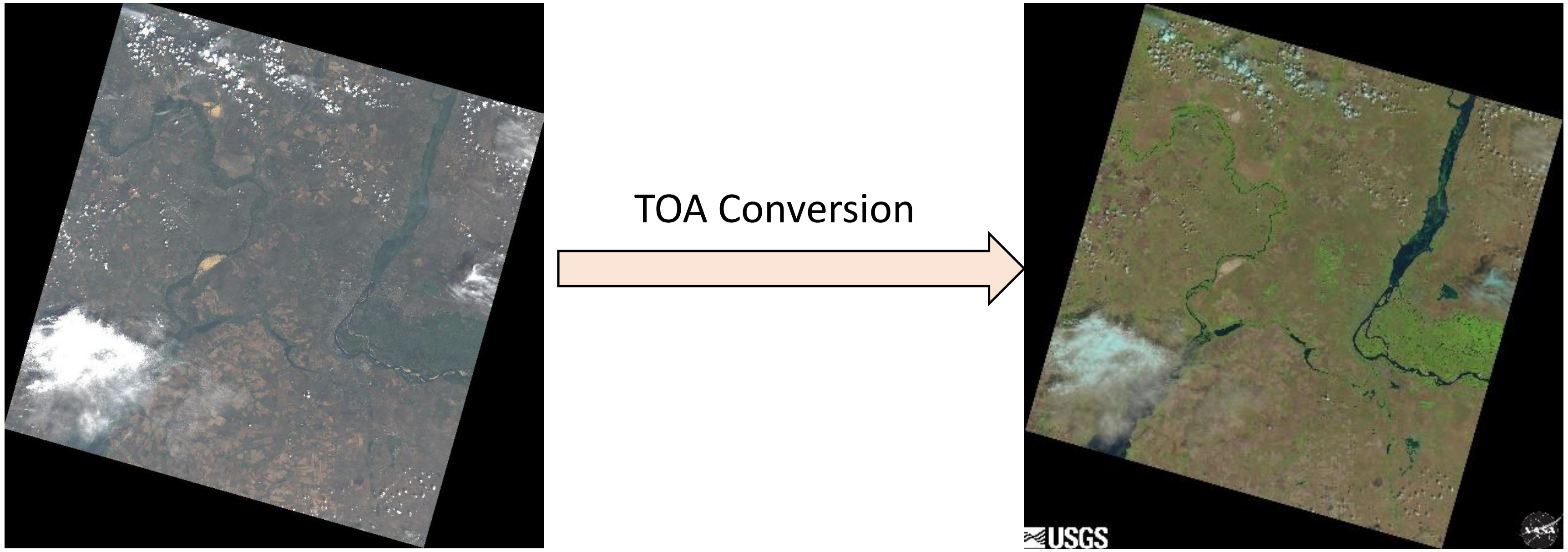
- 70/20/10: Training/Test/Validation Split
- **Training Patches**: 440,678 / **Test Patches**: 125, 908 / Validation Patches: 62954

Top of atmosphere conversion

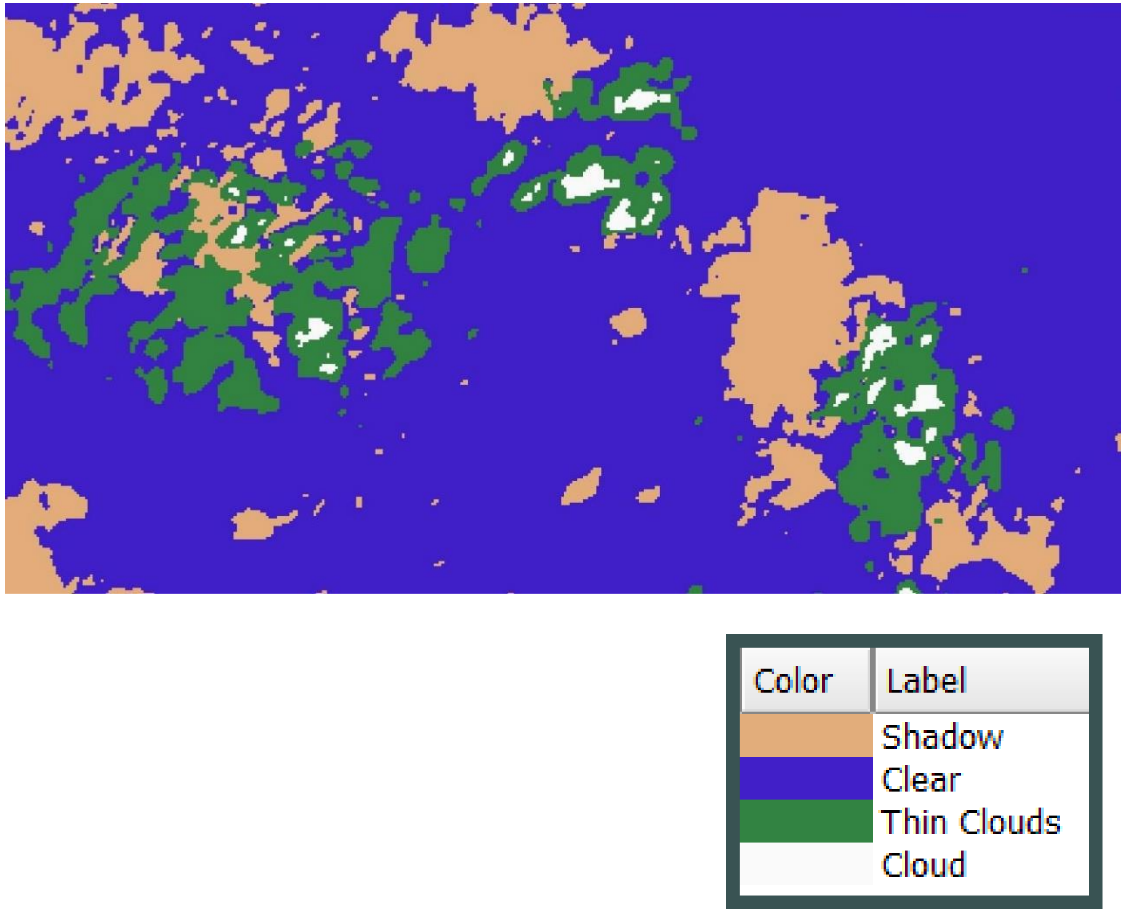
- Rescale raw pixels into Top of Atmosphere (TOA) reflection

$$\text{ToA} = \frac{M_\rho Q_{cal} + A_\rho}{\cos(\theta_{SZ})}$$

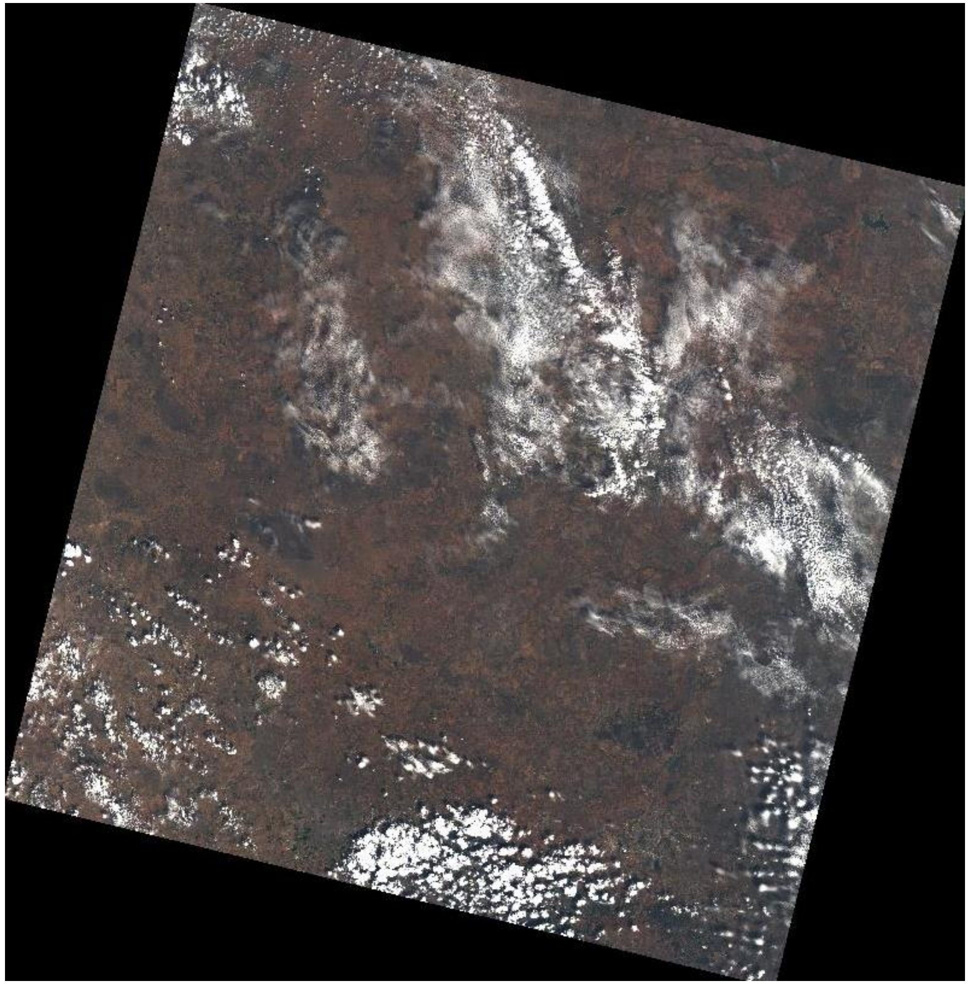
M_ρ = Band-specific multiplicative rescaling factor
A_ρ = Band-specific additive rescaling factor
Q_{cal} = Raw Band-Specific Pixel Value
θ_{SZ} = Local solar zenith angle

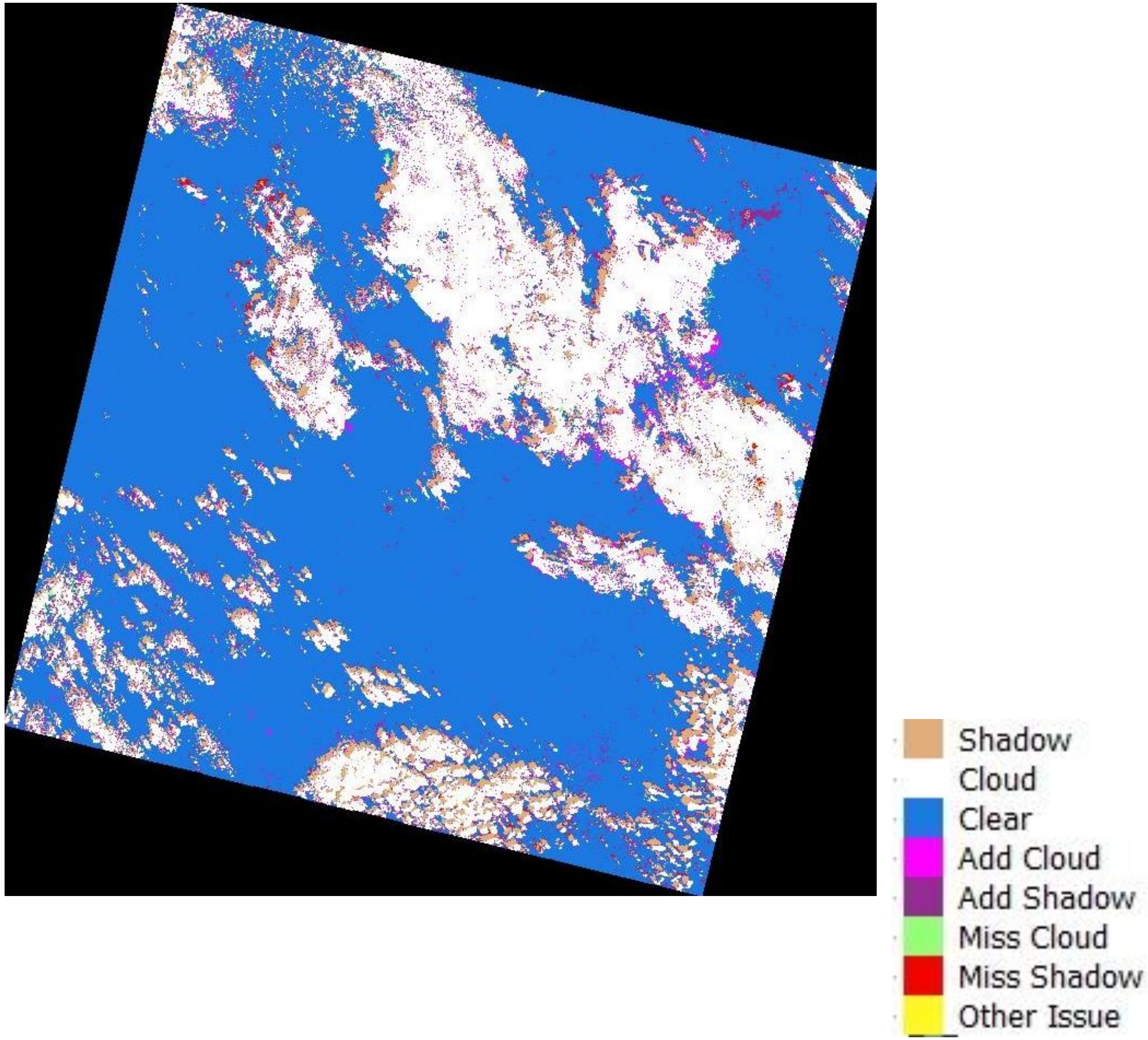


Cloud Detection Results

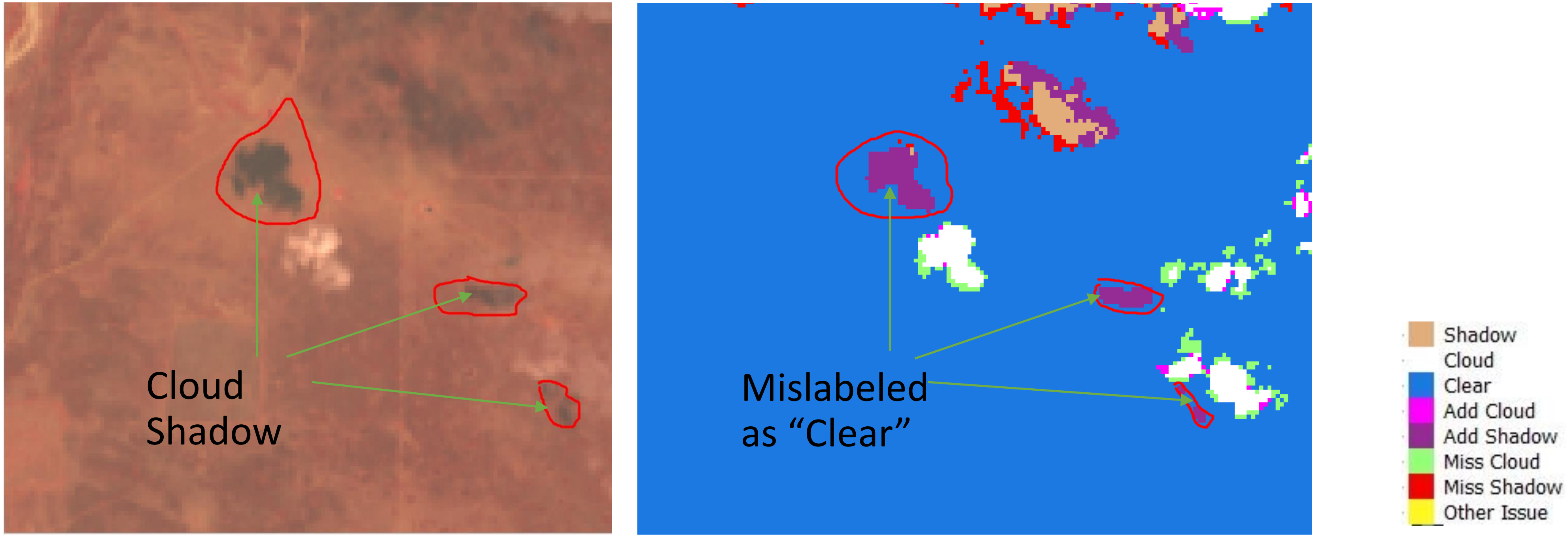


Cloud Results Analysis



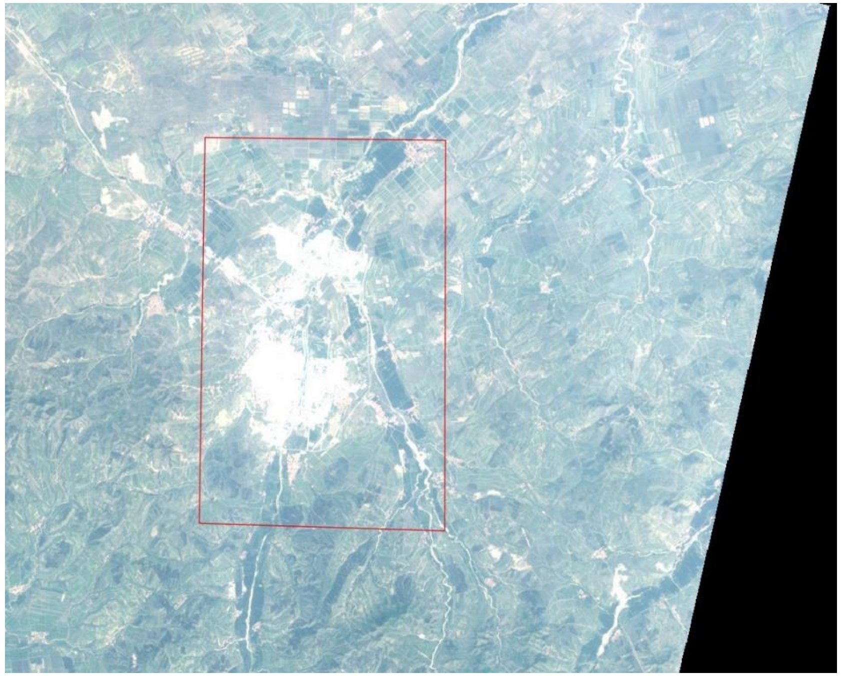


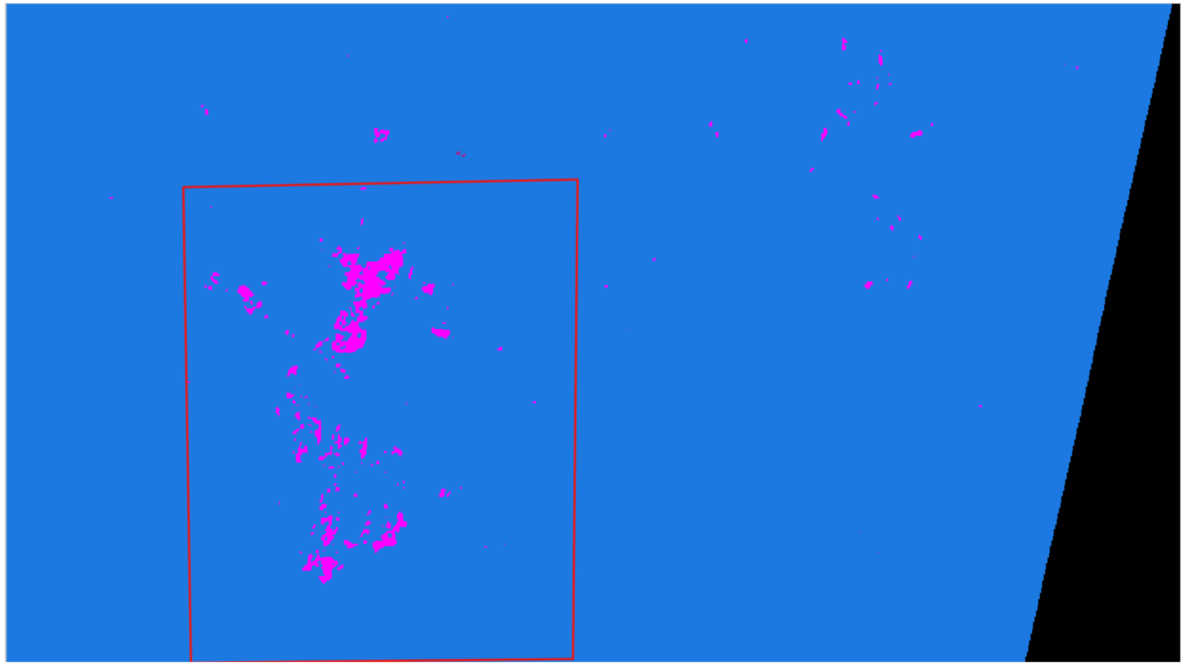
Improvement over humans ??



Human Classifier Thought These Dark Bodies Were “Clear” (probably thought they were water bodies. However, the FertyleNet correctly labeled these areas as cloud shadows!

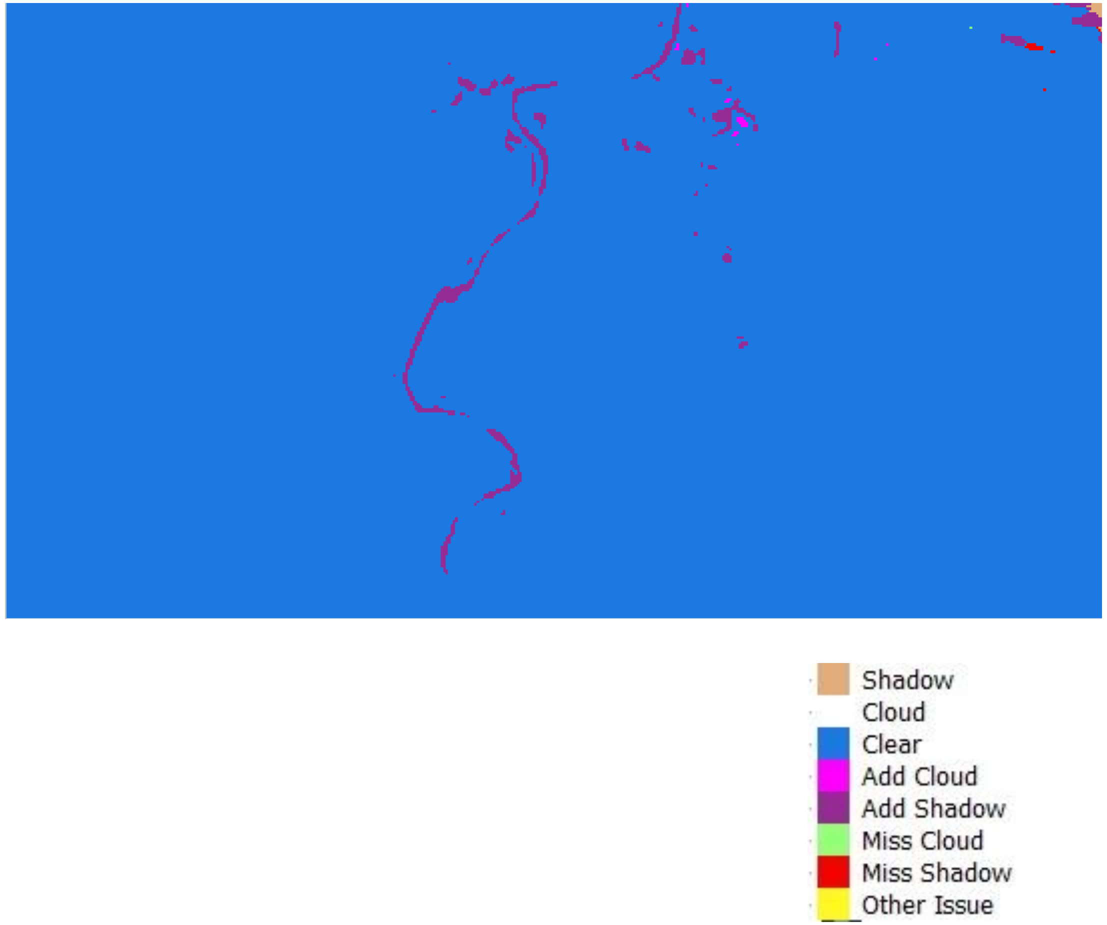
Improvement over humans ?? Not really…





Bright Urban Zones Misclassified as Clouds!

More classification issues



Rivers and other dark areas misclassified as Cloud Shadows!

Accuracy results

Test Set: **125,908 patches** (25%/75% heterogenous-homogenous mix)

Over 12 Grass/Cropland Scenes

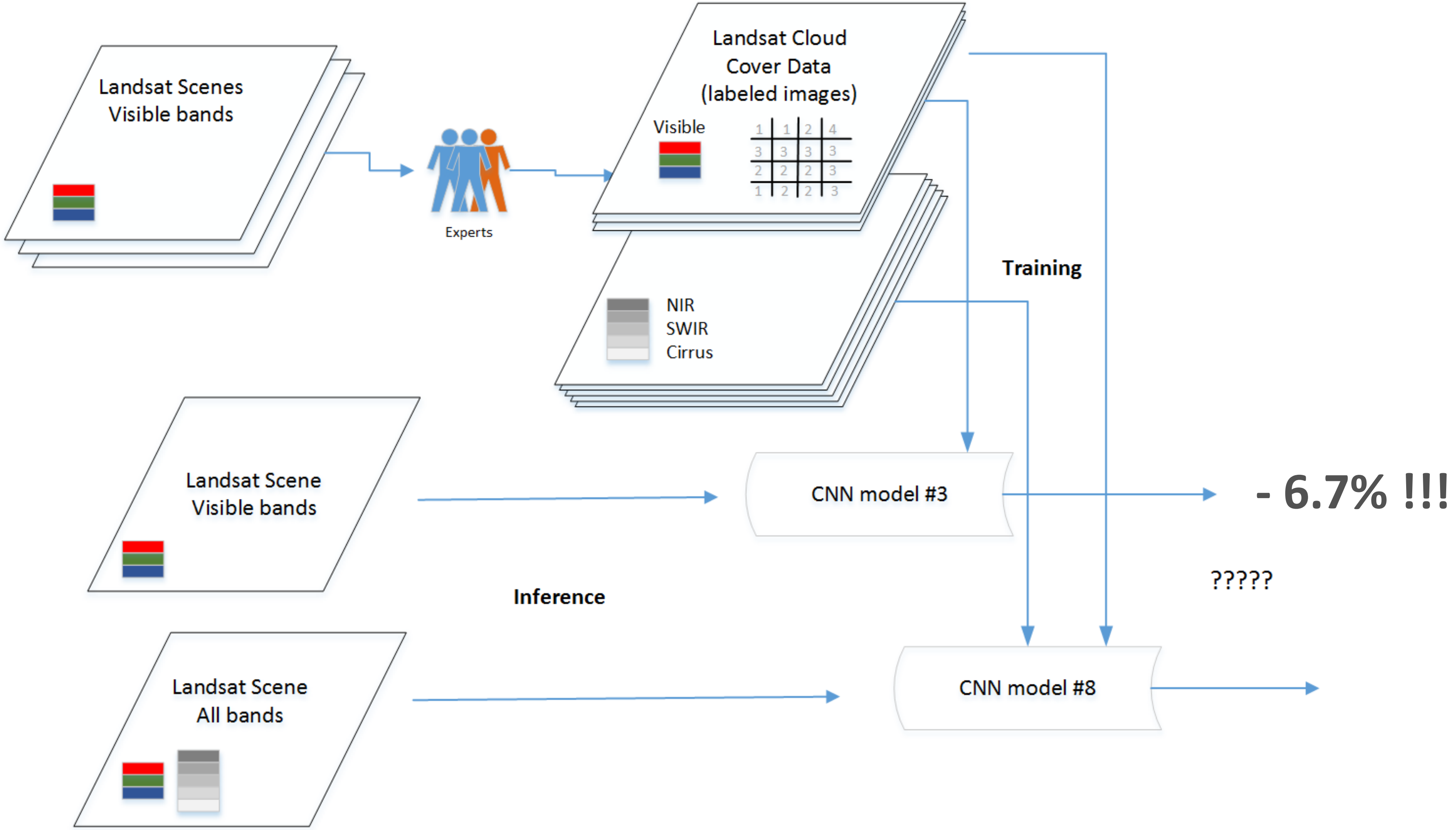
Model Name	Accuracy	Relative to baseline	Notes
Fmask - baseline	90.1%		TOA **No** thin clouds
Fertyle (Raw)	84.4%	-5.7%	
SinglePath CNN	92%	+0.9%	TOA With thin clouds
FertyleNet	94.9%	+4.8%	TOA With thin clouds

Performance sucks (for now)

FMASK – 2-3 minutes per scene

Fertyle Net ~ 2 hours per scene

Effect of invisible bands



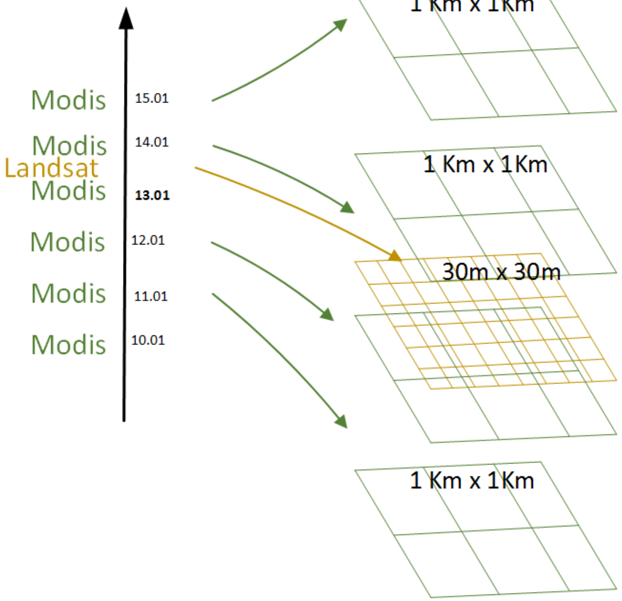
Software and hardware used

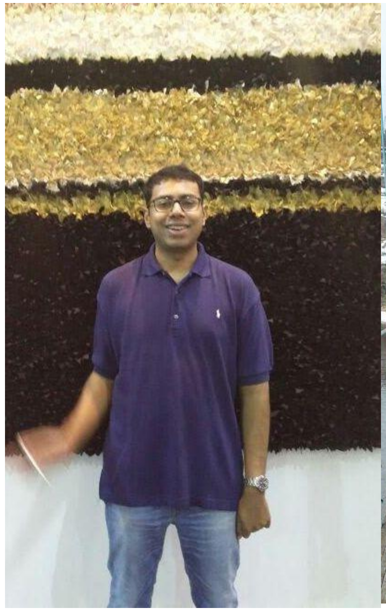
- Python Libraries For Preprocessing (landsat-util, GDAL, Scikit-Learn)
- Python Libraries for Deep Learning (Keras, TensorFlow)
- **Hardware**: Nvidia GeForce Titan X (3082 CUDA Cores, 336.5 GB/sec Memory Bandwidth)

Other Projects

Insects classification and quantification based on photo and video

Spatio-temporal blending of satellite images using Recurrent Neural Networks or similar methods





Thank you!

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