Irrigation (beta version) - Appendix

Collection 5

Version 1

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1 Overview of the classification method

The MapBiomas project produces, among other land use and land cover classes, annual agriculture maps in Brazil from 1985 to the present. Throughout the collections launched by the MapBiomas project, the need for a better characterization of the mapped agricultural regions was identified. In addition to the agriculture maps, the MapBiomas' Collection 5 included a beta version of irrigated agriculture maps in Brazil in the period of 2000 to 2019.

The irrigation products include maps of center pivot irrigation systems in Brazil and a first effort to map other irrigation systems in some municipalities located in the Brazilian semi-arid region. Since these new maps do not represent land use and land cover class, but rather a type of agricultural management, they are presented in a separate section from agriculture mapping indicating new maps as qualifiers for land use and land cover classes.

The first attempts in the MapBiomas project for mapping center pivot irrigation systems came through the Next Generation Mapping (NexGenMap) project. The objective of this initiative was to develop machine learning algorithms, tools and methods for producing the most current, detailed and accurate maps of land use and land cover using daily PlanetScope imagery, cloud computing, and new artificial intelligence algorithms. In the NextGenMap project, artificial intelligence algorithms were developed to map center pivot irrigation systems using PlanetScope imagery in a study area located in the Cerrado biome (SARAIVA et al., 2020).

The maps of other irrigation systems are the first effort to develop a method capable of mapping other irrigation systems besides the center pivot irrigation system, such as conventional sprinkler and localized irrigation. In Brazil, recent studies developed by the Brazilian National Water Agency and partners developed new methods for mapping irrigated agriculture using automatic algorithms and cloud computing, highlighting the importance of this theme (ANA, 2019b, 2020).

The mapping of 'Center pivot irrigation systems' class in the Brazilian territory was performed using Landsat imagery and an adapted U-Net architecture (RONNEBERGER et al., 2015), an image segmentation convolutional neural network architecture. The U-Net was trained using a set of samples collected for the year 2017. To increase the temporal and spatial consistency of the final maps, the raw result was post-processed using temporal and spatial filters (Figure 1).

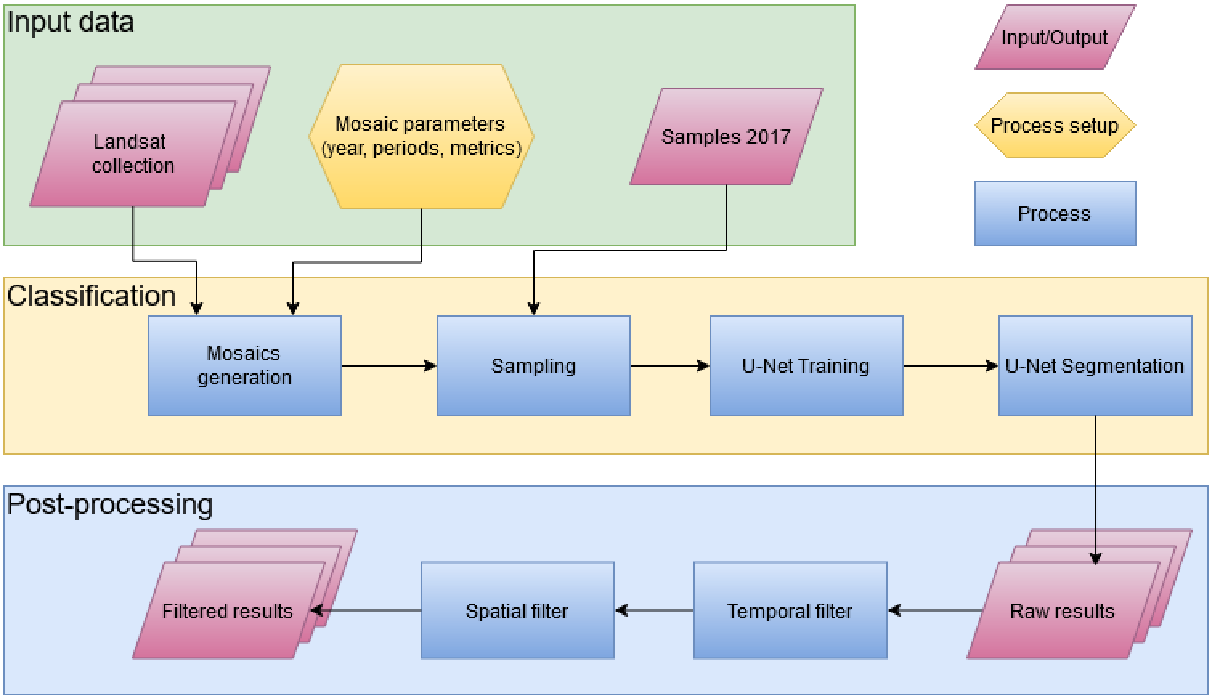

Figure 1. Classification process for mapping center pivot irrigation systems in MapBiomas Collection 5.

The 'Other irrigation systems' class was mapped only for some municipalities in the Brazilian semi-arid region using the Random Forest classifier (BREIMAN, 2001). The process used was similar to that used to map the 'Center pivot irrigation systems' class. The main differences are in the generation of samples, which uses a semi-automatic approach based on agriculture maps and estimates of the irrigated area by Brazilian municipalities (Figure 2). The scripts used to produce these irrigation maps are publicly available on GitHub (MAPBIOMAS, 2020).

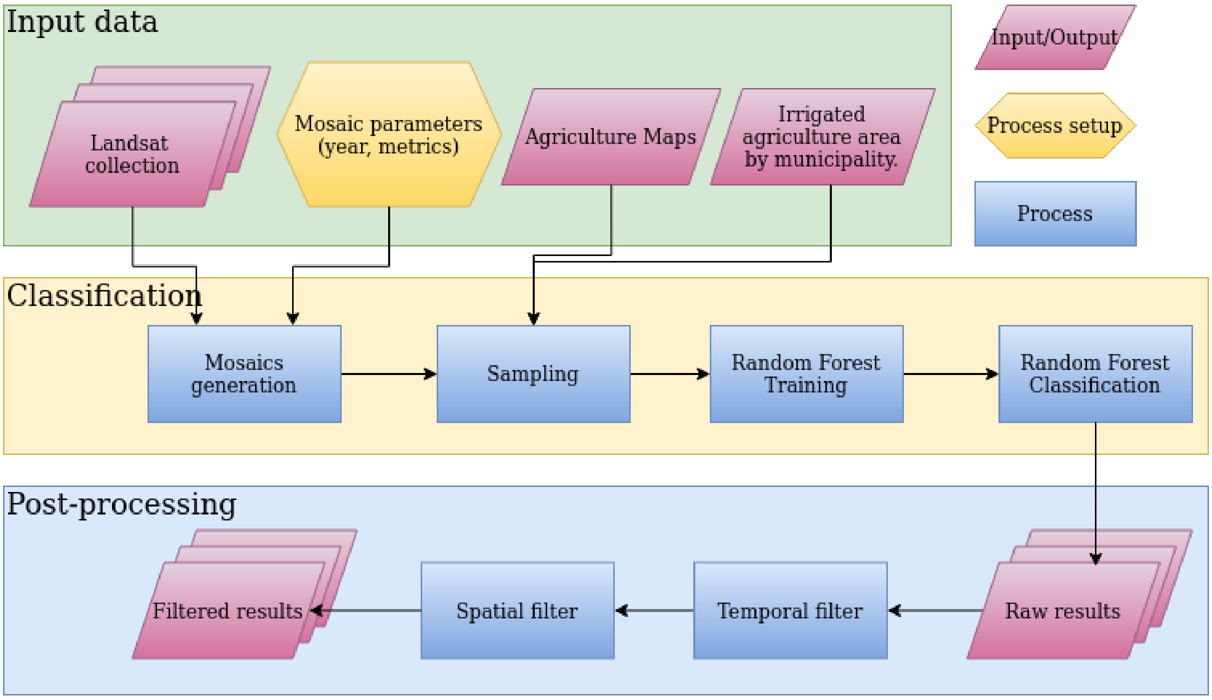

Figure 2. Classification process for mapping irrigated agriculture in MapBiomas Collection 5.

2 Center pivot irrigation systems

2.1 Image selection

The mapping of the center pivot irrigation systems used annual mosaics generated from available images in each year. Therefore, images from the Landsat series were obtained on the Google Earth Engine platform (Collection 1 Tier 1 TOA) in the period of 2000 to 2019. Only images with under 80% of cloud cover and shadows were considered.

2.2 Definition of regions for classification

The reference maps used to classify center pivot irrigation systems were produced by the Brazilian National Water Agency in partnership with Embrapa Milho e Sorgo, referring to the years 1985, 1990, 2000, 2005, 2010, 2014, and 2017 (ANA, 2019a). These mappings were produced using visual interpretation in images obtained by the Landsat 5, Landsat 8, and Sentinel 2A/2B satellites, as well as high-resolution images (<1 meter) from Google Earth.

For the delimitation of the study area, the Brazilian territory was divided into blocks of 0.5' x 0.5' degrees (~300 thousand ha each). Only blocks with occurrence of center pivot irrigation systems in any of the reference map years were selected. Figure 3 shows the 723 chosen blocks distributed across an area of approximately 212 million hectares to map center pivot irrigation systems in Brazil.

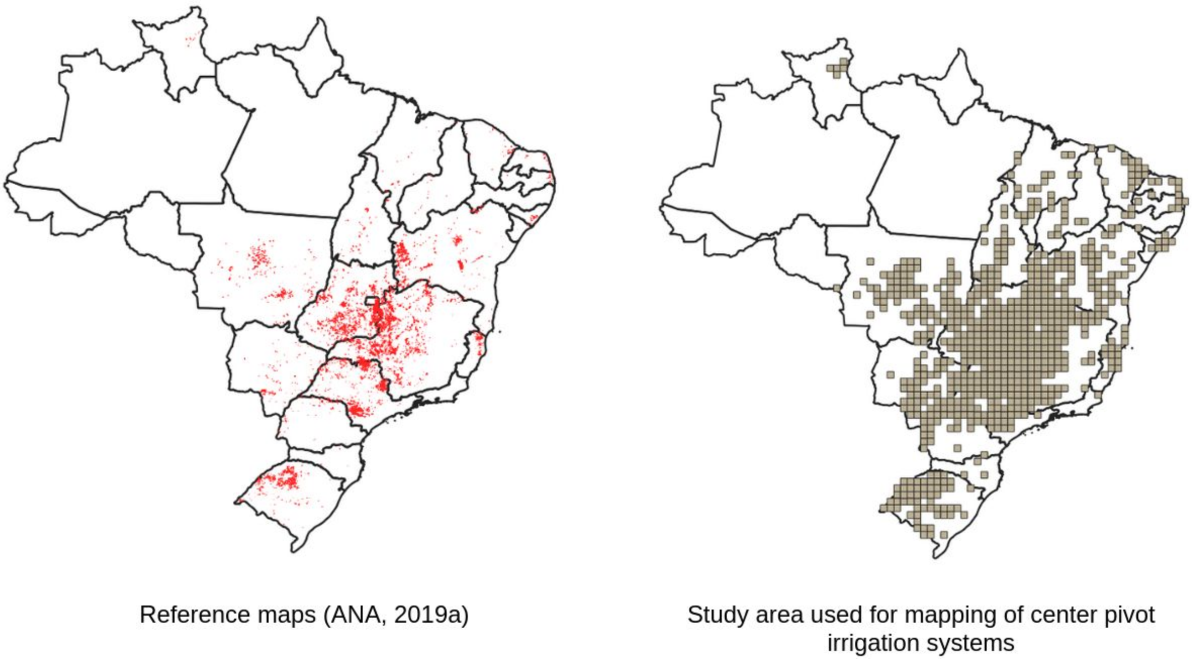

Figure 3. Study area for the mapping of center pivot irrigation systems in Brazil in the MapBiomas Collection 5.

2.3 Classification

2.3.1 Classification scheme

Each class of interest was mapped separately. Therefore, two independent classifications were performed to map: 1) Center pivot irrigation systems; 2) Other irrigation systems. The center pivot irrigation systems mapping considered only two possible classes for each pixel, center pivot irrigation systems, and non-center pivot irrigation systems.

2.3.2 Feature space

The feature space created for the center pivot irrigation systems mapping aimed to obtain the characteristics of the pivot at the time they were cultivated, as well as to highlight the differences in relation to the other targets, such as other agriculture areas, pasture, forest formation, etc. Therefore, three metrics were selected that showed the best results to distinguish the pivots in relation to the other targets:

- NDVI_p75, 75th percentile of NDVI values for all images;
- NDVI_p100, 100th percentile, or maximum value, of the NDVI values of all images, and;
- NDVI_stdDev, the standard deviation of the NDVI values for all images.

The mosaic generated is composed by the selected metrics. Each metric corresponds to a band in the image, as shown in Figure 4.

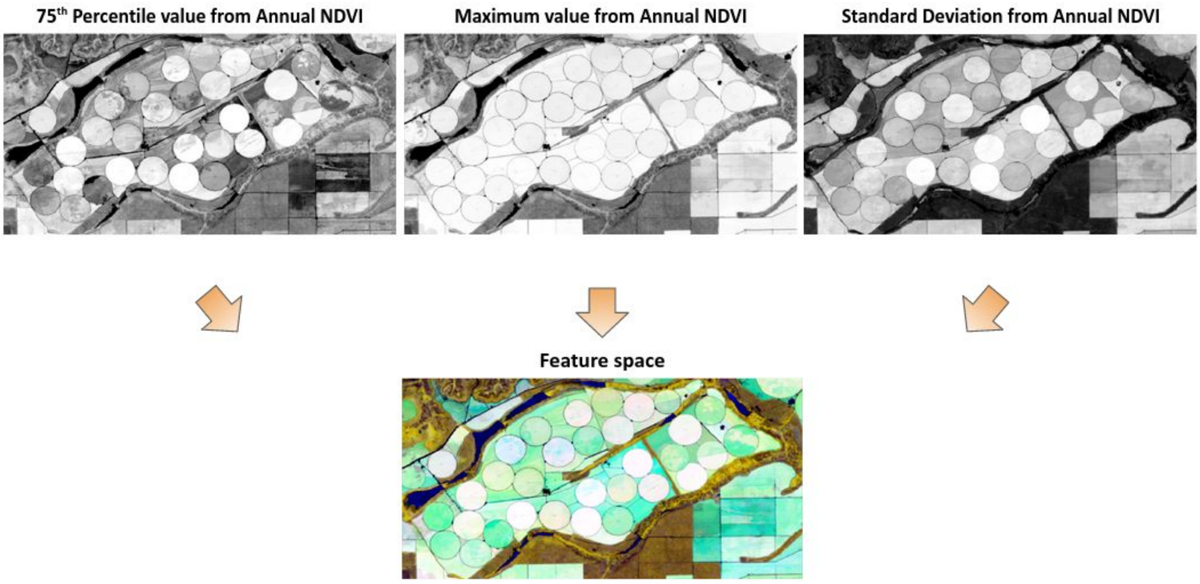

Figure 4. RGB visualization (NDVI p75, NDVI Maximum, NDVI stdDev) of an image used for training and mapping of the center pivot irrigation systems, generated for the year 2017.

The use of images with only three bands accelerated the process of training and classifying the pivots since the reduced amount of bands also reduced the computational infrastructure necessary for the processing of this data.

2.3.3 Classification algorithm, training samples and parameters

Due to the extensive study area (~212 Mha) and computational limitations, the model was trained using only a subset of blocks chosen from the population of 723 blocks. The choice of sample data is an important step for training Deep Learning models, once the samples must represent all the spatial and spectral variability of the population. For this, stratified sampling was performed based on the pivot area obtained from the reference maps. The sampling considered three strata: with low, medium and high coverage of center pivot irrigation systems. The stratum containing blocks with low coverage was created from the blocks whose pivot area was less than or equal to the median of the area of all blocks, that is, 50% of the blocks (361 blocks). The stratum with the high coverage was created from blocks whose sum of the area of its pivots covers about 50% of the pivot area of the entire population (total of 41 blocks). Finally, the remaining blocks (321 blocks) were used to create the layer with blocks containing a medium cover of center pivot irrigation systems. After creating the stratum, 20 blocks were randomly chosen for training and 10 blocks for testing in each of the three stratum. The training blocks were used to calibrate the model, while the test blocks were used later for the accuracy analysis of the model. Figure 5 illustrates the spatial distribution of the stratum and blocks chosen for training and testing the population model.

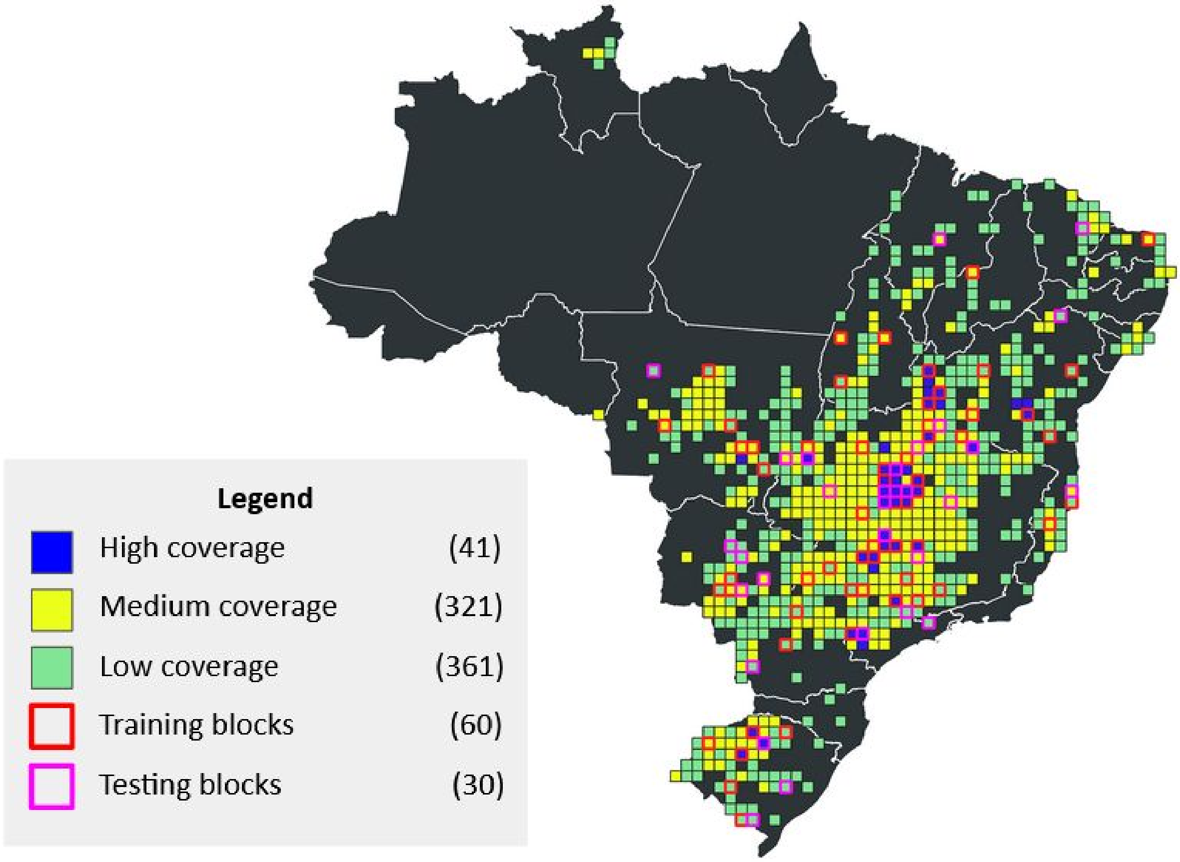

Figure 5. Spatial distribution of high, medium and low center pivot irrigation cover stratum and location of the blocks used for training and testing the model in Brazil.

As mentioned earlier, an adaptation of the U-Net convolutional neural network architecture was performed to map the center pivot irrigation systems. Figure 6 illustrates the modified U-Net architecture created.

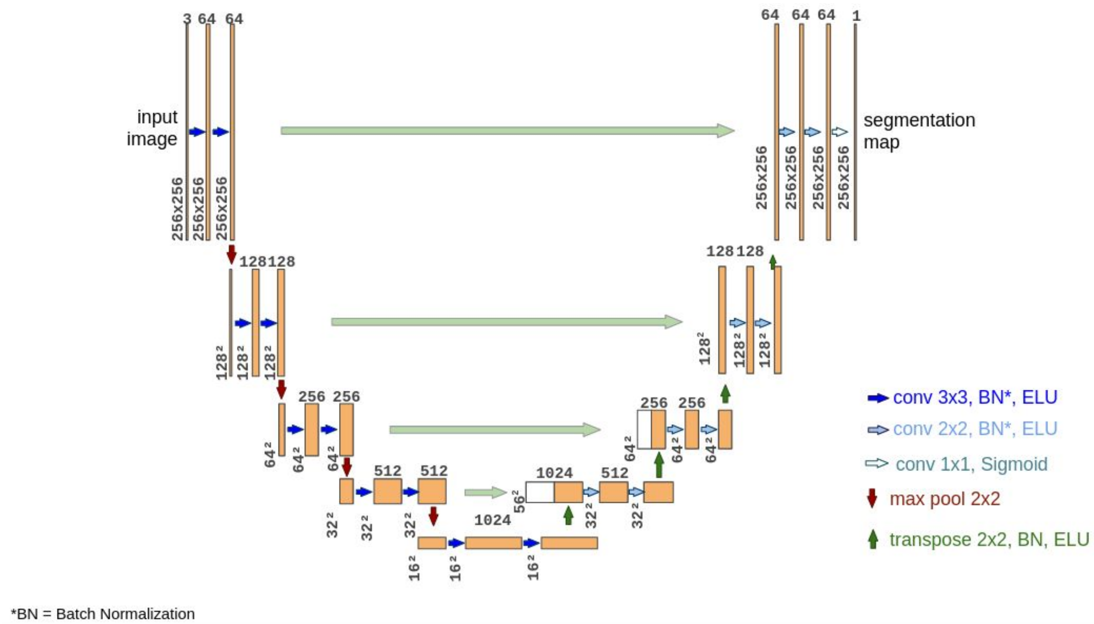

Figure 6. Adapted U-Net architecture, with its layers and connections, used for the mapping of center pivot irrigation systems.

This architecture was developed in Python, using the TensorFlow 2.0 library. The entire training and mapping process was carried out using the Google Colab platform using Google Drive to access the annual mosaics (generated in Google Earth Engine). Table 1 presents some hyperparameters used during model training.

Table 1. Hyperparameters for training the modified U-Net architecture.

Hyperparameter	Value
Chip size	256 x 256 pixels
Batch size	20
Epochs	100
Learning rate	0.001

The 2017 reference map was used for model training. In the training blocks, chips with 256 x 256 pixels were generated, 75% were allocated to the training data set and 25% for the validation data set. Figure 7 illustrates the process of subdividing training blocks into smaller chips to be used as input for model training.

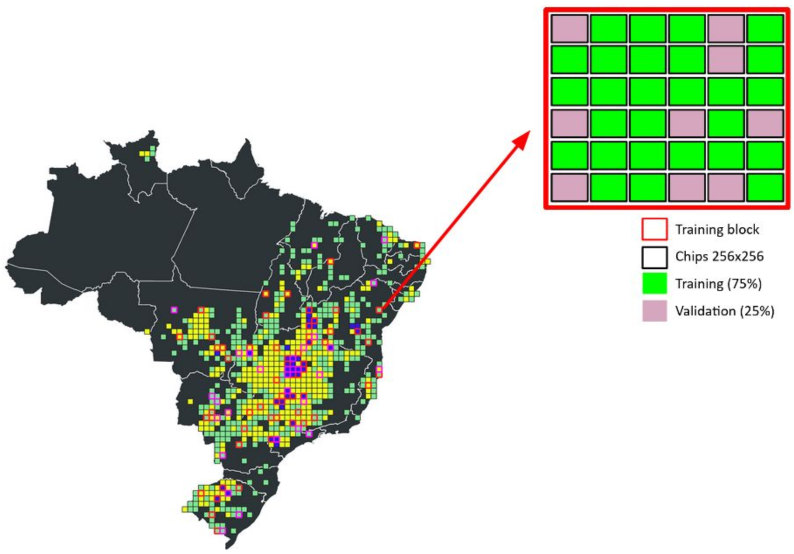

Figure 7. Examples of the training and validation chips allocated within the training block of the model.

The training set was used to learn the model and the validation set used to perform initial validations during model learning.

Once the network training process was completed, the classifier was applied throughout the Brazilian territory. In this step, 1024 x 1024 pixel chips were used. Increasing the size of the chips at the time of sorting not only decreases problems generated by the edges of the chips but also increases the memory capacity required for processing. Therefore, it was necessary to decrease the batch size to 1.

2.4 Post-Classification

2.4.1 Temporal filter

The temporal filter applied to maps of center pivot irrigation systems consisted of a five-year moving window in which the assessed pixel of the window was changed following two rules:

1. the pixel is changed to center pivot if at least one of the two previous years and at least one of the two subsequent years, that pixel was mapped as a pivot, indicating a possible model omission error;
2. pixels that were mapped as pivots only in the assessed pixel of the five-year window, indicating a possible inclusion error, have been removed from the classification.

2.4.2 Spatial filter

In the center pivot irrigation systems mapping it was used a spatial filter based on the erosion operation followed by an expansion operation using a circular kernel with a radius of 60 meters. This spatial filter helped to eliminate noise generated by the mapping, as well as smoothing the edges of the center pivot irrigation (Figure 8).

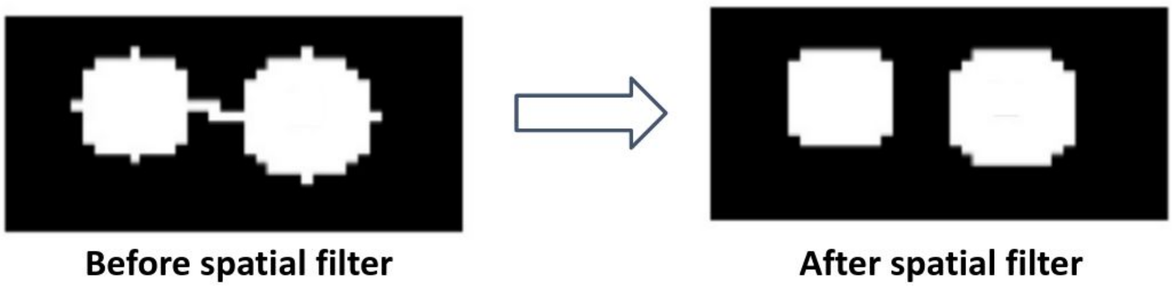

Figure 8. Example of correction of the spatial filter (on the right) in a classification that presents noise on the edges (on the left).

2.5 Validation strategies

The preliminary validation of the center pivot irrigation model used the test blocks of the 2017 mapping (see Figure 5), as these blocks were not used for the training the model. From the reference map, the user's and producer's accuracy was calculated for each of the individual stratum and also considering all strata at the same time. Table 2 presents the results of the preliminary model validation.

Table 2. Preliminary validation of the center pivot irrigation mapping for the year 2017, using the test blocks selected in each stratum.

Stratum	Producer's Accuracy	User's Accuracy

Low coverage	40.87%	71.39%
Medium coverage	86.37%	91.62%
High coverage	84.16%	96.19%
All strata	83.97%	95.38%

The preliminary accuracy analysis showed that, in 2017, the model performed better in regions with higher center pivot coverage. Considering all strata in 2017, the model presented an omission error of 16% and an inclusion error of 5%. In terms of pixel area, compared to surveys carried out by *Atlas da Irrigação* (ANA, 2017), ANA/Embrapa (ANA, 2019a) and *Censo Agropecuário* (IBGE, 2009, 2019), the mapping of central pivots showed greater agreement in the period from 2000 to 2010. For the years after 2010, the mapping underestimated the mapped area by an average of 14% (Figure 9).

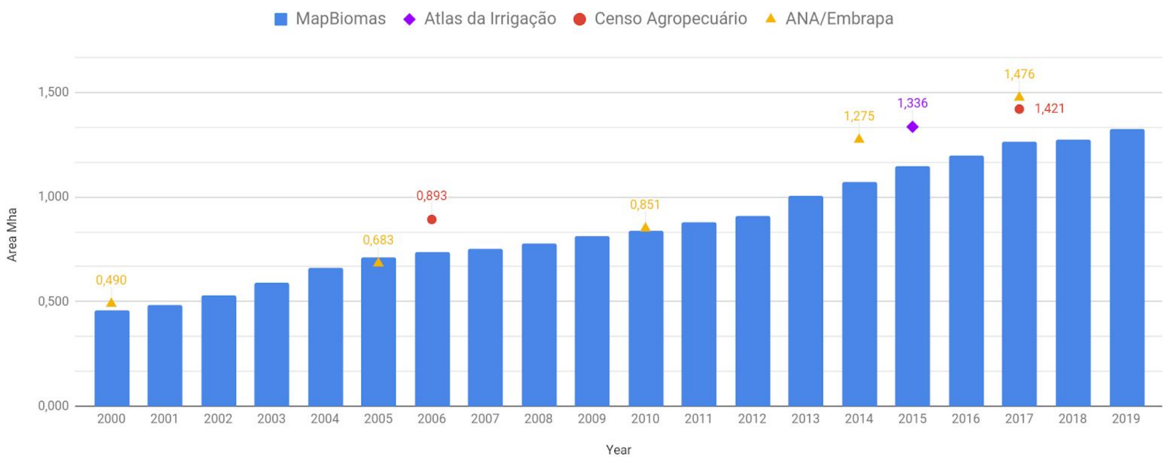

Figure 9: Results of automatic mapping of center pivot irrigation systems in Brazil based on Landsat images for the period from 2000 to 2019 compared to surveys carried out by the *Atlas da Irrigação* (ANA, 2017), ANA/Embrapa (ANA, 2019a) and the *Censo Agropecuário* (IBGE, 2009, 2019).

3 Irrigated agriculture in semi-arid region

3.1 Image selection

The mapping of irrigation in semi-arid region used normalized Landsat mosaics, a reflectance normalization product based on Landsat imagery and the Moderate-Resolution Imaging Spectroradiometer (MODIS) products created in the MapBiomas Collection 5 for the Agriculture classification (see Appendix of Agriculture and Forest Plantation). In addition to the normalized Landsat mosaics, data from Shuttle Radar Topography Mission - SRTM (FARR et al., 2007) and climatic data from TerraClimate (ABATZOGLOU et al., 2018) were used.

3.2 Definition of regions for classification

In the mapping of other irrigation systems, the study area was restricted to the Brazilian semi-arid region. In this region, due to water requirements, irrigation is almost a mandatory requirement to reduce production risks and/or increase productivity.

According to the 'Atlas da Irrigação' (ANA, 2017), in 2015, of the 1262 municipalities that make up the Brazilian semi-arid region, only 19 had at least 5,000 hectares of irrigated agriculture. Together, these 19 municipalities are responsible for approximately 315 thousand hectares (44%), out of the total of 708 thousand hectares that make up the irrigated area of the Brazilian semi-arid region. Due to the lack of reference maps available on this topic, and because it is a first effort, the mapping was carried out in these 19 municipalities with the most significant amount of irrigated agriculture in the region. In addition to these, another 15 municipalities in the states of Bahia and Pernambuco located around the São Francisco River were included in the mapping area. These 15 municipalities are located in a region considered an important fruit center production in Northeast Brazil. Figure 10 shows the spatial distribution of the 34 municipalities to map 'Other Irrigation System' class.

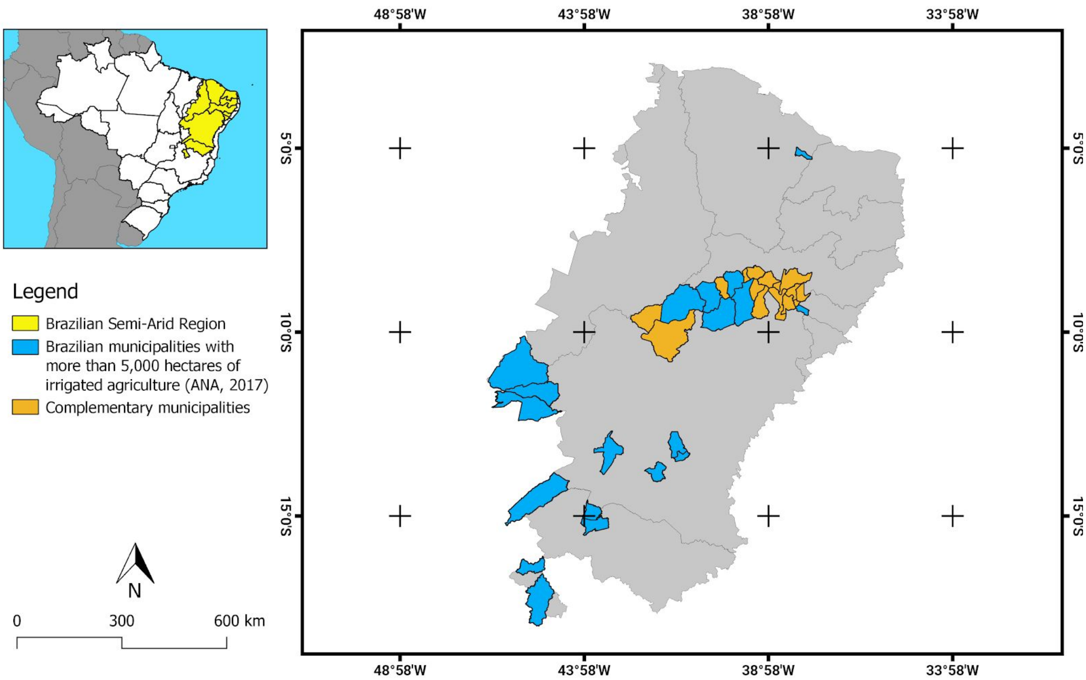

Figure 10. The municipalities used to map 'Other Irrigation Systems' class in the Northeast of Brazil.

3.3 Classification

3.3.1 Classification scheme

The irrigated areas in the semi-arid region are composed of the mapping of the 'Center pivot irrigation systems' class, in which the methodology was presented in Section 2, and the mapping of the 'Other irrigation systems' presented in this section.

The mapping of 'Other irrigation systems' class considered three possible classes, 'Irrigated agriculture', 'Non-irrigated agriculture' and 'Non-agriculture'. The regions that were mapped by both methodologies and allocated to the classes 'Center pivot irrigation systems' and 'Irrigated agriculture', were reclassified to the class of 'Center pivot irrigation systems'. The regions that were mapped as 'Irrigated agriculture', but were not mapped as 'Center pivot irrigation systems', were converted to the class 'Other irrigation systems'.

3.3.2 Feature space

For mapping of other irrigation systems, in addition to the data available from the Landsat program satellites, auxiliary metrics from other sources were added. The slope, with 30 meters of spatial resolution, was derived from the elevation obtained in the digital terrain model Shuttle Radar Topography Mission - SRTM (FARR et al., 2007). The actual evapotranspiration, precipitation, and water requirements, with approximately 4 kilometers of spatial resolution, were derived from climatic data obtained from the TerraClimate (ABATZOGLOU et al., 2018), a set of monthly climate data and water climate balance for the global land surface. Auxiliary metrics can complement the information obtained by optical sensors and assist in the identification of irrigated agriculture (Deines et al., 2019). Table 3 presents the set of annual metrics used to map irrigated agriculture in the Brazilian semi-arid region.

Table 3. Set of metrics used to map irrigated agriculture in the Brazilian semi-arid region.

Provider	Bands and Spectral indices	Metrics
Landsat	RED NIR SWIR1 TIR1 EVI2 (Jiang et al, 2008) NDWI (Gao, 1996) CAI (Nagler et al, 2003)	EVI2 Quality Mosaic, Minimum, Median , and standard deviation values
SRTM (Farr et al., 2007)	Slope	--
TerraClimate (Abatzoglou et al., 2018)	Actual Evapotranspiration Precipitation Water Requirements	Accumulated

3.4 Classification algorithm, training samples and parameters

Due to the absence of georeferenced reference data on irrigated agriculture and the hydrological characteristics in the Brazilian semi-arid , the premise adopted was that crops with greater vegetative vigor are those that received irrigation at some time of the year, which this directed collection of samples from training.

The collection of samples for the training of the classification model was carried out for the years 2016 and 2017 in the selected municipalities, and followed the steps:

1. samples from three classes were collected: ‘Irrigated Agriculture’, ‘Non-irrigated Agriculture’ and ‘Non-Agriculture’;
2. Agriculture maps produced by Agrosatélite for the harvest 2016/2017 were used for the sample collection. The samples of the classes 'Irrigated Agriculture' and 'Non-irrigated Agriculture' were obtained inside of the agriculture map, and the samples for the class 'Non-agriculture' were obtained outside of the agriculture mask.
3. for the 'Irrigated Agriculture' class, a mask of the regions with the highest annual values of the EVI2 vegetation index was created so that the area (in hectares) of the chosen regions was close to the irrigated agriculture area of the municipality according to the *Atlas da Irrigação* (ANA, 2017) and the *Censo Agropecuário* (IBGE, 2019);
4. for the ‘Non-irrigated Agriculture’ class, regions located within the agriculture mask were selected that were not chosen for the ‘Irrigated Agriculture’ class;
5. stratified sampling of one thousand points was carried out for each 100 thousand hectares of the area of each municipality and as a criterion for sampling the percentage of the area of each class.

For the classification process of other irrigation systems areas, the Random Forest classifier was used. The parameters used in Random Forest are shown in Table 4.

Table 4. Parameters used in Random Forest for the classification of other irrigation systems in the semi-arid region in Brazil.

Parameter name	Value
Decision trees	100
Samples	1,000 samples for every 100,000 hectares
Variables	32 variables
Variables per split	$\sqrt{Number\ of\ Variables}$
Classes	3 classes

It was trained one classifier per municipality, with samples collected in the years 2016 and 2017 and used for the classification from the years 2000 to 2019. The classification result contains the three classes: 'Irrigated agriculture', 'Non-irrigated agriculture' and 'Non-agriculture'. The 'Irrigated agriculture' class does not differentiate the types of irrigation systems, so in post-processing, the pixels mapped as central irrigation pivots in the specific approach for mapping central irrigation pivots were removed from the 'Irrigated Agriculture' class, remaining only the other irrigation systems.

3.5 Post-Classification

The post-classification process of irrigation agriculture maps included the application of temporal and spatial filters.

3.6 Temporal filter

In the other irrigation systems mapping, it was also used a five-year moving window, but using a different rule from the center pivot irrigation systems. In this filter, if the evaluated pixel was in the same class as at least three other pixels (previous, ahead or both), it will remain in that class. However, if the evaluated pixel was not of the same class as at least three pixels (previous, ahead or both), the class was changed.

3.7 Spatial filter

In the other irrigation systems it was used a convolutional spatial filter, with a 5 x 5 kernel, to remove or add the filtered pixel (central pixel) to the mapping result. For more details, see section 6.4.1 in Appendix of Agriculture and Forest Plantation.

3.8 Validation strategies

Due to the absence of georeferenced reference data for the "Other Irrigation System" class, this beta version does not have an accuracy analysis for this class. In terms of the pixel area, Figure 11 presents the mapped area of irrigated agriculture in the 34 selected Brazilian municipalities compared to surveys carried out by the *Atlas da Irrigação* (ANA, 2017) and the *Censo Agropecuário* (IBGE, 2009, 2019).

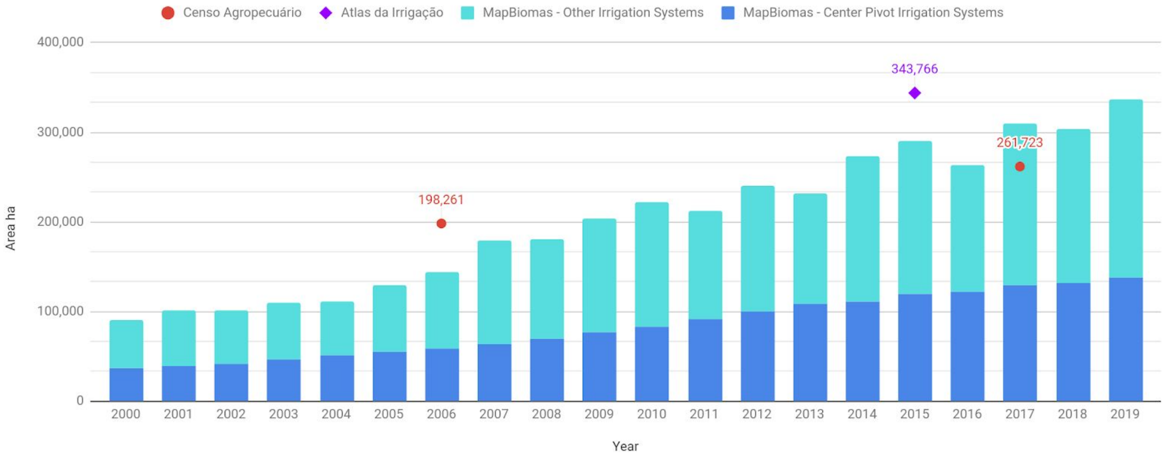

Figure 11. Results of the automatic irrigation mapping of the 34 Brazilian municipalities chosen in the study area for the period from 2000 to 2019 compared to surveys carried out by the *Atlas da Irrigação* (ANA, 2017) and the *Censo Agropecuário* (IBGE, 2009, 2019).

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