Mining – Appendix

Collection 7

Version 1

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1 Overview

Today, Brazil is among the five largest producers of iron ore, niobium, bauxite, and manganese in the world (Bray, 2020), exporting varied mineral inputs, with a high level of purity and internationally recognized quality.

Despite its low representativeness in area, as it is a rare coverage class, the national trend associated with this land use shows a frank expansion, jumping from ~ 50,000 hectares in 1985 to ~ 350,000 hectares in 2021, a value ~7 times higher than reported in 1985.

In comparison to Collection 6, the Collection 7 mining mapping preserves the same methodology, although it substantially improves the quantity and quality of the training samples while increasing the areas/grids where the mining recognition algorithm is run.

The U-Net classifier (Ronneberger et al., 2015), a CNN classifier based on Deep Learning model, is maintained as a classifier. The stack of reference data include now data from: CPRM (Brazilian Geological Service), AhkBrasilien (Brazil-Germany Chamber of Commerce and Industry), INPE (National Institute for Space Research) and from ISA (Instituto Socioambiental) and AMW (Amazon Mining Watch). The whole classification process is described below, Figure 1.

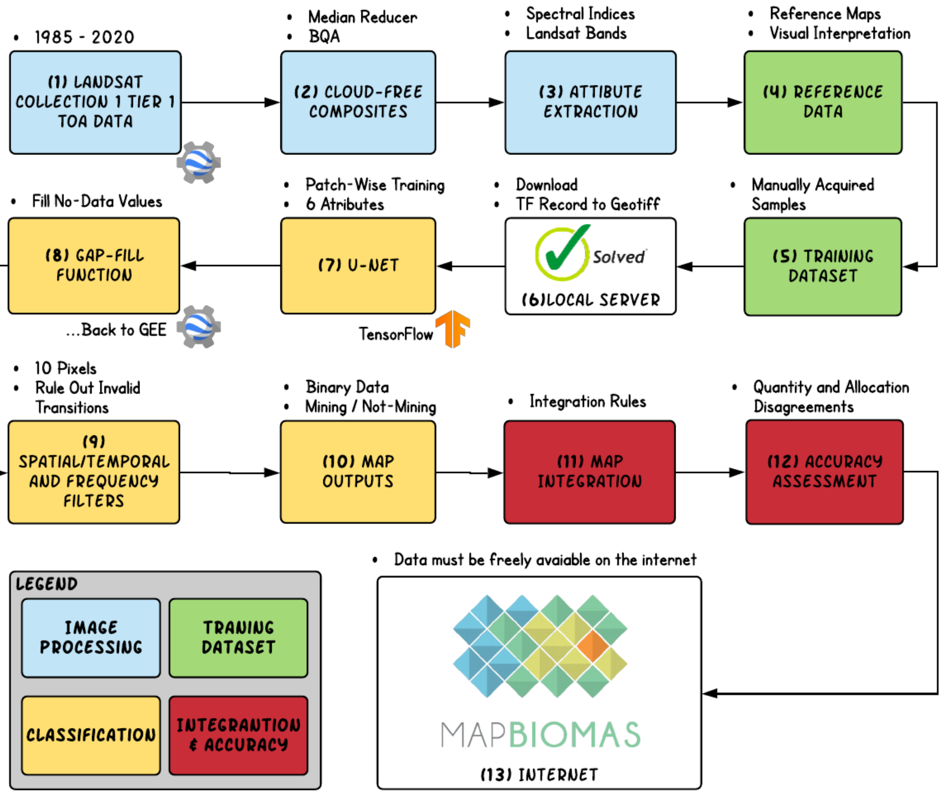

Figure 1 – Processing diagram. The steps related to image processing are in blue. The steps in green are related to the sample design. Classification procedures are in yellow. The accuracy assessment phase is in red and, finally, the data availability is in salmon. BQA denotes Band Quality Assessment.

2 Landsat Mosaics

The classification of the cross-cutting theme "**Mining**" uses Landsat mosaics that differs from the mosaics used to classify the natural vegetation of the Brazilian biomes. The Mining mosaics were cropped to comprise areas where mining sites are known to exist. These Landsat mosaics are the third generation of the methodology developed specifically for these cross-cutting themes.

The annual cloud free mosaics were generated inside the Google Earth Engine platform (GEE). All raster data and its sub-products derived from the United States Geological Survey (USGS) Landsat Collection 2 Tier 1 Top of Atmosphere (TOA) data, which includes Level-1 Precision Terrain (L1TP).

2.1 Definition of the temporal period

The Mining annual cloud-free composites are generated by calculating the median pixel value from January 1 to December 31 of each year.

2.2 Mosaic Subsets

2.2.1 Mining

For each year, Landsat Collection 2, Tier 1, TOA data was used to produce annual cloud-free composites, ranging from the 1st of January to the 31st of December. The cloud/shadow removal script takes advantage of the quality assessment (QA) band and the GEE median reducer. When used, QA values can improve data integrity by indicating which pixels might be affected by artifacts or subject to cloud contamination. In conjunction, GEE can be instructed to pick the median pixel value in a stack of images. By doing so, the engine rejects values that are too bright (e.g., clouds) or too dark (e.g., shadows) and picks the median pixel value in each band over time.

Subsequently, the annual mosaics were subset to the area that comprises the so-called "searching grids". Each grid constitutes an area where mining activity is more likely to occur (areas flagged as a mining site according to any of the reference data used) and to exclude large areas where such targets are not expected to occur.

2.2.2 Reference Data

Brazil, but especially the Brazilian Amazon (BA), counts with a huge variety of publicly available datasets, from geological surveys and change detection platforms to deforestation early-warning systems. Thus, mining data availability is highly diverse in terms of scale, type and timeframe. Spatially explicit data may be found in higher or lower resolution, with a greater or lesser degree of human intervention, for scientific or journalistic use, but out of which a great set of spatial references of artisanal and industrial mining sites can be acquired/inferred. The reference dataset here adopted comes from the aggregation of multiple sources of data, such as; Deter-B (http://terrabrasilis.dpi.inpe.br/), MapBiomas Alert (http://alerta.mapgiomas.org), RAISG (http://www.amazoniasocioambiental.org), ISA (https://www.socioambiental.org/), CPRM-GeoSGB (https://geosgb.cprm.gov.br/), Ahkbrasilien (https://www.ahkbrasilien.com.br/), AMW (https://amazonminingwatch.org/) and additional visual interpretations.

Table 1 – Reference data used. references were visually analyzed and converted to bounding boxes. The existence of a bounding box triggers the activation a searching grid

Class	References
Mining	Deter-B: http://terrabrasilis.dpi.inpe.br/ MapBiomas Alert: http://alerta.mapgiomas.org RAISG: http://www.amazoniasocioambiental.org ISA: https://www.socioambiental.org/ CPRM-GeoSGB: https://geosgb.cprm.gov.br/ Ahkbrasilien: https://www.ahkbrasilien.com.br/ AMW: https://amazonminingwatch.org/ and Additional visual interpretations

The references were visually analyzed and converted to bounding boxes. The existence of a bounding box triggers the activation of a searching grid, Figure 2. Each grid represents the area in which the deep-learning mining recognition algorithm is executed. In Figure 2, the yellow grids are additions exclusive to the Collection 7.

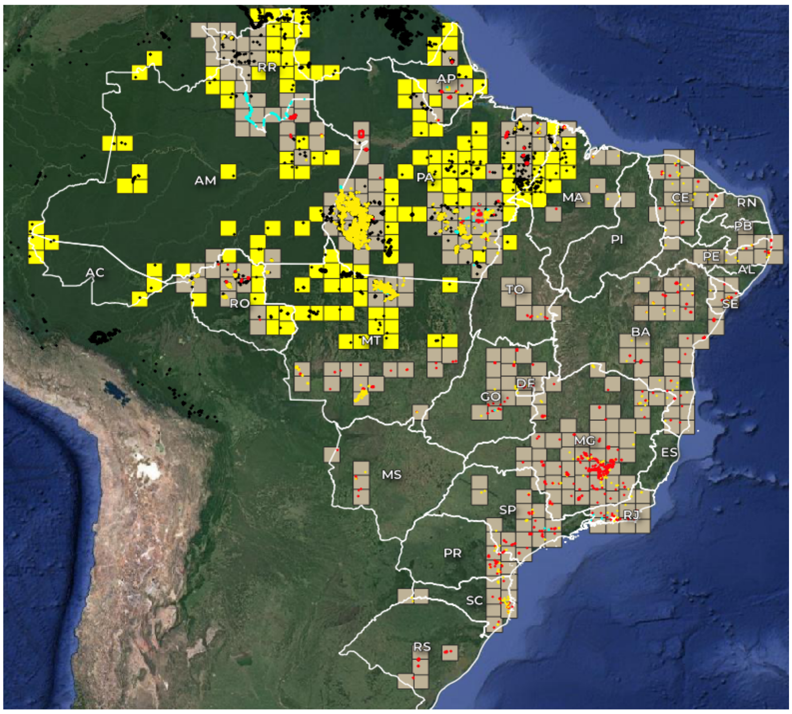

Figure 2 – The dots are the reference sites. The squares are the searching grids. The yellow grids are present exclusively in Collection 7.

3 Classification

The automatic classification of the Landsat mosaics was performed entirely on local servers, based on a U-Net classifier, a deep learning model. Once the sample acquisition is finished, the U-net classification is run, resulting in the pre-filter classification product. The classified data is injected back into GEE, where spatial-temporal filters and visual inspection occur, Figure 3.

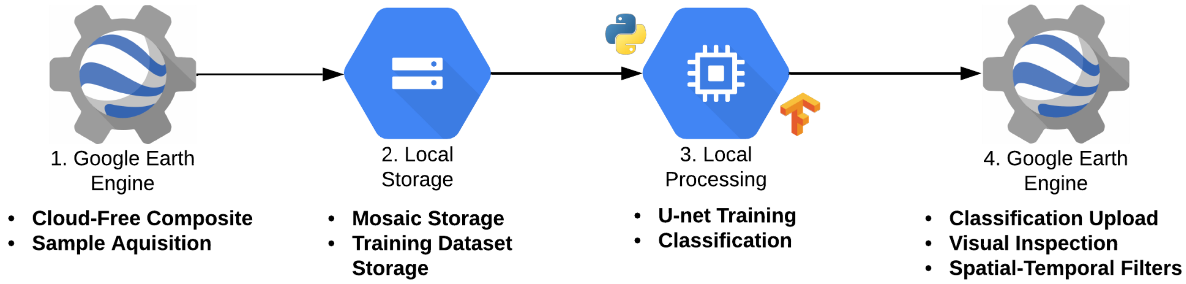

Figure 3 - Mining Detection Earth Engine-TensorFlow pipeline. The process is structured in 4 steps. First (1), GEE is used to generate the cloud-free composites and create the initial training dataset. Second (2), the mosaics and training data are downloaded and stored locally. Three (3), initiates patch-wise training and classification. In the fourth step (4), the classified product is spatial-temporally filtered. The filtered product is visual and statistically inspected. Multiple iterations may be used until a satisfactory degree of spatial and temporal quality is achieved.

3.1 Classification scheme

For the supervised classification of the Landsat mosaics, we have selected training samples (geometries) captured inside of the previously generated bounding boxes (searching grids). As any supervised algorithm our U-net based approach depends upon human labeled data, categorized as mining (Mi) and not-mining (N-Mi). Guided by the existence of reference dataset, the mining and not-mining samples are visually delineated. It is essential to highlight that no differentiation is made between artisanal or industrial mining samples. Therefore, from this point on, every time mining samples or classes are mentioned, it includes the artisanal or industrial patterns as well. The dissociation between such patterns, garimpo or industrial, as well as the main substance being exploited are the result of post-classification and visual analysis.

Once the sample acquisition is finished, the U-net classification is run, resulting in the pre-filter classification product. The classified data is injected back into GEE, where spatial-temporal filters and visual inspection occur. This phase was undertaken to correct misclassified data and ensure the necessity of acquiring (or not) more training samples. Table 2 shows the classifier parameters.

Table 2 - Classifier attributes and classification parameters. In total, six (6) distinct attributes were used.

Parameters	Values
Classifier	U-Net
Tile-Size	256 x 256 px
Samples	8400
Attributes	Swir1, Nir1, Red, MNDWI, NDVI, and NDSI
Classes	2 (Mining and Not-Mining)

4 Mining Class, Mining Type and Main Substances

Since the Collection 6, the MapBiomas Platform counts with a specific mining related modulus. Thus, it is strictly important to understand the origin of each mining related product.

In this sense, the pattern recognition of a mining site, regardless of its nature or main substance, is a task performed by the U-Net classifier, in a binary fashion [mining (Mi) and not-mining (N-Mi)] as previously explained.

Once this mining class is noise filtered and integrated, it composes the final version of the MapBiomas LULC data, and it is lastly flagged as a pixel value of “30”, the numeric id representing mining pixels. Then, this mining raster data is intersected with the CPRM-GeoSGB dataset, from which the attributes of substances (Gold, Iron, Silver Copper…) and extraction type (garimpo or industrial) are extracted. Thus, and so, the recognition of mining sites is U-Net related, while the categorization of its nature/type or main substances are the results of spatial operation involving third-party references, Figure 4.

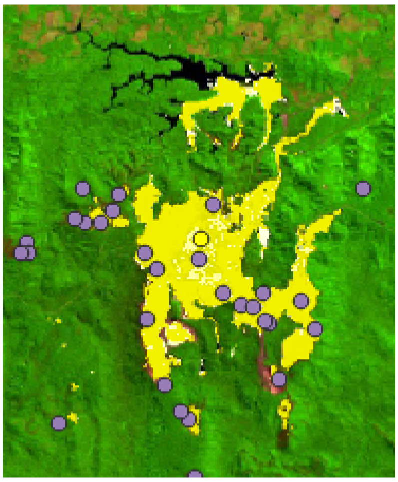

Figure 4 – The dots are the CPRM-GeoSGB dataset. The Yellow pixels the mining class. The recognition of the mine nature and mined substances are the resultant aggregation of both datasets.

ocorrências Ocorrências_minerais — Total de feições: 34238, Filtrada: 34238, Selecionada: 1

	STATUS_ECONOMICO	IMPORTANCIA	LOCALIZACAO_MINA	SITUACAO_MINA	VO_INATIVIDADE_I	TUACAO_GARIMP	VID.	SUBSTANCI
1	Mina	Depósito	NULL	Ativo(a)	NULL	Ativo(a)	NU...	Ferro
2	Mina	Depósito	NULL	Inativo(a)	Paralisado(a)	Inativo(a)	Par...	Brita
3	Mina	Depósito	Open pit	Inativo(a)	Paralisado(a)	Inativo(a)	Par...	Brita

The product published on the Mining Modulus, aggregates both attributes, in a three-digit identifier, resulting in the information expressed in Table 3.

Table 3 - The product published on the Mining Modulus, aggregates both attributes, in a three-digit identifier

class_id	level_1	level_2	level_3
101	2. Industrial	2.2 Metálicas	Metálicas
102	2. Industrial	2.2 Metálicas	2.2.01 Ferro
103	2. Industrial	2.2 Metálicas	2.2.02 Manganês
104	2. Industrial	2.2 Metálicas	2.2.03 Níquel
105	2. Industrial	2.2 Metálicas	2.2.04 Amianto
106	2. Industrial	2.2 Metálicas	2.2.05 Molibidênio
107	2. Industrial	2.2 Metálicas	2.2.06 Titânio
108	2. Industrial	2.2 Metálicas	2.2.07 Cromo
109	2. Industrial	2.2 Metálicas	2.2.08 Cobre
110	2. Industrial	2.2 Metálicas	2.2.09 Alumínio
111	2. Industrial	2.2 Metálicas	2.2.10 Magnésio
112	2. Industrial	2.2 Metálicas	2.2.11 Bário
113	2. Industrial	2.2 Metálicas	2.2.12 Nióbio
114	2. Industrial	2.2 Metálicas	2.2.13 Estanho
115	2. Industrial	2.2 Metálicas	2.2.14 Ouro
116	2. Industrial	2.3 Não Metálicas	Não Metálicas
117	2. Industrial	2.3 Não Metálicas	2.3.01 Minerais Classe 2
118	2. Industrial	2.3 Não Metálicas	2.3.02 Fluor
119	2. Industrial	2.3 Não Metálicas	2.3.03 Fósforo
120	2. Industrial	2.3 Não Metálicas	2.3.04 Gráfita
121	2. Industrial	2.3 Não Metálicas	2.3.05 Silício
122	2. Industrial	2.3 Não Metálicas	2.3.06 Calcário
123	2. Industrial	2.4 Pedras Preciosas & Rochas Ornamentais	Pedras Preciosas & Rochas Ornamentais
124	2. Industrial	2.4 Pedras Preciosas & Rochas Ornamentais	Pedras Preciosas
125	2. Industrial	2.4 Pedras Preciosas & Rochas Ornamentais	Rochas Ornamentais
126	2. Industrial	2.1 Energéticas	Energéticas
127	2. Industrial	2.1 Energéticas	2.1.01 Carvão mineral
128	2. Industrial	2.1 Energéticas	2.1.02 Urânio
129	2. Industrial	2.1 Energéticas	2.1.03 Gás natural e petróleo
214	1. Garimpo	1.1 Metálicas	1.1.02 Estanho
215	1. Garimpo	1.1 Metálicas	1.1.01 Ouro
216	1. Garimpo	1.2 Não Metálicas	Não Metálicas
217	1. Garimpo	1.2 Não Metálicas	1.2.01 Minerais Classe 2
223	1. Garimpo	1.3 Pedras Preciosas & Rochas Ornamentais	Pedras Preciosas & Rochas Ornamentais
224	1. Garimpo	1.3 Pedras Preciosas & Rochas Ornamentais	1.3.01 Pedras preciosas
225	1. Garimpo	1.3 Pedras Preciosas & Rochas Ornamentais	1.3.02 Rochas Ornamentais

5 Post-classification

Due to the pixel-based nature of the classification method and the very long temporal series, a chain of post-classification filters was applied. The post-classification process includes the application of a gap-fill, a temporal, a spatial, and a frequency filter.

5.1 Gap-Fill filter

The chain starts by filling in possible no-data values. In a long time-series of severely cloud-affected regions, such as tropical coastal zones, it is expected that no-data values may populate some of the resultant median composite pixels. In this filter, no-data values ("gaps") are theoretically not allowed and are replaced by the temporally nearest valid classification. In this procedure, if no "future" valid position is available, then the no-data value is replaced by its previous valid class. Up to three prior years can be used to fill in persistent no-data positions. Therefore, gaps should only exist if a given pixel has been permanently classified as no-data throughout the entire temporal domain. To keep track of pixel temporal origins, a mask of years was built, as shown in Figure 5.

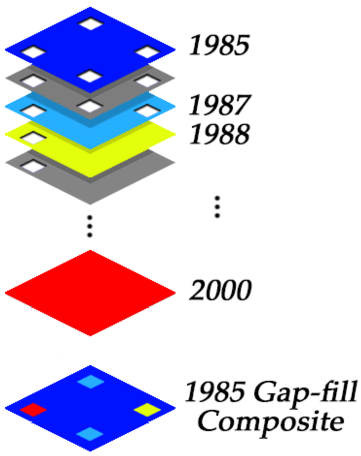

Figure 5 – Gap-filling mechanism. The next valid classification replaces existing no-data values. If no "future" valid position is available, then the no-data value is replaced by its previous valid classification, based on up to a maximum of three (3) prior years. To keep track of pixel temporal origins, a mask of years was built.

5.2 Temporal filter

After gap filling, a temporal filter was executed. The temporal filter uses sequential classifications in a 3-year unidirectional moving window to identify temporally non-permitted transitions. Based on a single generic rule (GR), the temporal filter inspects the central position of three consecutive years ("ternary"), and if the extremities of the ternary are identical but the center position is not, then the central pixel is reclassified to match its temporal neighbor class, as shown in Table 4.

Table 4 - The temporal filter inspects the central position of three consecutive years, and in cases of identical extremities, the center position is reclassified to match its neighbor. T1, T2, and T3 stand for positions one (1), two (2) and three (3), respectively. GR means "generic rule," while Mi and N-Mi represent mining and non-mining pixels.

Rule	Input (Year)			Output		
	T1	T2	T3	T1	T2	T3
GR	Mi	N-Mi	Mi	Mi	Mi	Mi
GR	N-Mi	Mi	N-Mi	N-Mi	N-Mi	N-Mi

5.3 Spatial filter

Next, a spatial filter was applied. To avoid unwanted modifications to the edges of the pixel groups (blobs), a spatial filter was built based on the "connectedPixelCount" function. Native to the GEE platform, this function locates connected components (neighbors) that share the same pixel value. Thus, only pixels that do not share connections to a predefined number of identical neighbors are considered isolated, as shown in Figure 6. In this filter, at least ten connected pixels are needed to reach the minimum connection value. Consequently, the minimum mapping unit is directly affected by the spatial filter applied, and it was defined as 10 pixels (~1 ha).

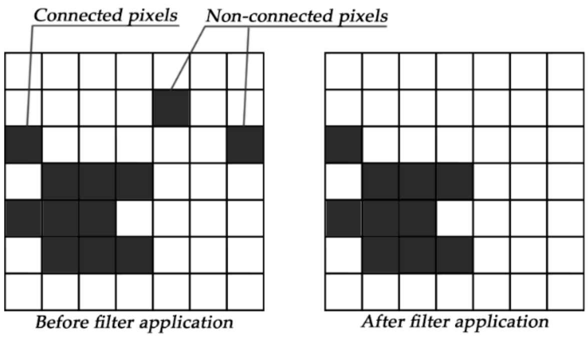

Figure 6 – The spatial filter removes pixels that do not share neighbors of identical value. The minimum connection value was 10 pixels.

5.4 Frequency filter

The last step of the filter chain is the frequency filter. This filter takes into consideration the occurrence frequency of a given class throughout the entire time series. Thus, all class occurrences with less than 10% temporal persistence (3 years or fewer out of 37) are filtered out and incorporated into the non-class binary. This mechanism contributes to reducing the temporal oscillation of the classification signal, decreasing the number of false positives, and preserving consolidated class pixels.

5.5 Integration with biomes and cross-cutting themes

After the application of the filter-chain, the cross-cutting themes and the Biomes data are integrated. This integration is guided by a set of specific hierarchical prevalence rules

(Table 5). As output of this step, a final vegetation cover/land use map for each chart of the MapBiomas project.

Table 5 - Prevalence rules for combining the output of digital classification with the cross cutting themes in Collection 7.

CLASSE	PREVALÊNCIA 7.0
4.4. Mining	1
4.1. Beach, Dune and Sand Spot	2
1.3. Mangrove	3
5.2.1. Aquacultura	4
2.3. Salt-Flat	5
Water (GT-Water)	6
4.2. Urban Infrastructure	7
Agriculture	8
3.2.1.2. Sugar Cane	9
3.2.1.1. Soy	10
3.2.1.3. Rice	11
3.2.1.4. Cotton (beta)	12
3.2.1.5. Other Temporary Crops	13
3.2.1. Perennial Crop	14
3.2.2.1. Coffee	15
3.2.2.2. Citrus	16
3.2.2.3. Outras Lavouras Perenes	17
3.2.2. Lavoura temporária	18
4.5. Rocky Outcrop	19
4.3. Other Non-Vegetated Areas	20
5.1. River, Lakes and Oceans	21
5.2.2. Reservoirs (Power Plant and Water Supply)	22
5.2.3. Artificial Lakes and Dams	23
5.2.4. Outros corpos d'água artificiais	24
1.1. Formação Florestal	25
1.2. Formação Savânica	26
1.5. Restinga Arborizada	27
2.1. Área Úmida Natural não Florestal	28
2.2. Formação Campestre (Campo)	29
2.5. Restinga Herbácea/Arbustiva	30
2.4. Outra Formação não Florestal	31
3.1. Pastagem	32
3.3 Mosaico de usos	33

References

Deng, Y., Wu, C., Li, M., & Chen, R. (2015). RNDSI: A ratio normalized difference soil index for remote sensing of urban/suburban environments. *International Journal of Applied Earth Observation and Geoinformation*, *39*, 40–48. https://doi.org/https://doi.org/10.1016/j.jag.2015.02.010

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. *CoRR*, *abs/1505.0*. http://arxiv.org/abs/1505.04597

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, *8*(2), 127–150. https://doi.org/http://dx.doi.org/10.1016/0034-4257(79)90013-0

USGS. (2017). *LANDSAT COLLECTION 1 LEVEL 1 PRODUCT DEFINITION*. Earth Resources Observation and Science (EROS) Center. https://landsat.usgs.gov/sites/default/files/documents/LSDS-1656_Landsat_Level-1_Product_Collection_Definition.pdf