Modelling pan-tropical land cover and land-use change trajectories of newly deforested areas

Alejandro Coca-Castro[1]
[1] King's College London, United Kingdom (alejandro.coca_castro@kcl.ac.uk)

Research context

Raw MODIS 16d NDVI (2004-2016) time series for a given pixel

Forest cover

Well consolidated

Land trajectories following forest change

A decent level of mapping but few advances for monitoring **(Knowledge GAP!)**

Forest change

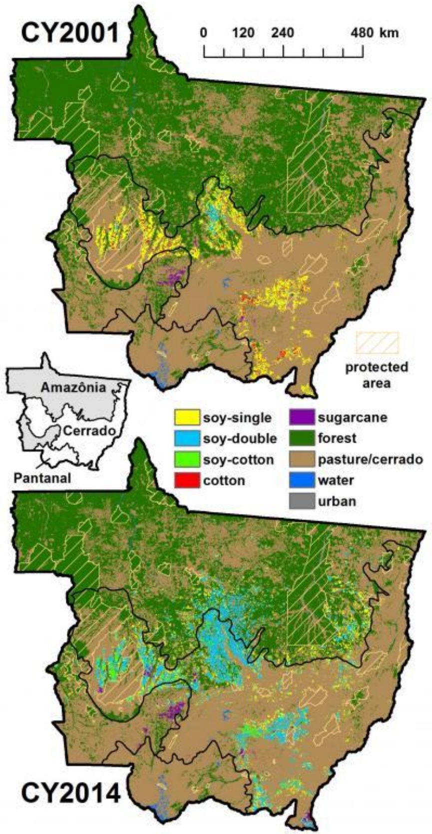
Well consolidated

Why land-change information over pantropical deforested areas?

- Supports national plans of payments for forest conservation schemes and climate mitigation.
- Contributes in modelling policy and planning scenarios for (agro)ecosystems management and conservation in tropics

Study area 1

Description of the study area



Matogrosso (MT) state, Brazil

Area = 903,357 km^2 (around three times larger than the area of Germany = 357,376 km^2)

Why?

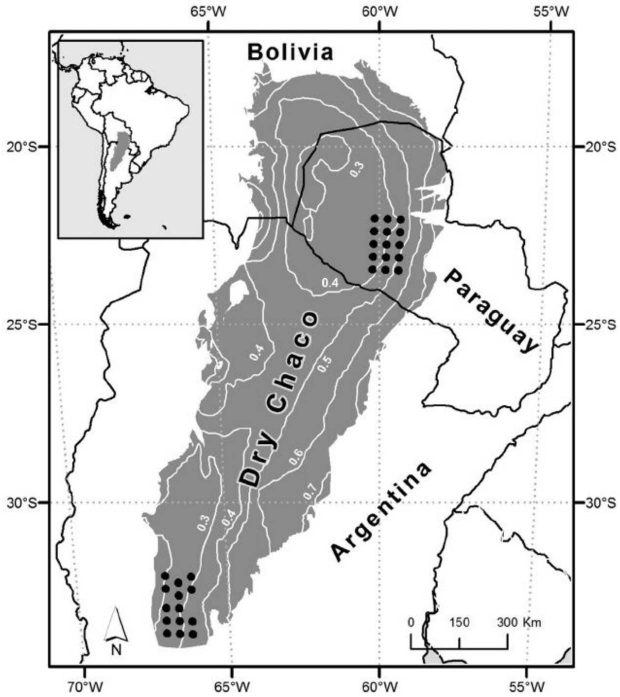
Benchmark area for studies of land change

Multiple sources to verify/validate

Dominant forest type: Evergreen (humid)

Study area 2

Description of the study area



Dry Chaco (DC), Bolivia-Paraguay-Argentina

Area = 1 Mkm^2 (around three times larger than the area of Germany = 357,376 km^2)

Why?

Benchmark area for studies of land change

Multiple sources to verify/validate

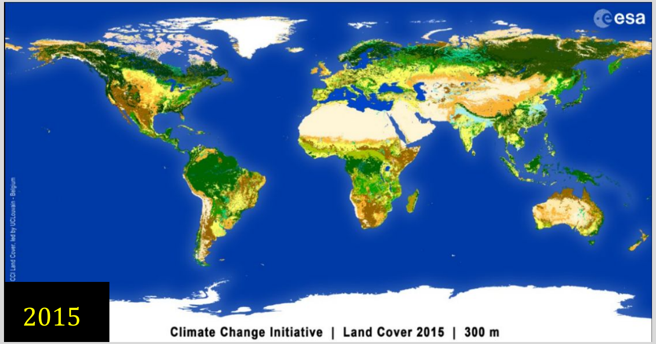
Dominant forest type: Deciduous (dry)

Reference land cover & land use (LCLU) data

Description of the main LCLU reference dataset used for the pilot tests

Coarse resolution land cover maps

“ESA CCI” land cover maps
Produced by ESA and collaborators
Geographical extent: Global
38 land-cover classes (UN-LCCS)
Multisensor-based 300m
Dates: annual from 1992 to 2015



Steps for generating the train/test/evaluation data:

- Target pixels: Selection of unchanged (stable) pixels according to ESA 1992-2015 (The quality band “flag 4” provides the location of those unchanged pixels)
- Extract MODIS MOD13Q1 red, blue, nir, mir reflectance values and labels for unchanged pixels (and neighbours 3x3) from 2001 to 2003

Land classes according to the reference dataset

Table 3-3: Correspondence between the IPCC land categories used for the change detection and the LCCS legend used in the CCI-LC classes.

IPCC Classes considered for the change detection		LCCS legend used in the CCI-LC maps	
1. Agriculture		10, 11, 12	Rainfed cropland
		20	Irrigated cropland
		30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)
		40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (< 50%)
2. Forest		50	Tree cover, broadleaved, evergreen, closed to open (>15%)
		60, 61, 62	Tree cover, broadleaved, deciduous, closed to open (> 15%)
		70, 71, 72	Tree cover, needleleaved, evergreen, closed to open (> 15%)
		80, 81, 82	Tree cover, needleleaved, deciduous, closed to open (> 15%)
		90	Tree cover, mixed leaf type (broadleaved and needleleaved)
		100	Mosaic tree and shrub (>50%) / herbaceous cover (< 50%)
		160	Tree cover, flooded, fresh or brakish water
		170	Tree cover, flooded, saline water
3. Grassland		110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
		130	Grassland
4. Wetland		180	Shrub or herbaceous cover, flooded, fresh-saline or brakish water
5. Settlement		190	Urban
6. Other	Shrubland	120, 121, 122	Shrubland
	Sparse vegetation	140	Lichens and mosses
		150, 151, 152, 153	Sparse vegetation (tree, shrub, herbaceous cover)
	Bare area	200, 201, 202	Bare areas
	Water	210	Water

Experimental sets based on Rußwurm and Körner (2017) approach

Description of the input data and methods

Input data (X) consist of 23 MODIS TERRA observations in a year period (Jan to Dec) with 37 features (nbands * npixels + fraction of the year)
where:
nbands = 4 [blue, red, mir, nir]
npixels = 9 [target pixel and 3x3 neighbours]

Dates for model train/test: 2001-2003, excluding 2000 due <23 observations
Dates for model use: 2004, 2010, 2014 (to check spatial/temporal consistency)

Two types of label data (Y) (experimental sets):

1) Keeping raw land cover LCCS 38-classes
2) Aggregating raw land cover LCCS classes to IPCC general 9-classes

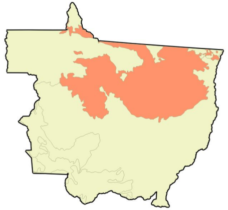
Experimental sets based on Rußwurm and Körner (2017) approach

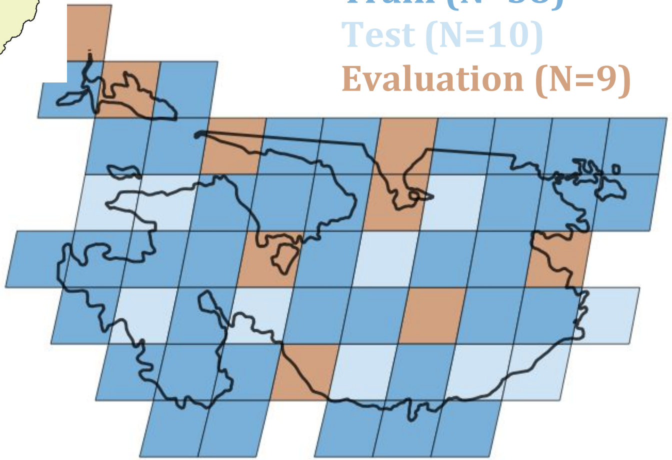
Spatial distribution of the train, test and evaluation sets

Pixels selection: only labels > 100 with occurrences, 100 random samples by label by tile*

Matogrosso (MT)

Subset "homogeneous area": Matogrosso Seasonal forest





TILES (N=57)

4:1:1

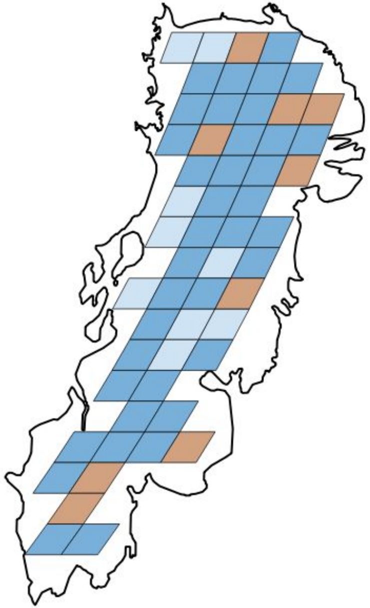
Train (N=38)

Test (N=10)

Evaluation (N=9)

Dry cacho (DC)

Subset "homogeneous area": Dry Forest



TILES (N=55)

4:1:1

Train (N=37)

Test (N=9)

Evaluation (N=9)

* Tiles consist of 400 pixels X 400 pixels (datacubes built with [rastercube package](#))

Experimental sets based on Rußwurm and Körner (2017) approach

Settings of the models and implementation

60 networks trained by each architecture (LSTM, RNN, CNN)
30 epochs
Layers - l: {1,2,3}
Recurrent cells (RNN/LSTM) or # of neurons (CNN) - r: {37,64,148,222}
5 folds
dropout = 0.5

Implementation -
Modified source code from Rußwurm and Körner (2017)
Models built with Tensorflow v.1.0.1.
GPU processing (GeForce GTX 1080)

TensorFlow

Experimental sets based on Rußwurm and Körner (2017) approach

Post-processing and verification (model use)

OUTPUT:

- Consist of the predicted label by observation by year
- The mode (‘the most frequently occurring predicted label’) was computed for each 23 observations to assign the predicted label by year

VERIFICATION:

1. 2004-2015 ESA reference maps for Chaco and Matogrosso
2. 2004, 2010 and 2014 Terraclass (only for Matogrosso)

Results

Best architectures by experimental test by zone by model

Study area	Dataset	LSTM		RNN		CNN	
		l	*r*	*l*	*r*	*l*	*r*
MT	38 classes	2	222	1	64	1	222
MT	9 classes*	2	222	1	64	1	222
DC	38 classes	1	64	1	148	1	222
DC	9 classes	Processing	Processing	Processing	Processing	Processing	Processing

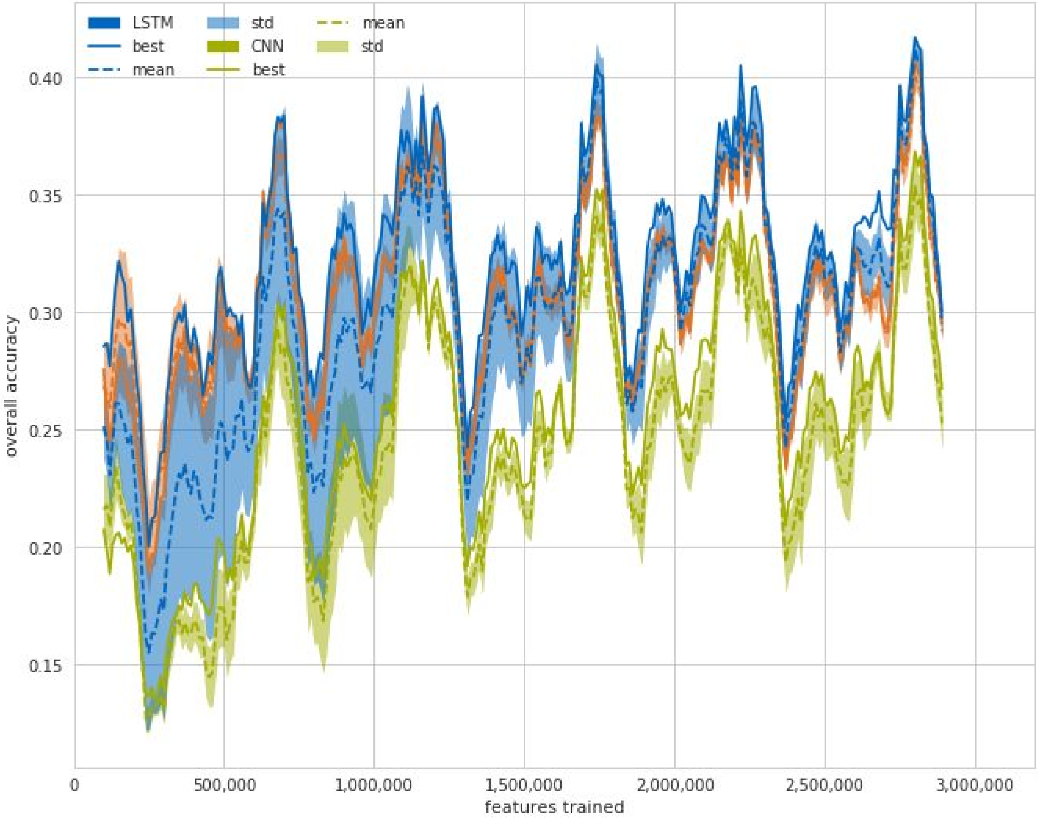
* Temporal results / Only using 1 fold

Matogrosso: results using ESA-CCI 38-classes

Results: Evolution of overall validation accuracy performance of CNN, RNN, and LSTM architectures

Comments:

- A “seasonal” pattern observed along the training process (noise?)
- RNN & LSTM obtained similar results (overall accuracy between 0.15 and 0.35)
- Larger variations (std) during the first iterations (<1.5M) in comparison latest iterations in particular for LSTM

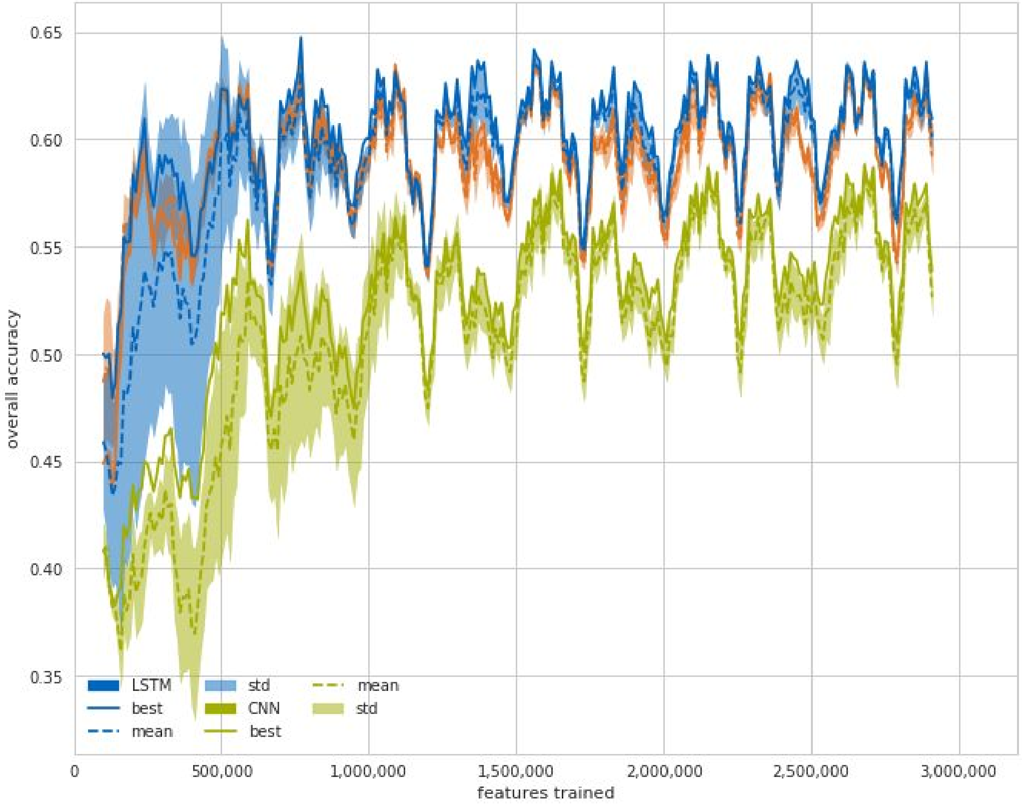


Matogrosso: results using IPCC general 9-classes

Results: Evolution of overall validation accuracy performance of CNN, RNN, and LSTM architectures

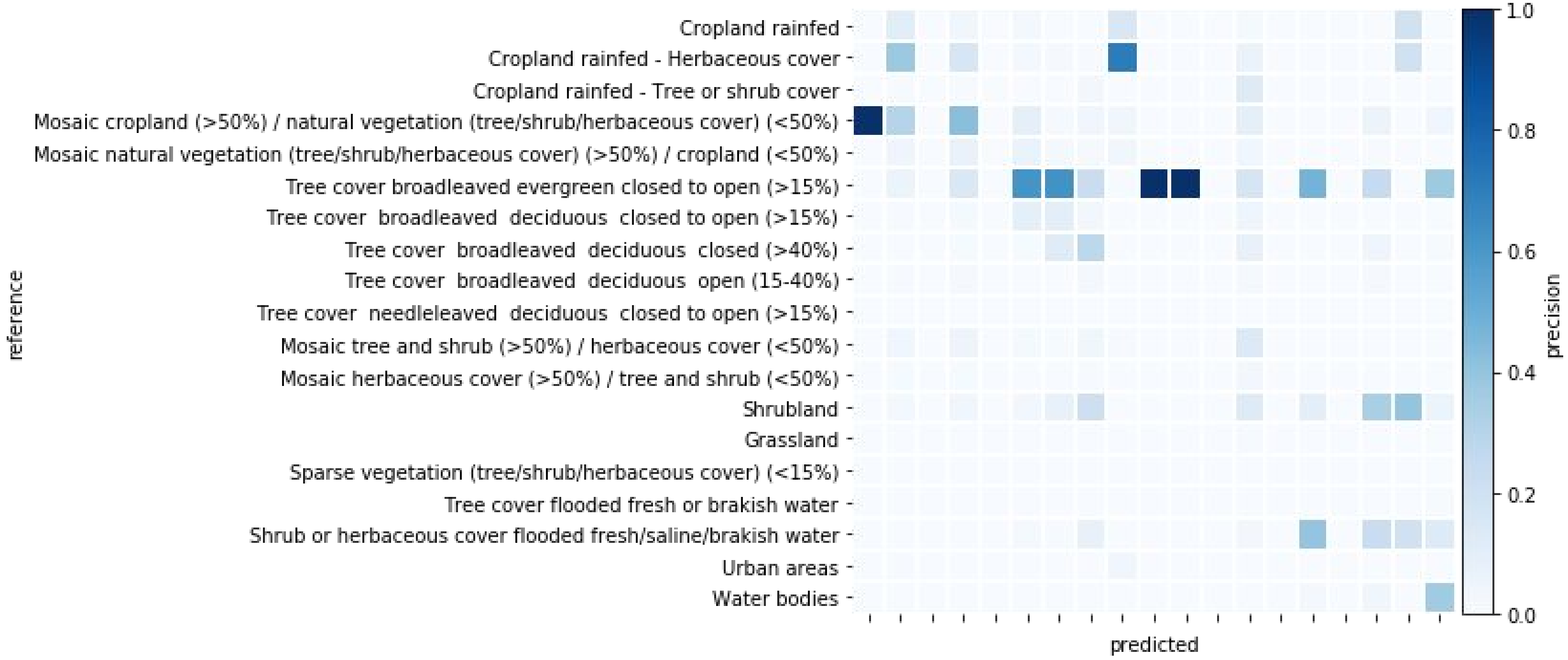
Comments:

- A similar “seasonal” pattern observed in the dataset of 38-classes along the training process but producing higher accuracy values
- RNN & LSTM obtained similar results (overall accuracy between 0.45 and 0.62)
- Larger variations (std) during the first iterations (<1M) in comparison latest iterations > bigger std for LSTM



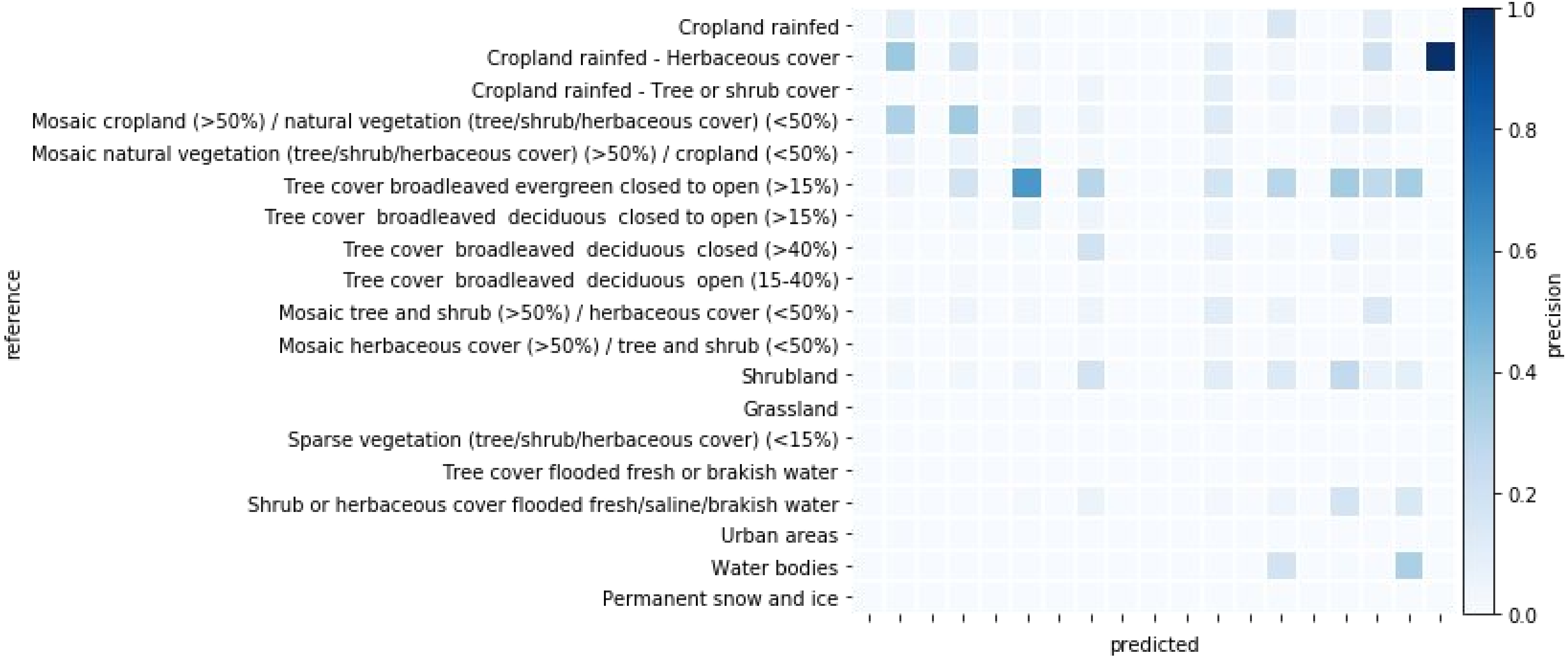
Matogrosso: results using ESA-CCI 38-classes

Results: Confusion matrix by the best LSTM model architecture



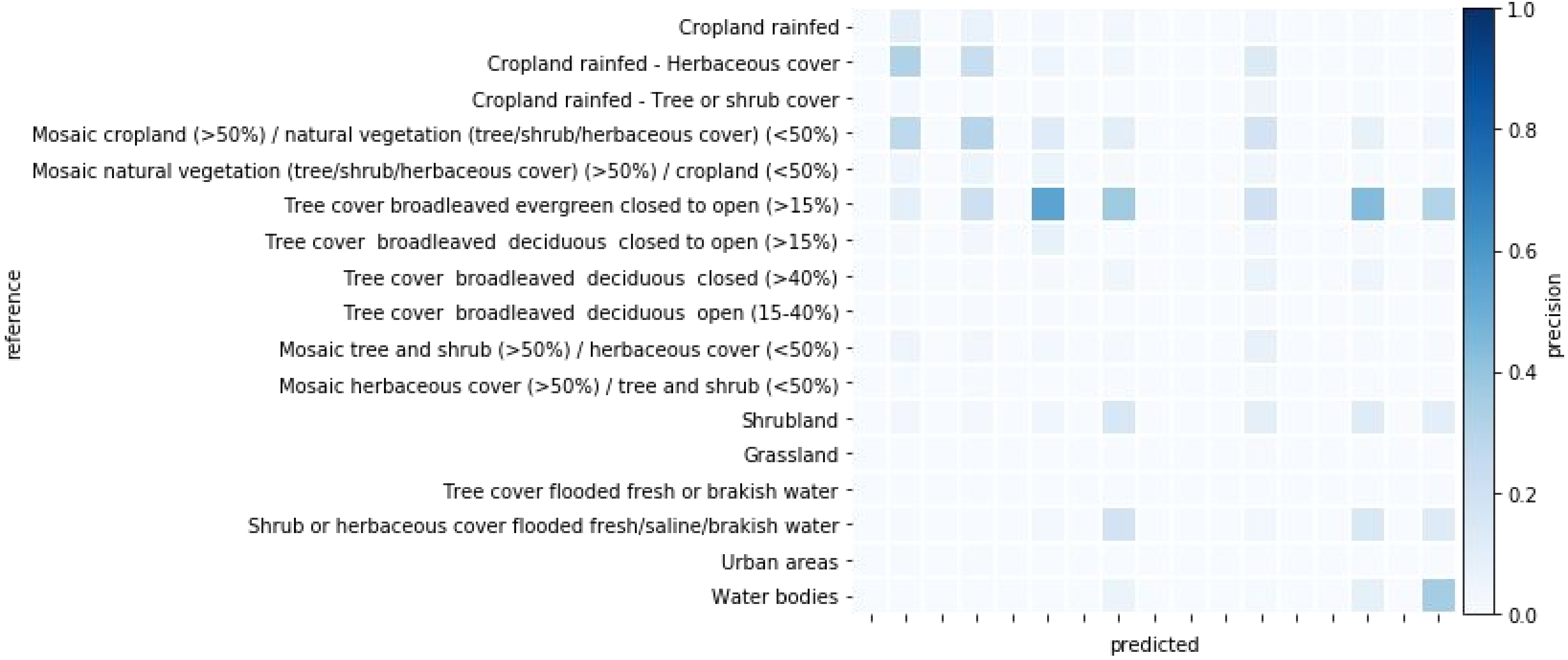
Matogrosso: results using ESA-CCI 38-classes

Results: Confusion matrix by the best RNN model architecture



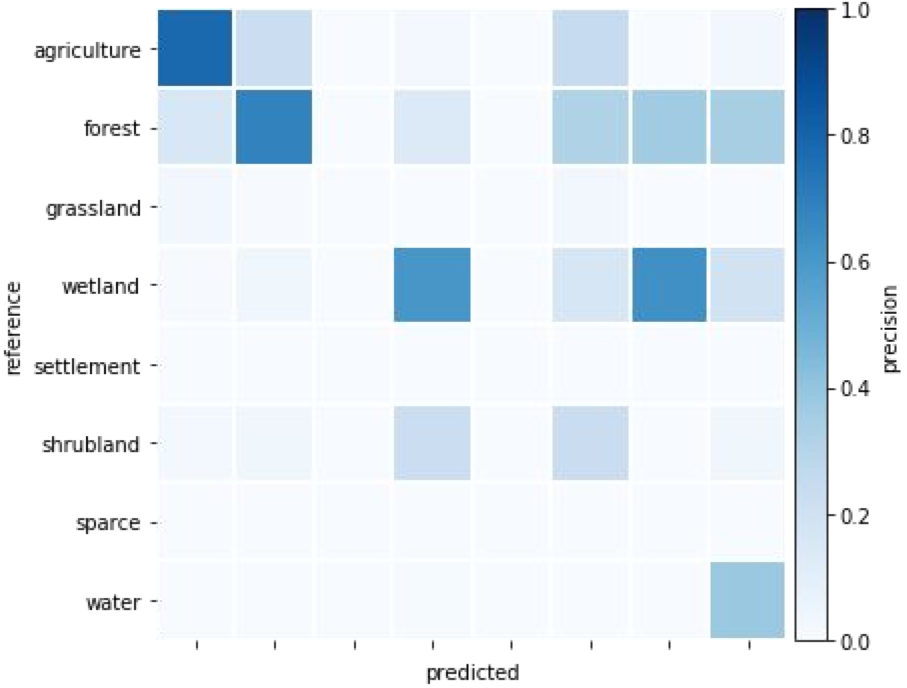
Matogrosso: results using ESA-CCI 38-classes

Results: Confusion matrix by the best CNN model architecture



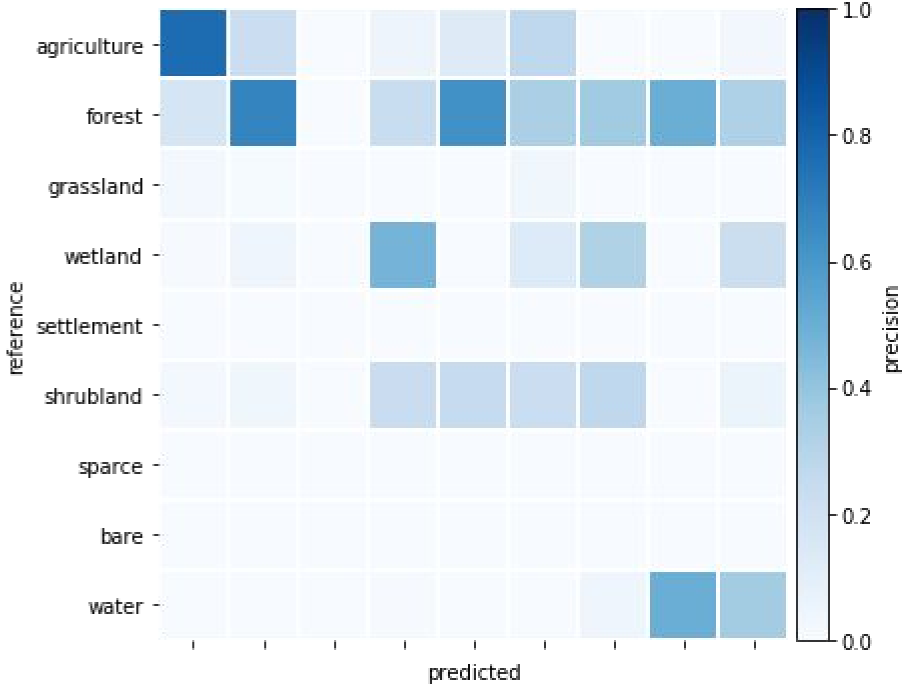
Matogrosso: results using IPCC general 9-classes

Results: Confusion matrix by the best LSTM model architecture



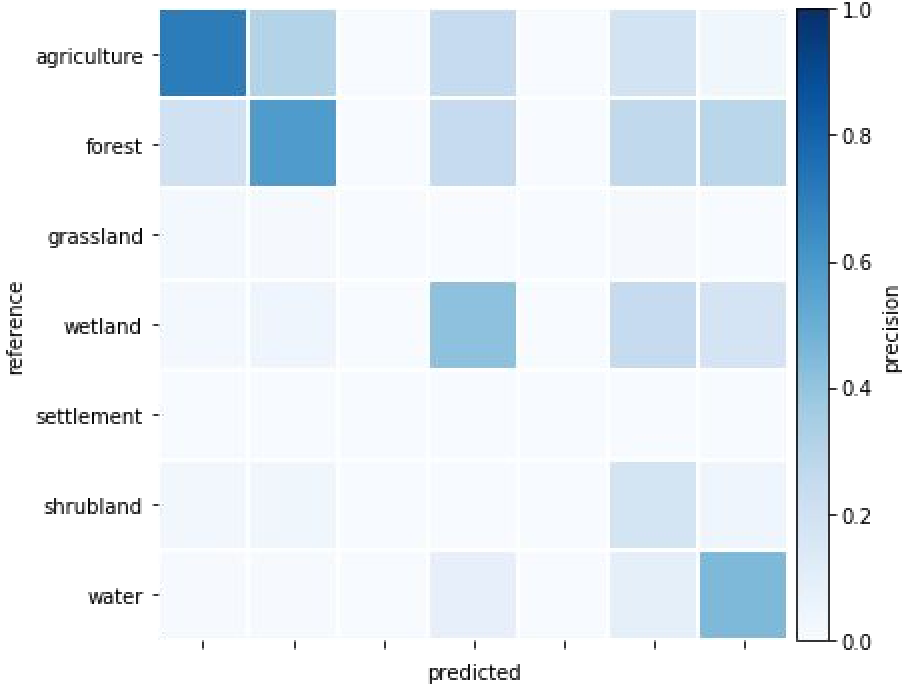
Matogrosso: results using IPCC general 9-classes

Results: Confusion matrix by the best RNN model architecture



Matogrosso: results using IPCC general 9-classes

Results: Confusion matrix by the best CNN model architecture

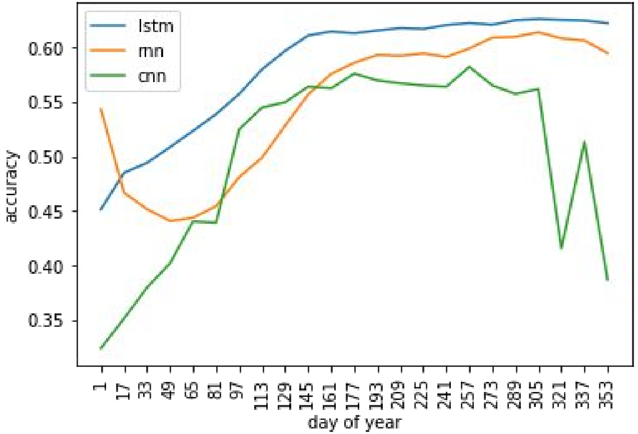


Matogrosso: results using ESA-CCI 38-classes & IPCC general 9-classes

Results: performance of the best networks with increasing number of observations

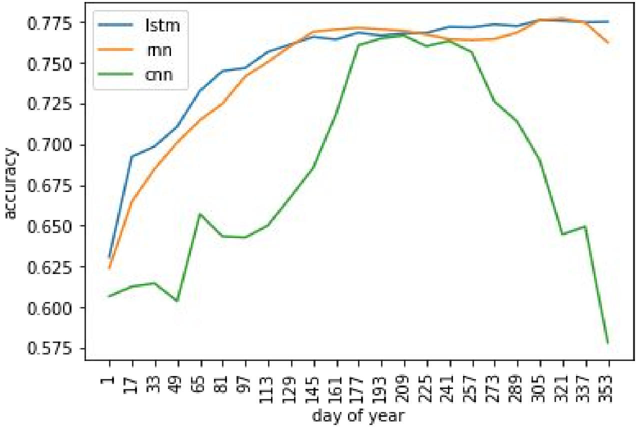
ESA-CCI
38-classes

	LSTM	RNN	CNN
	all	all	all
accuracy	58.3	54.9	50.0
kappa	29.1	26.2	19.7
precision	36.0	33.4	29.3
recall	42.3	39.7	34.4
fscore	37.7	34.7	28.1



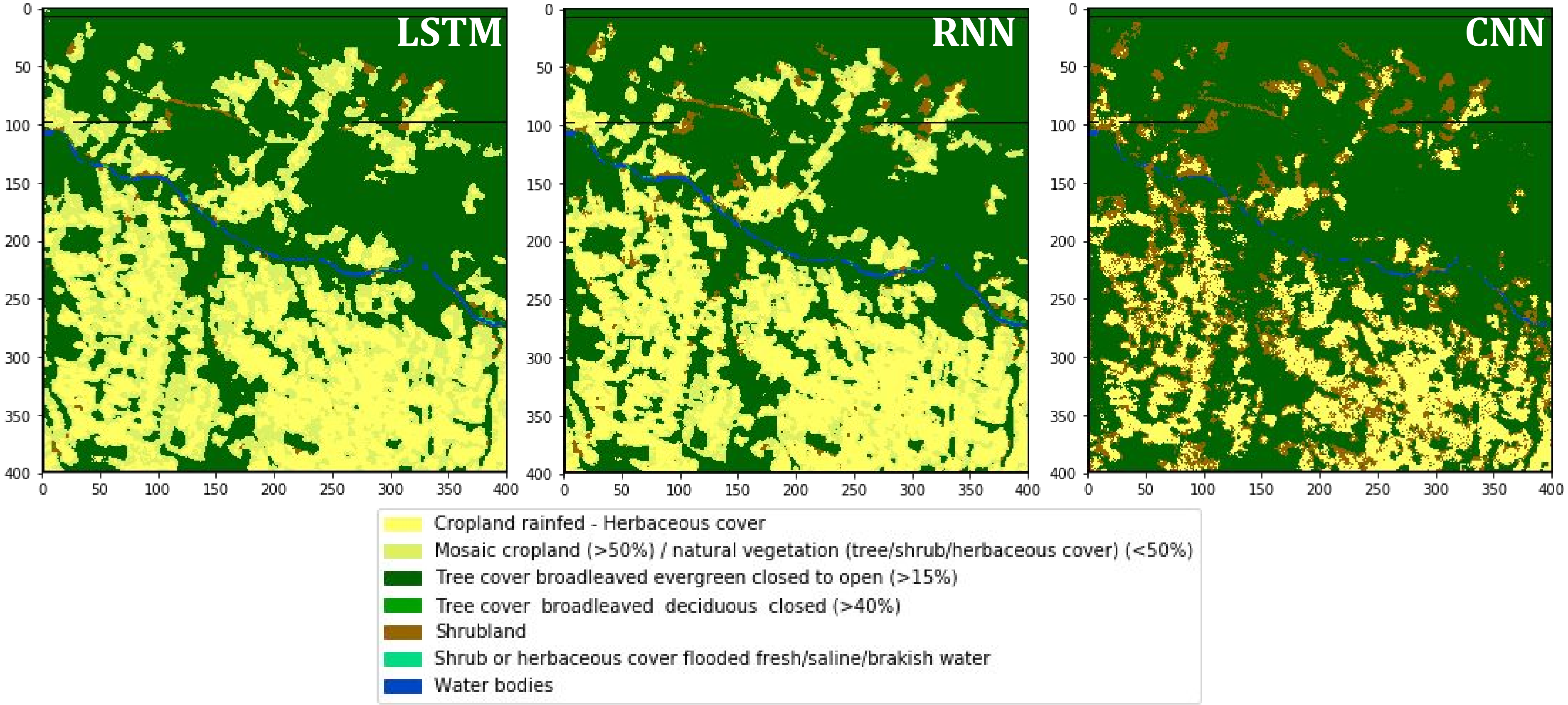
IPCC
9-classes

	LSTM	RNN	CNN
	all	all	all
accuracy	75.1	74.5	68.2
kappa	48.7	46.8	32.6
precision	68.7	66.9	60.0
recall	69.4	68.4	61.4
fscore	67.8	66.4	57.7



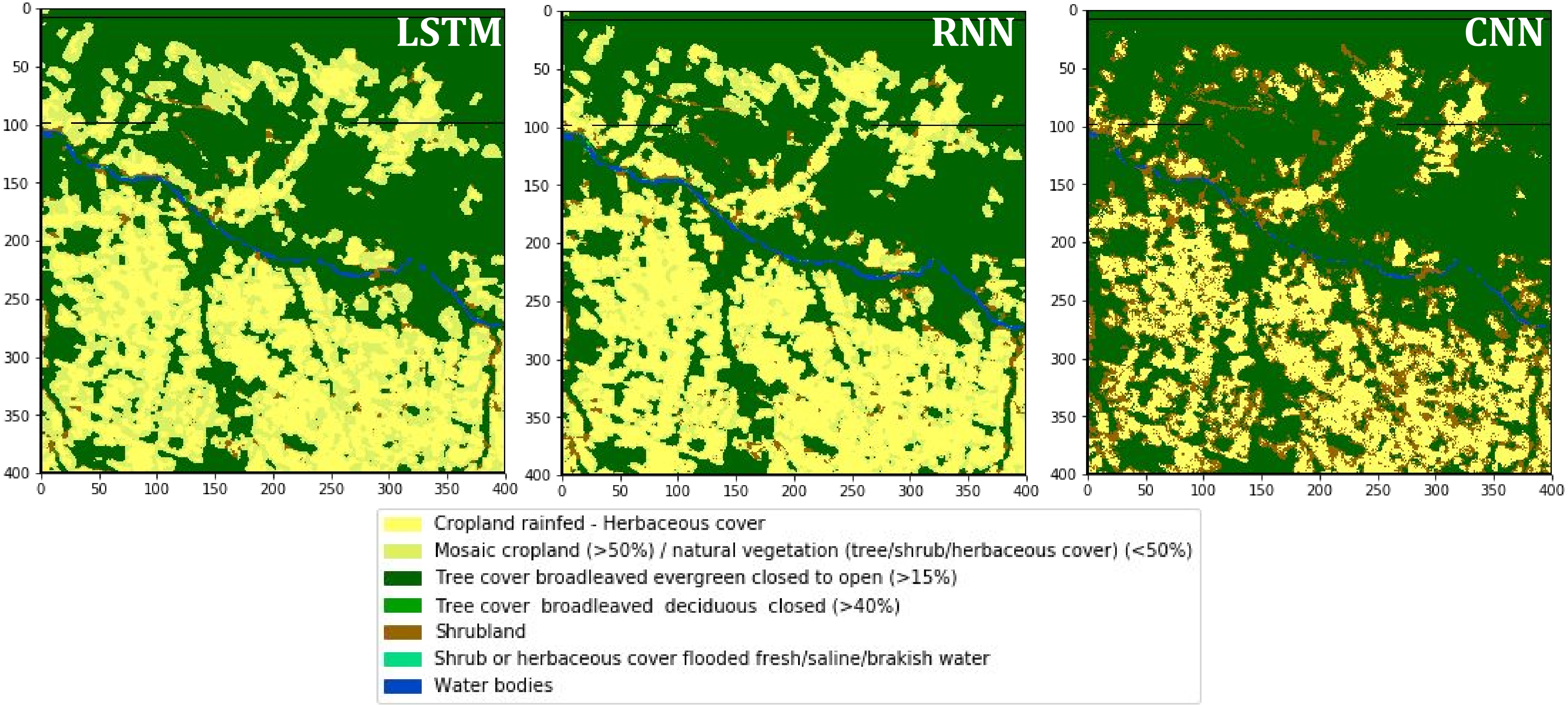
Matogrosso: model use - best models using ESA-CCI 38-classes

2004 maps by model



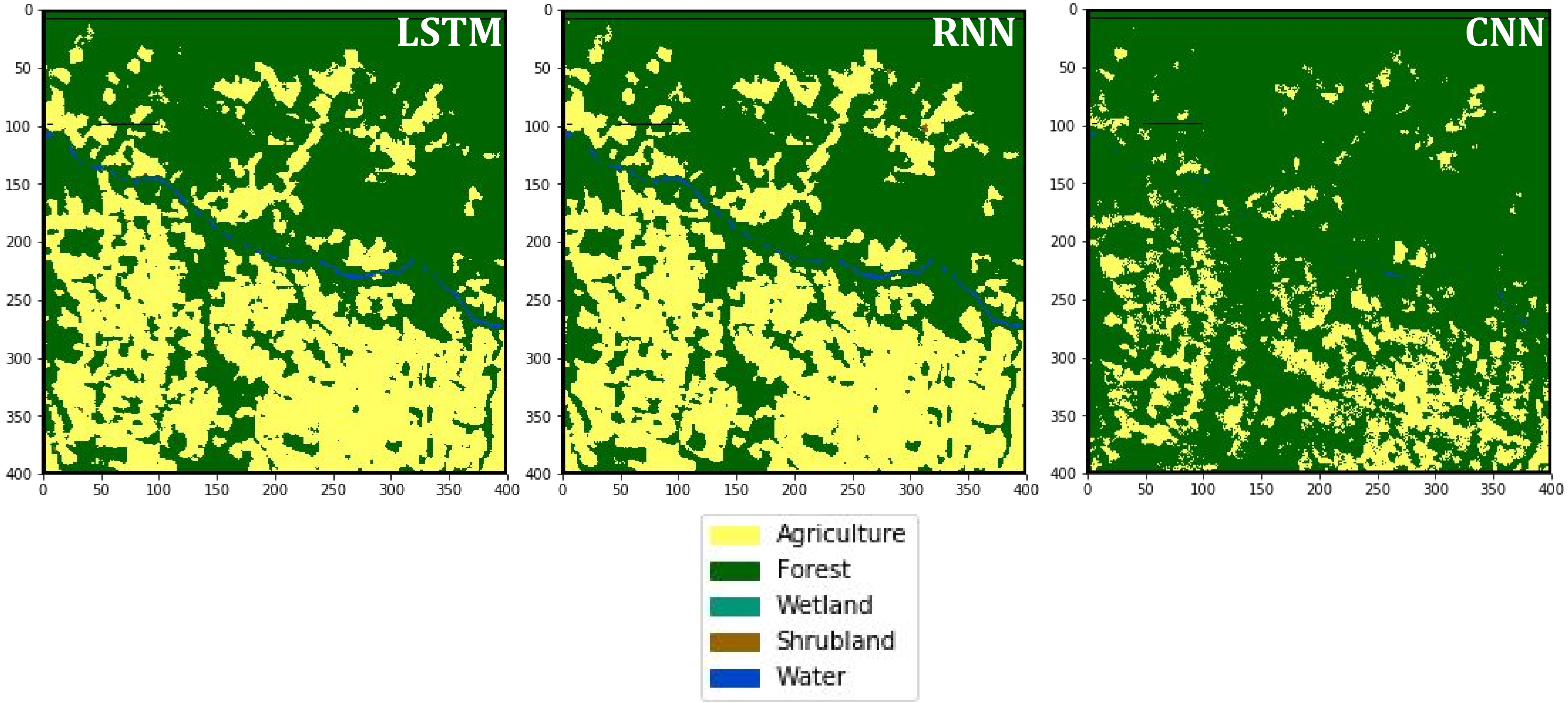
Matogrosso: model use - best models using ESA-CCI 38-classes

2014 maps by model



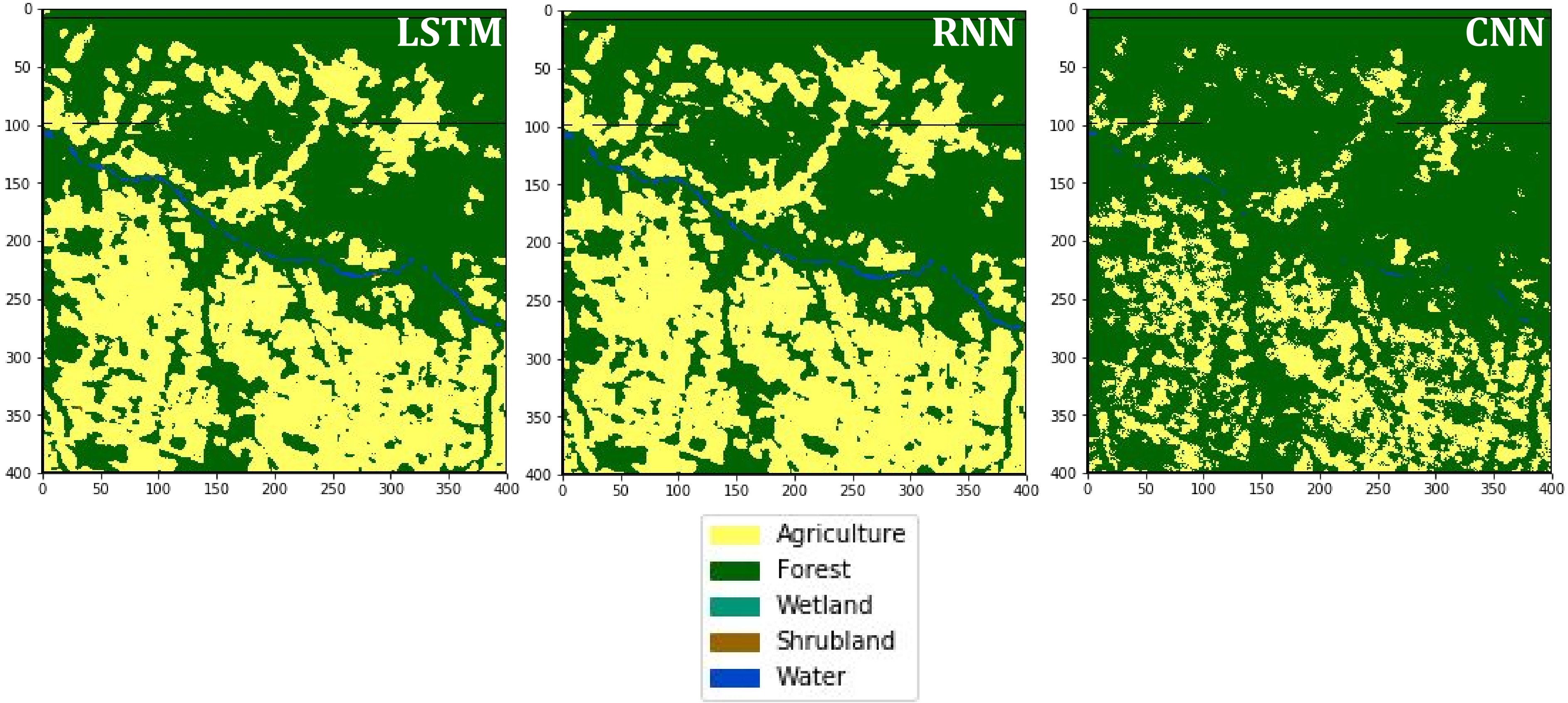
Matogrosso: model use - best models using IPCC general 9-classes

2004 maps by model



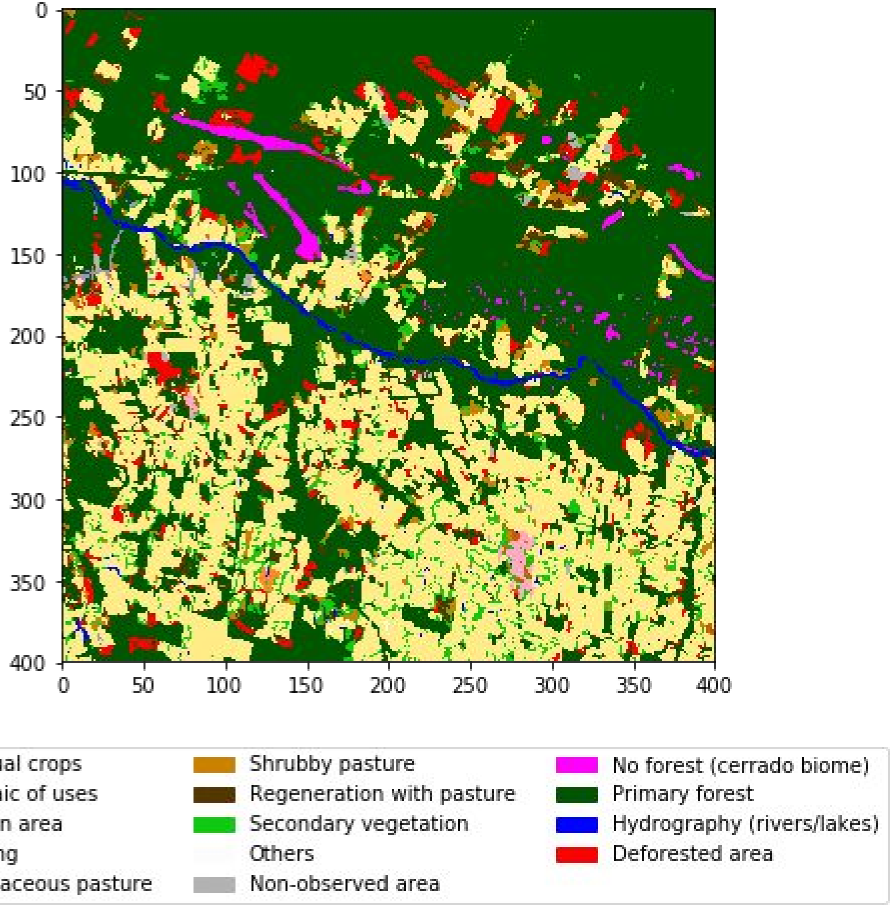
Matogrosso: model use - best models using IPCC general 9-classes

2014 maps by model

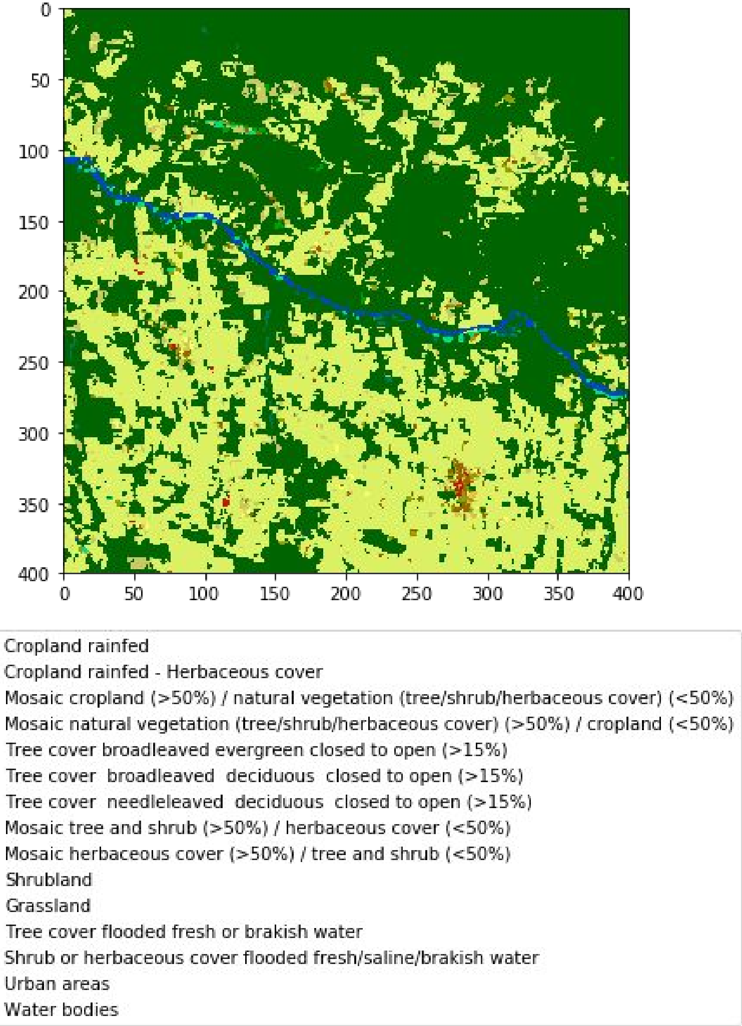


Verification by dataset:
Year 2004

Terraclass

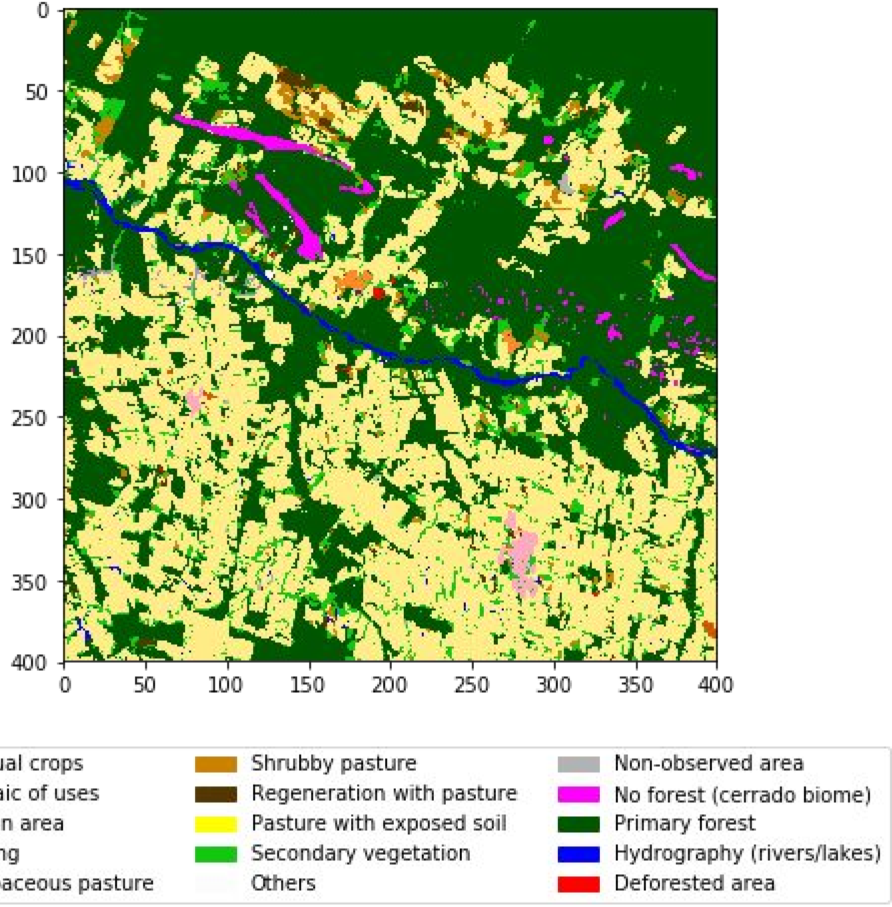


ESA-CCI

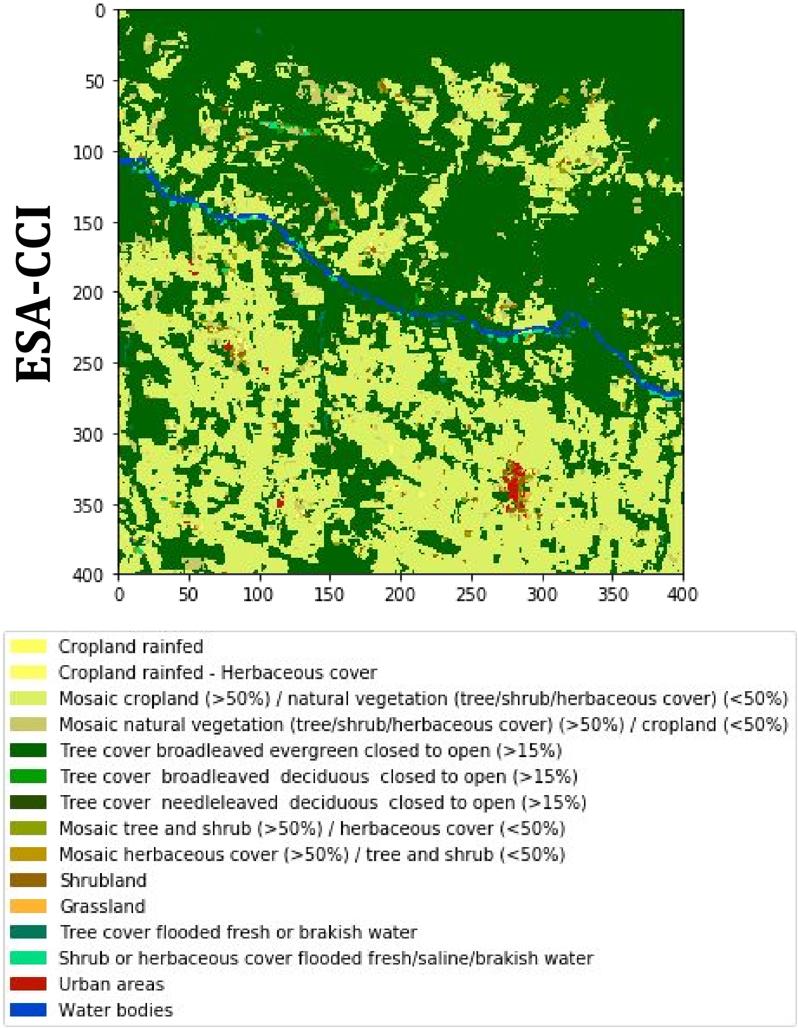


Verification by dataset:
Year 2014

Terraclass



ESA-CCI



Implications

- The structure of the input data [surface reflectance of target pixel + neighbours and the fraction of the year] seems to provide consistent spatial and temporal results according to the reference datasets (and Google earth & Bing satellite images - not show here)
- Classes such as crop, shrubland, forest, water are in overall well distinguish by the models, in particular by the LSTM and RNN models
- Classes such as urban, bare, sparse vegetation are hardly discriminated
- The models built with the ESA-CCI 38 classes provide a reasonable spatial consistency of the classes mapped even their performance (metrics) is lower than models built with the IPCC general 9-classes
- LSTM and RNN models are favoured with the increase of number of observations which is not the case of CNN (mono-temporal approach)

Caveats

- The structure of the input data with neighbours might affect the model separability of certain classes such as urban, scarce, bare
- Models present different optimal architectures according to the input of the data. The stratification by homogeneous regions (ecoregions) might be a good starter to optimise models' performance
- Relation of 4:1:1 to split train, test, validation might affect the selection of the optimal architecture
- For modelling land trajectories at large scale, the models assessed consume large volume of labelled data
- For applications, the study of land trajectories with the generated maps are limited to the mapped classes in the study area and thus certain trajectories as active/fallow cropland and forest regrowth are not mapped

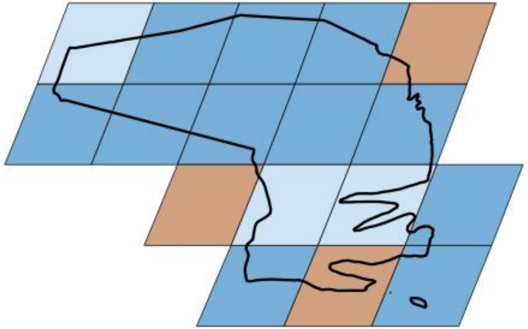
Future work

Based on the recent work by Jia et al (2017) ‘Predict Land Covers with Transition Modeling and Incremental Learning’ the following settings might be desired for future work over the types of deep learning architectures assessed:

- Add transition rules to the models, in particular for LSTM and RNN to avoid inconsistent or rare transitions (bare to forest)
- Add as input feature, distance metrics of the label class between the target pixels and neighbours
- Adapt the models with incremental learning:
    - To update the model with the latest spectral features
    - To become aware of the land cover transition in more recent years

Source code and sample data

- Source code is a modified version of Rußwurm and Körner (2017) source code. For this research, the evaluation data contain an additional layer of information about the coordinates (xy), year, day of observation and fraction number by pixel. This information allows mapping, visualising and verifying the outputs (i.e GIS software)
- The sample data correspond to a small area (Alto Paraguay state, Paraguay) mainly located in the dry chaco ecoregion (17 tiles)



TILES (N=17)
4:1:1
Train (N=11)
Test (N=3)
Evaluation (N=3)