

# Exploratory analysis of Recurrent deforestation warnings in the Brazilian Amazon

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# Introduction

- ▶ Deforestation by successive degradation remains a challenging question in the scientific literature.
- ▶ We think an answer to this question lies down in DETER data.
- ▶ This answer could play an important role, for example, in the brazilian estimation of greenhouse gases.
- ▶ We used DETER data from 2016 to 2021 of the Amazon Biome in Brazil.

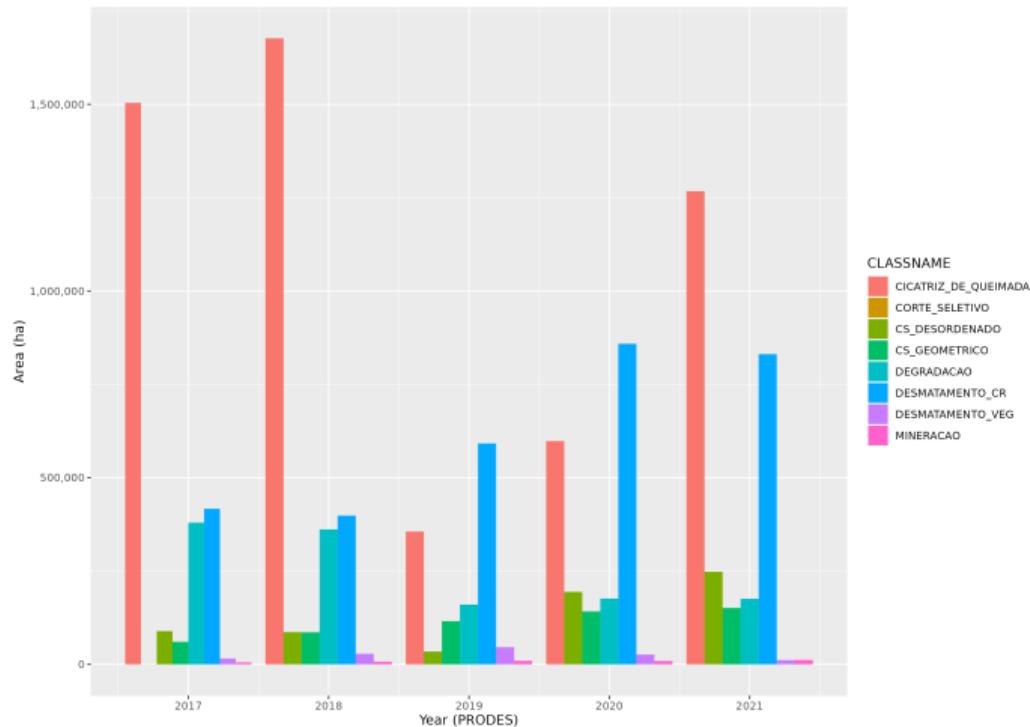
## What is DETER?

- ▶ DETER is a GIS which produces a fast assessment of deforestation and forest degradation in the Brazilian Amazon [SDA<sup>+</sup>06].
- ▶ DETER employs Linear Mixture Models of CBERS imagery and human experts to deter and issue warnings of deforested (or degraded) areas larger than 3 ha [DAMV<sup>+</sup>22].
- ▶ Annually, DETER takes from PRODES the current forested area, starting anew issuing warnings.

# DETER warnings

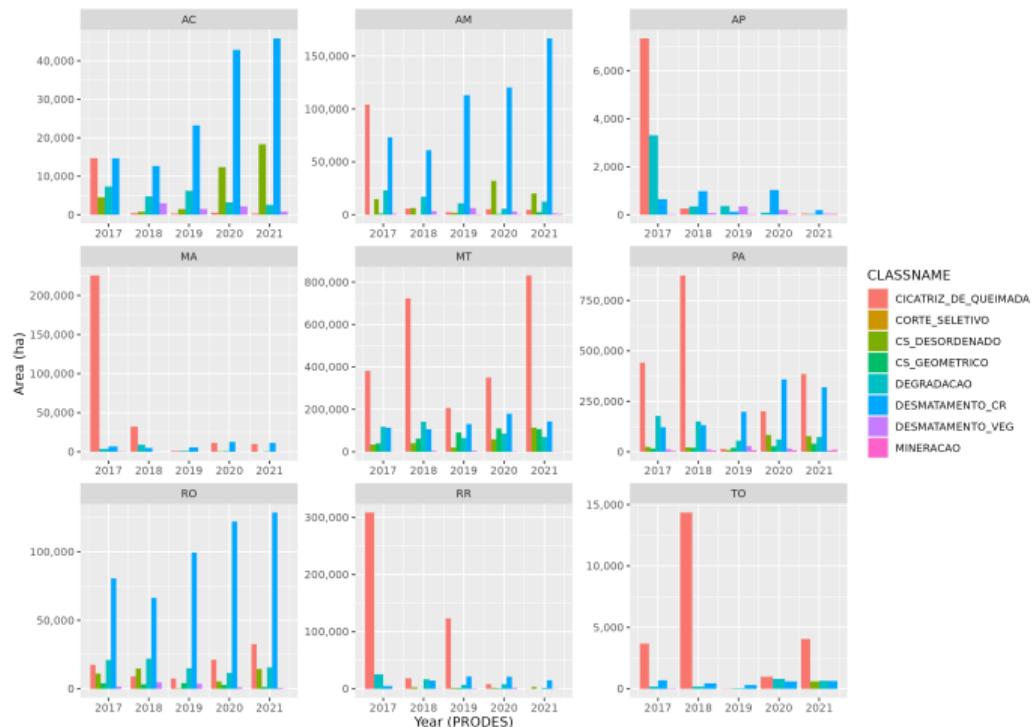


# DETER warnings by class



Burn scars and clear cut are the most common warnings.

# DETER warnings by class and state

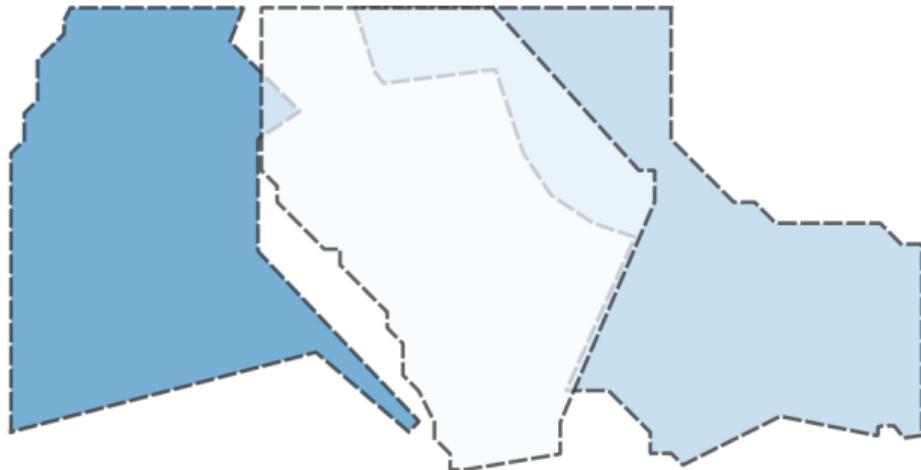


Burn scars and clear cut are the most common warnings.

## DETER warnings and time

- ▶ The spatial properties of DETER warning are inconsistent along time (shape, size, position, orientation).

## Warnings are inconsistent along time

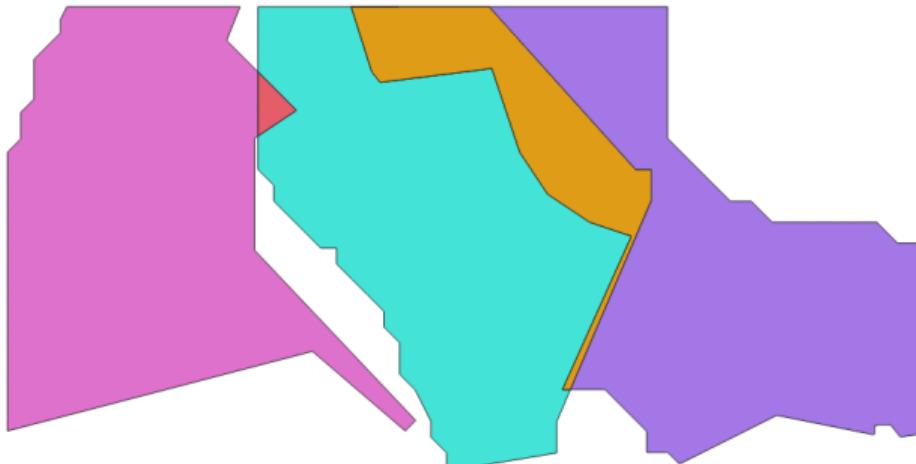


DETER warnings don't fit along time.

## DETER subareas

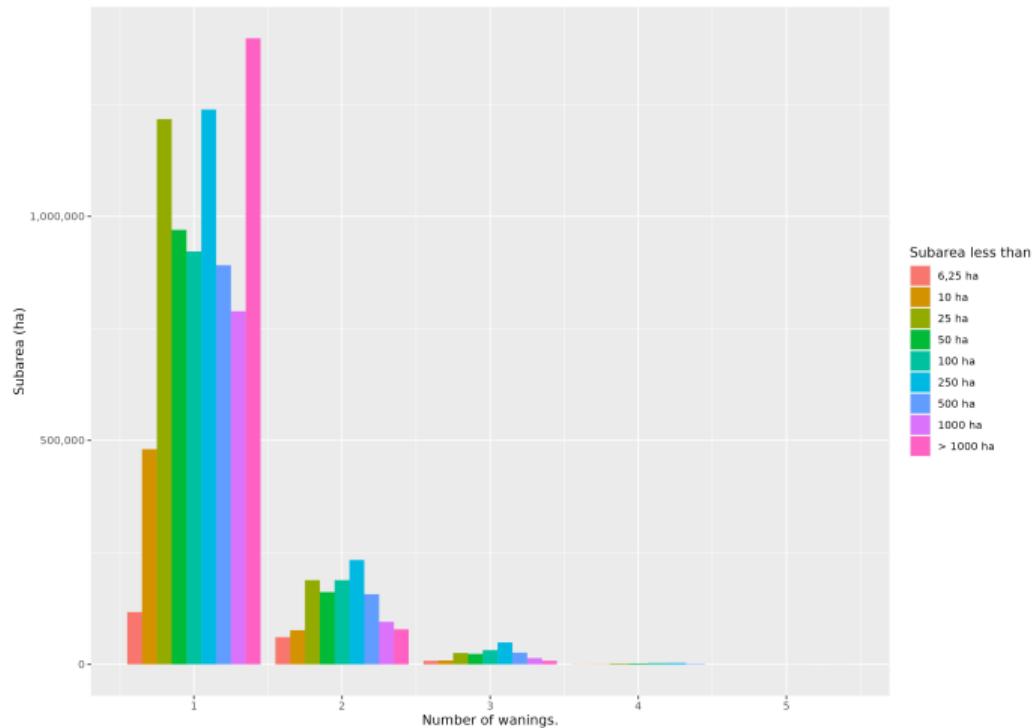
- ▶ The spatial properties of DETER warning are inconsistent along time (shape, size, position, orientation).
- ▶ DETER subareas maintain their spatial properties along time.

## DETER subareas



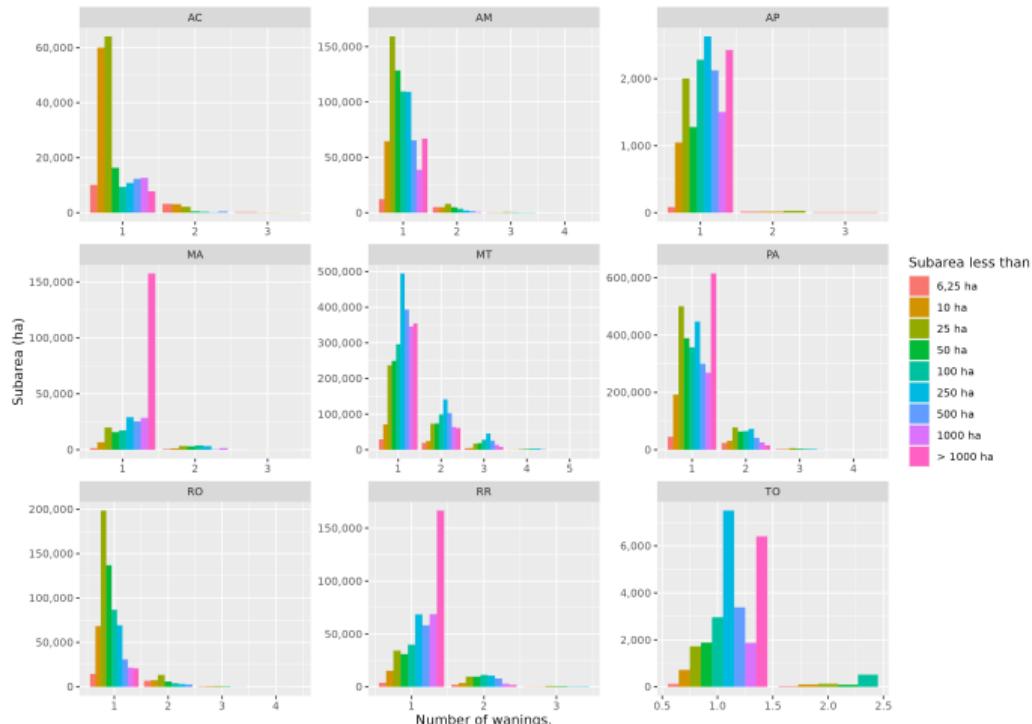
From 3 DETER warnings, we get 7 subareas!

# DETER subareas



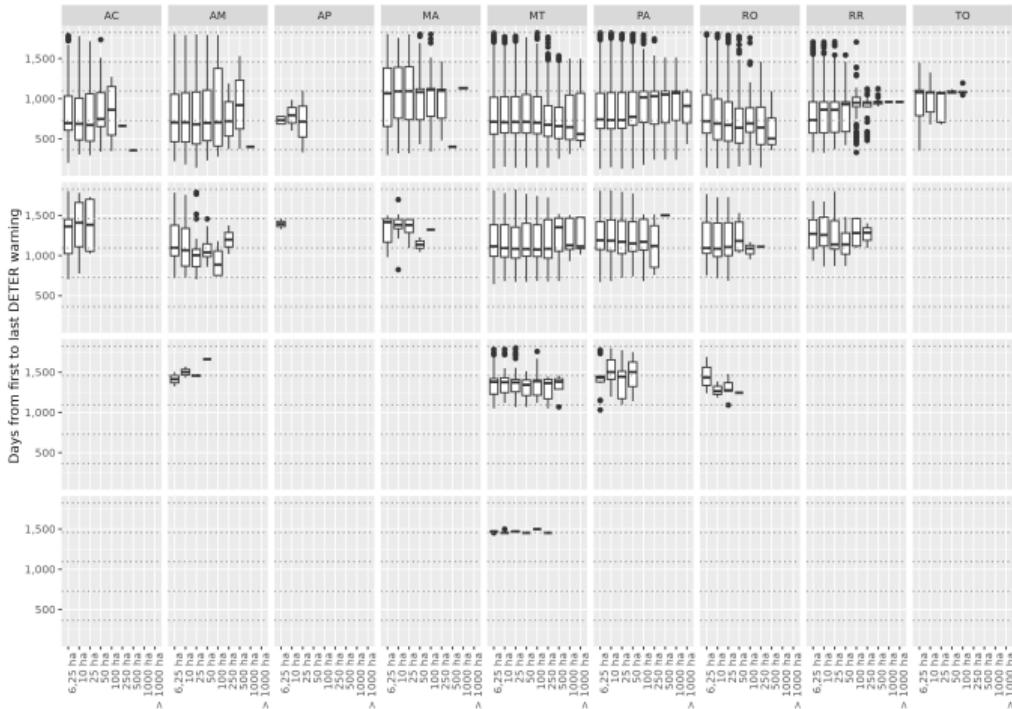
There are subareas with up to 5 recurrent warnings.

# DETER subareas



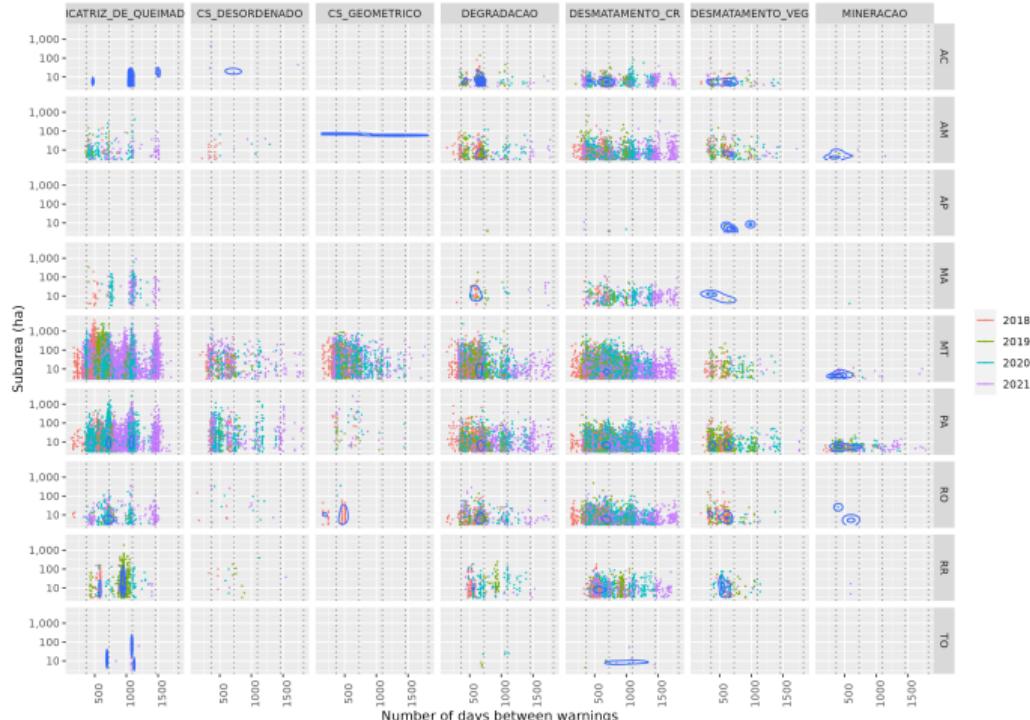
The warning recurrence changes by brazilian state.

# DETER subareas



Number of days between first and last warning.

# DETER subareas

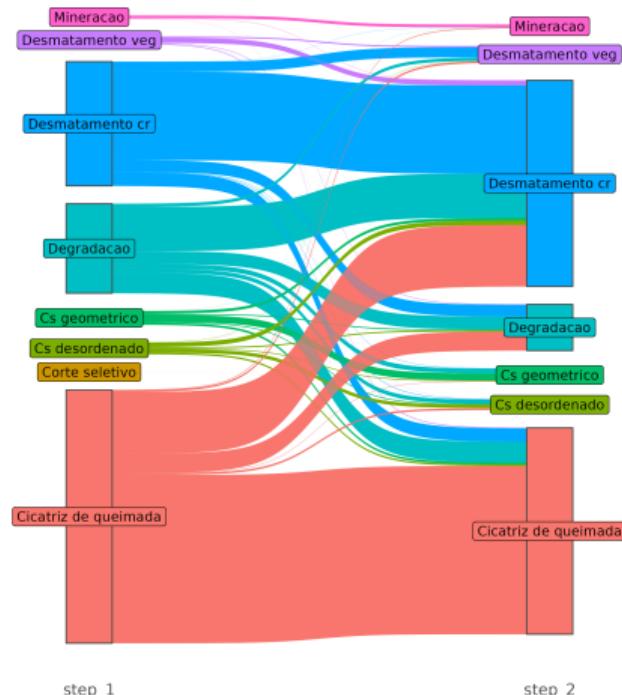


The number of days between warnings behaviour in space and time.

## Subarea trajectories

- ▶ Overlaped subareas organized along time describe trajectories of change.

# DETER subareas (2 warnings)

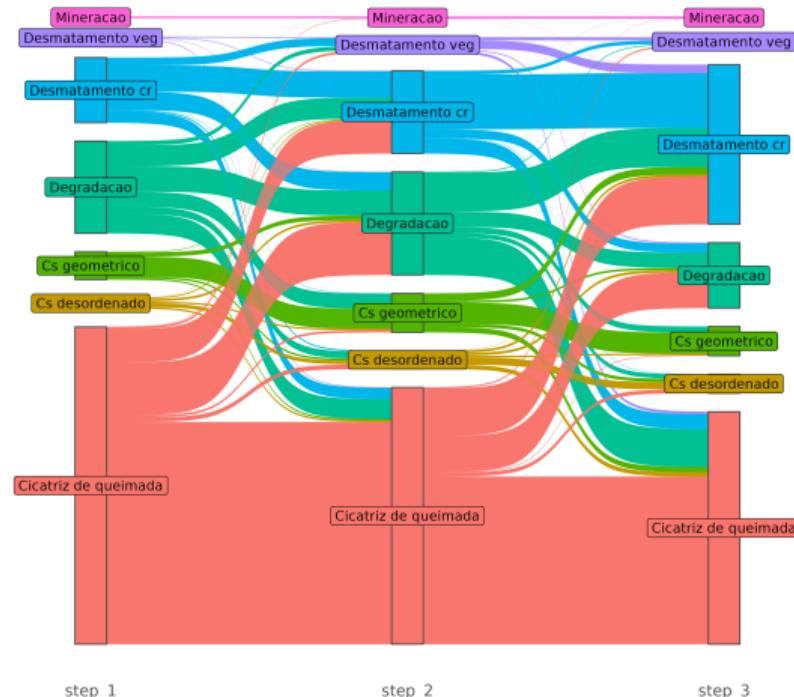


Trajectory of subareas with 2 wanings.

## DETER - Top 5 trajectories (2 warnings) |

position_1	position_2	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	Cicatriz de queimada	673806.1	15015	54.5	33.5
Cicatriz de queimada	Desmatamento cr	89540.6	5493	7.2	12.3
Desmatamento cr	Desmatamento cr	71670.7	7882	5.8	17.6
Cs geometrico	Cs geometrico	53594.9	623	4.3	1.4
Degradacao	Desmatamento cr	52004.1	3935	4.2	8.8
Total	-	1236329.4	44831	100.0	100.0

# DETER subareas (3 warnings)

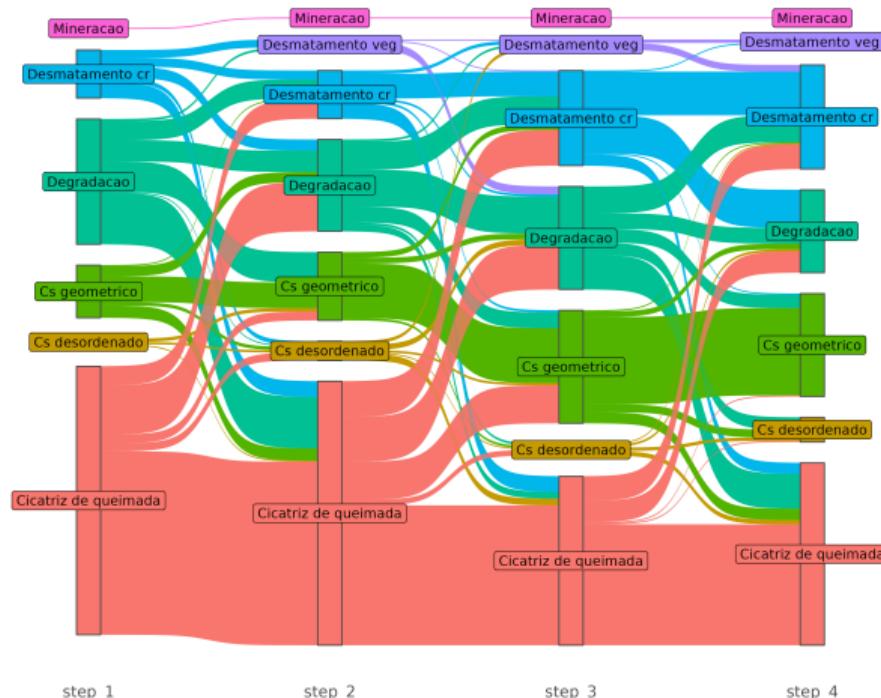


Trajectory of subareas with 3 wanings.

## DETER - Top 5 trajectories (3 warnings) |

position_1	position_2	position_3	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	96013.6	1789	49.5	29.6
Cicatriz de queimada	Cicatriz de queimada	Degradação	11700.9	345	6.0	5.7
Cicatriz de queimada	Degradação	Cicatriz de queimada	11374.3	336	5.9	5.6
Cs geométrico	Cs geométrico	Cs geométrico	10345.3	145	5.3	2.4
Cicatriz de queimada	Cicatriz de queimada	Desmatamento cr	8944.6	423	4.6	7.0
Total	-	-	193940.4	6041	100.0	100.0

# DETER subareas (4 warnings)

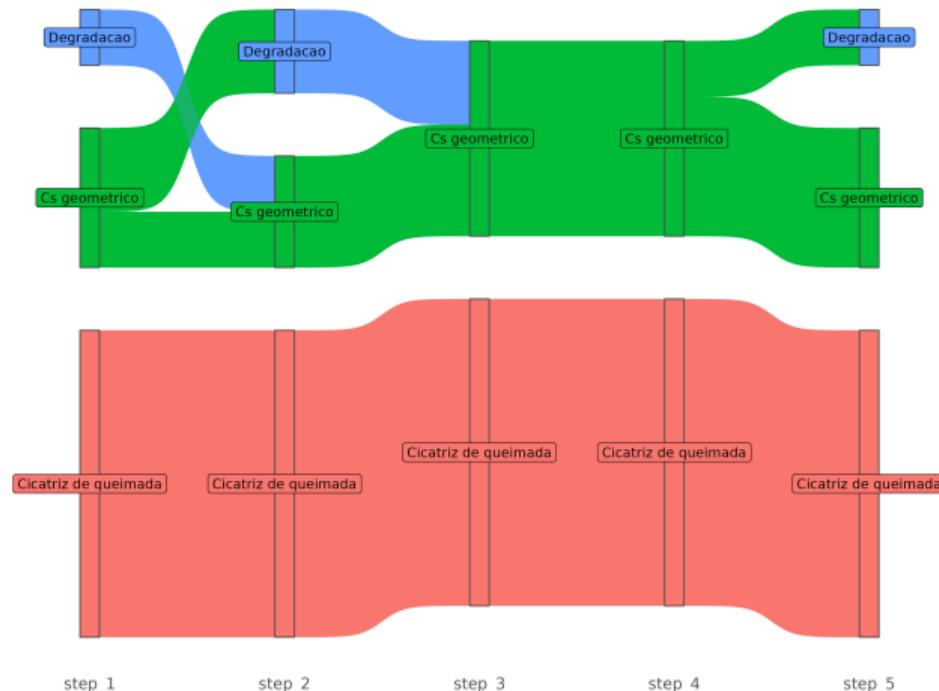


Trajectory of subareas with 4 wanings.

## DETER - Top 5 trajectories (4 warnings) |

position_1	position_2	position_3	position_4	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	3003.6	92	24.4	20.5
Cs geometrico	Cs geometrico	Cs geometrico	Cs geometrico	892.2	16	7.3	3.6
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Degradação	725.4	12	5.9	2.7
Cicatriz de queimada	Cicatriz de queimada	Desmatamento cr	Degradação	525.2	10	4.3	2.2
Degradação	Cs geometrico	Cs geometrico	Cs geometrico	515.6	16	4.2	3.6
Total	-	-	-	12296.1	449	100.0	100.0

# DETER subareas (5 warnings)



Trajectory of subareas with 5 wanings.

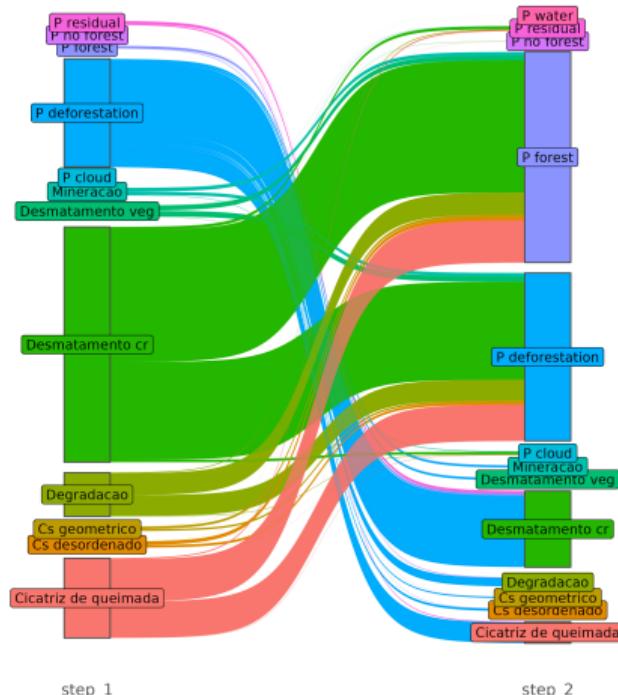
## DETER - Top 5 trajectories (5 warnings) |

position_1	position_2	position_3	position_4	position_5	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	289.7	11	70.7	61.1
Degradacao	Cs geo- metrico	Cs geo- metrico	Cs geo- metrico	Degradacao	80.5	2	19.7	11.1
Cs geo- metrico	Degradacao	Cs geo- metrico	Cs geo- metrico	Cs geo- metrico	32.9	3	8.0	16.7
Cs geo- metrico	6.5	2	1.6	11.1				
Total	-	-	-	-	409.7	18	100.0	100.0
Total	-	-	-	-	409.7	18	100.0	100.0

## DETER & PRODES

- ▶ Add to the trajectories the PRODES class corresponding to each DETER subarea.
- ▶ The selected class corresponds to the mode of PRODES' pixels in each DETER subarea.
- ▶ Use PRODES' view date to sort trajectories.

# DETER & PRODES subareas (2 warnings)

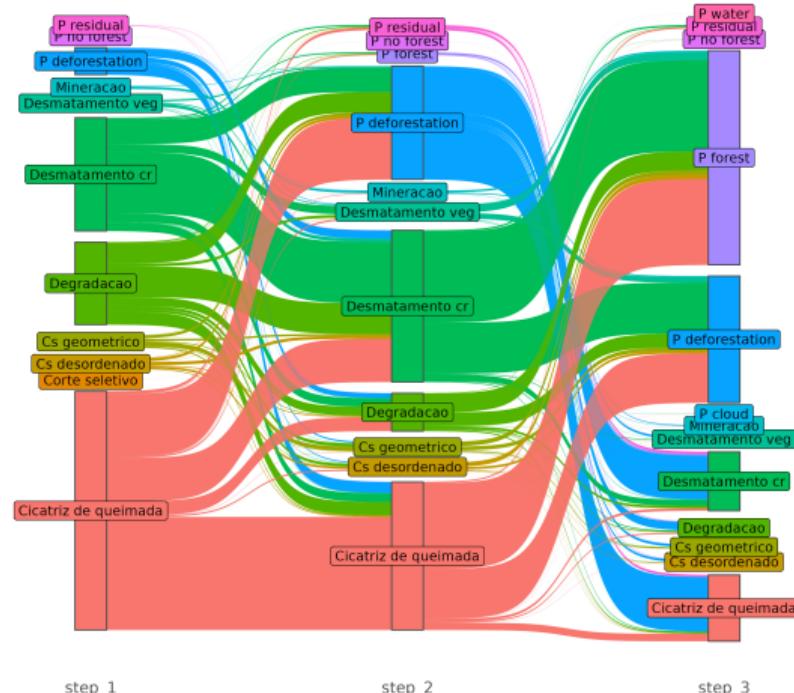


Trajectory of subareas with 2 wanings.

## DETER & PRODES - Top 5 trajectories (2 warnings) |

position_1	position_2	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	P forest	1041281.5	12645	18.8	8.4
Cicatriz de queimada	P deforestation	927627.3	10848	16.8	7.2
Desmatamento cr	P forest	838982.5	39589	15.2	26.3
Desmatamento cr	P deforestation	575218.9	29323	10.4	19.5
P deforestation	Desmatamento cr	386346.7	21391	7.0	14.2
Total	-	5537714.8	150521	100.0	100.0

# DETER & PRODES subareas (3 warnings)

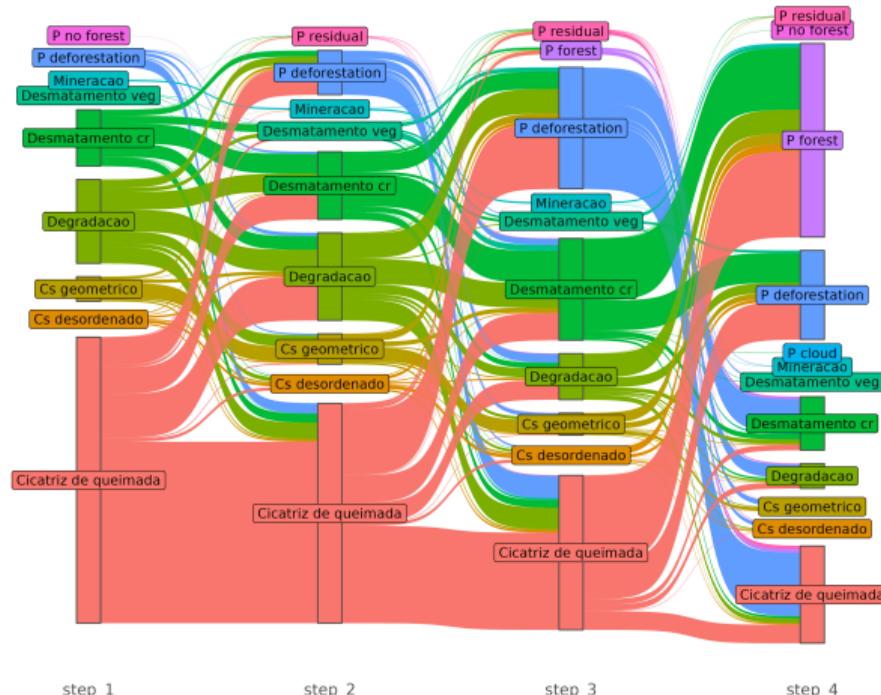


Trajectory of subareas with 3 wanings.

## DETER & PRODES - Top 5 trajectories (3 warnings) I

position_1	position_2	position_3	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	Cicatriz de queimada	P forest	227564.0	4775	24.9	14.2
Cicatriz de queimada	Cicatriz de queimada	P deforestation	124744.1	2836	13.7	8.4
Cicatriz de queimada	P deforestation	Cicatriz de queimada	115222.7	2983	12.6	8.9
Cicatriz de queimada	Desmatamento cr	P forest	30929.6	1888	3.4	5.6
Desmatamento cr	Desmatamento cr	P forest	24851.9	2624	2.7	7.8
Total	-	-	912412.3	33581	100.0	100.0

# DETER & PRODES subareas (4 warnings)

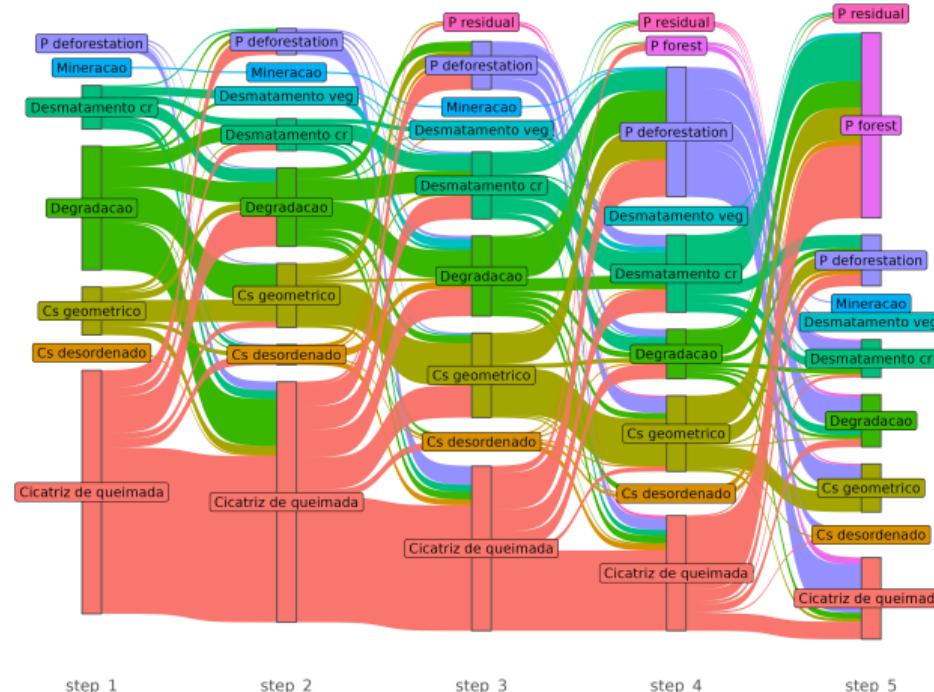


Trajectory of subareas with 4 wanings.

## DETER & PRODES - Top 5 trajectories (4 warnings) I

position_1	position_2	position_3	position_4	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	P forest	32093.7	524	22.5	11.8
Cicatriz de queimada	Cicatriz de queimada	P deforestation	Cicatriz de queimada	21441.9	387	15.0	8.7
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	P deforestation	10783.9	236	7.6	5.3
Cicatriz de queimada	P deforestation	Cicatriz de queimada	Cicatriz de queimada	5683.2	116	4.0	2.6
Cicatriz de queimada	Cicatriz de queimada	Degradação	P forest	5222.6	102	3.7	2.3
Total	-	-	-	142544.6	4451	100.0	100.0

# DETER & PRODES subareas (5 warnings)

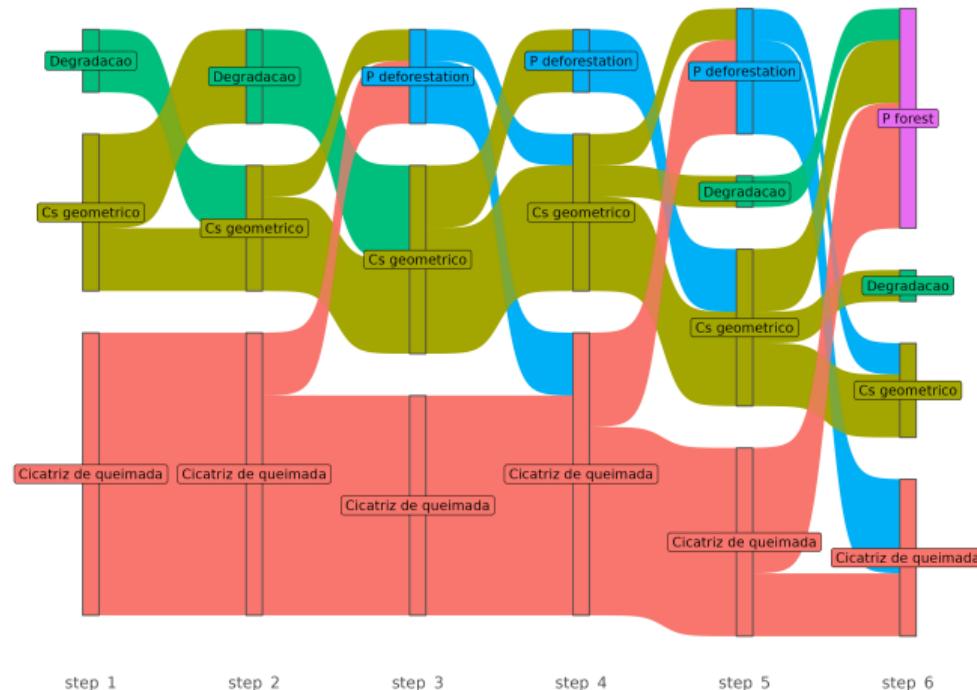


Trajectory of subareas with 5 wanings.

## DETER & PRODES - Top 5 trajectories (5 warnings) I

position_1	position_2	position_3	position_4	position_5	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	P forest	1290.8	33	14.6	10.1
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	P defor- estation	Cicatriz de queimada	384.5	14	4.3	4.3
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	P defor- estation	364.5	8	4.1	2.5
Cicatriz de queimada	P defor- estation	Cicatriz de queimada	Cicatriz de queimada	Degradação	308.7	3	3.5	0.9
Degradação	Cs geo- metrico	Cs geo- metrico	Cicatriz de queimada	P forest	279.9	1	3.2	0.3
Total	-	-	-	-	8845.8	326	100.0	100.0

# DETER & PRODES subareas (6 warnings)



Trajectory of subareas with 6 wanings.

## DETER & PRODES - Top 5 trajectories (6 warnings) I

position_1	position_2	position_3	position_4	position_5	position_6	area_ha	n_traj	p_area	p_traj
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	P forest	187.4	4	47.6	25.0
Degradacao	Cs geo- metrico	Cs geo- metrico	P defor- estation	Cs geo- metrico	Degradacao	74.3	1	18.9	6.2
Cicatriz de queimada	Cicatriz de queimada	P defor- estation	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	55.7	2	14.2	12.5
Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	Cicatriz de queimada	P defor- estation	Cicatriz de queimada	30.4	3	7.7	18.8
Cs geo- metrico	Degradacao	Cs geo- metrico	P defor- estation	Cs geo- metrico	Cs geo- metrico	21.9	1	5.6	6.2
Total	-	-	-	-	-	393.5	16	100.0	100.0

## DETER & PRODES - proximity in time I

- ▶ There is a potential DETER-PRODES overlap in our analysis.
- ▶ DETER warnings and PRODES deforestation polygons could refer to the same event.
- ▶ The next slide reports the DETER warnings closest in time to PRODES polygons.

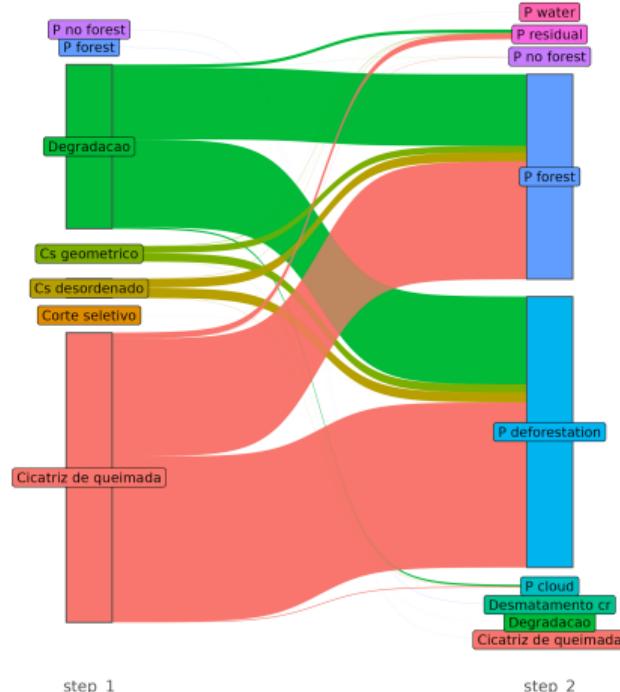
## DETER & PRODES - Top 5 proximity in time I

CLASSNAME	closest_class	total_ha	n	median_days	median_days_abs	sd_days	sd_abs
P deforestation	Cicatriz de queimada	1620833.2	26272	300	396	687.2	496.9
P forest	Cicatriz de queimada	1338484.8	19411	688	688	516.1	515.8
P deforestation	Desmatamento	1049533.4	57922	64	383	731.8	504.0
P forest	cr Desmatamento	939836.4	47172	649	649	488.8	488.4
P deforestation	cr Degradacao	391152.0	11266	353	478	731.9	511.0

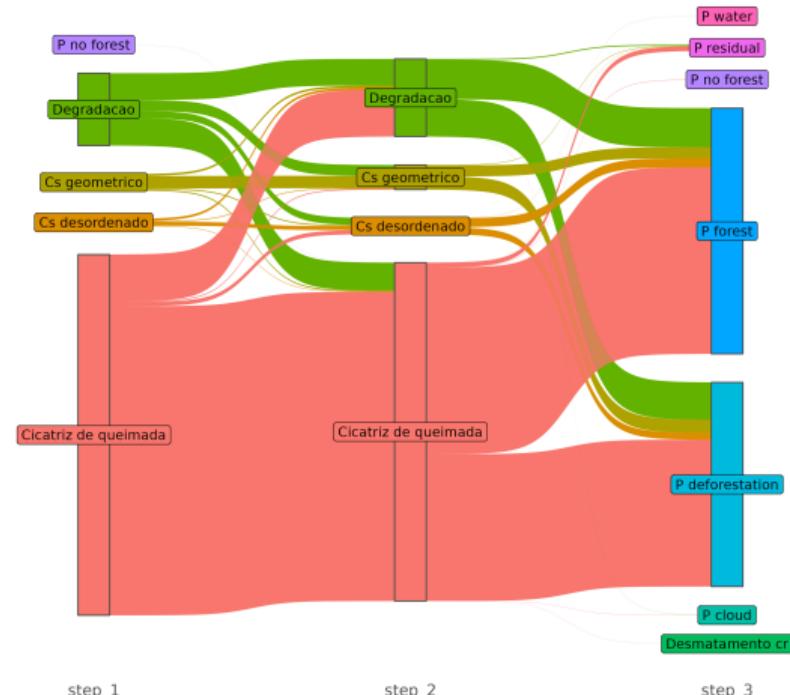
## Analysis 1

- ▶ Trajectories have one event in each PRODES year. There were 70/517059 with more than one.
- ▶ Trajectories related to mining were excluded.
- ▶ Trajectories end as soon as they reach deforestation.
- ▶ Trajectories include at least one PRODES event.

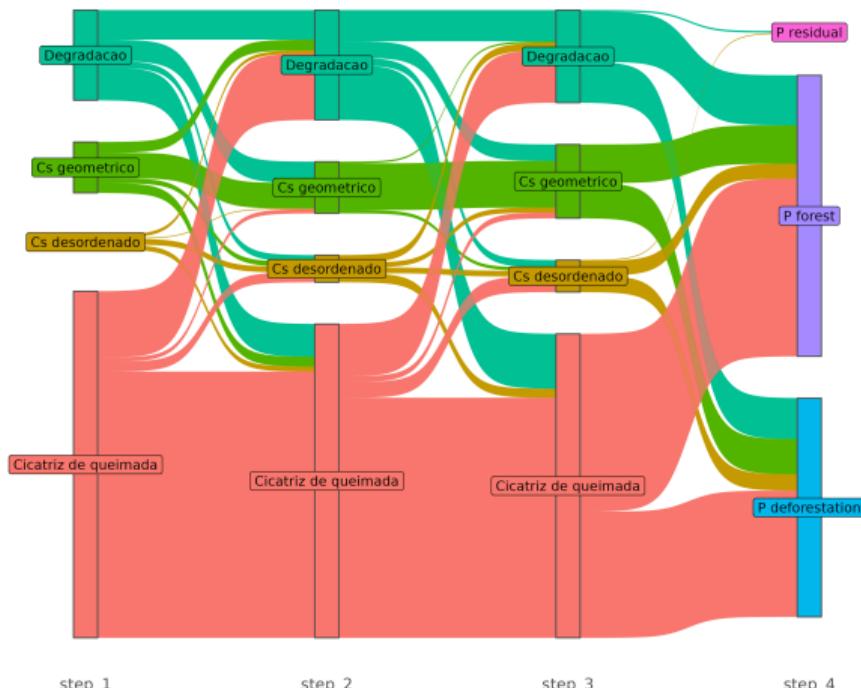
# Analysis 1 (2 warnings)



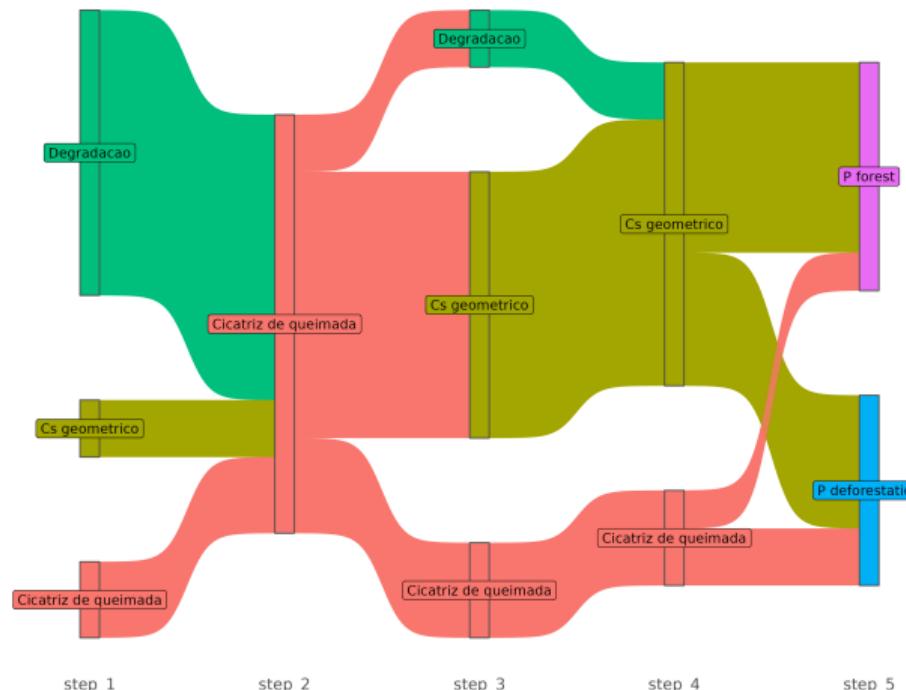
# Analysis 1 (3 warnings)



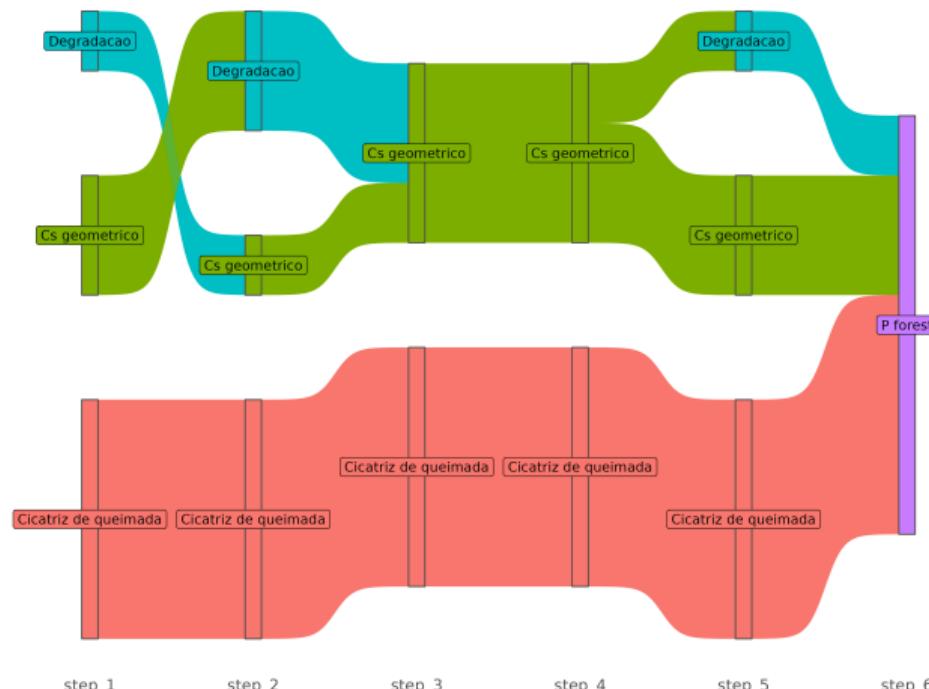
# Analysis 1 (4 warnings)



# Analysis 1 (5 warnings)



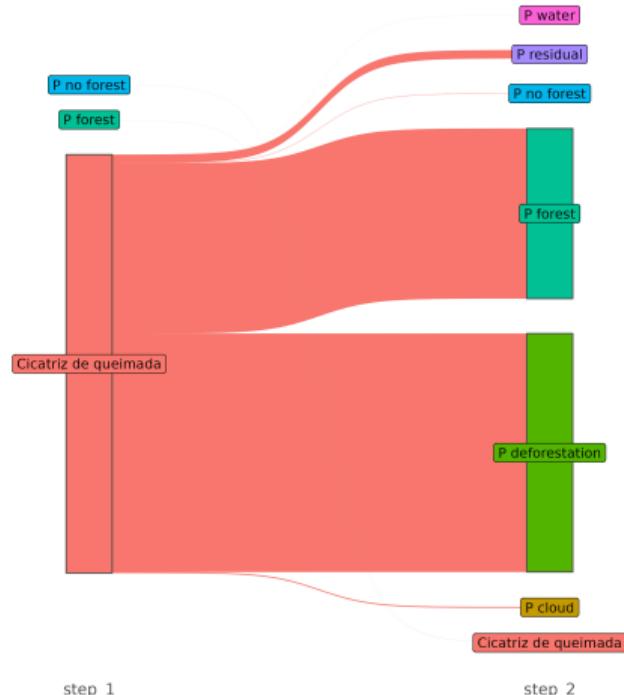
# Analysis 1 (6 warnings)



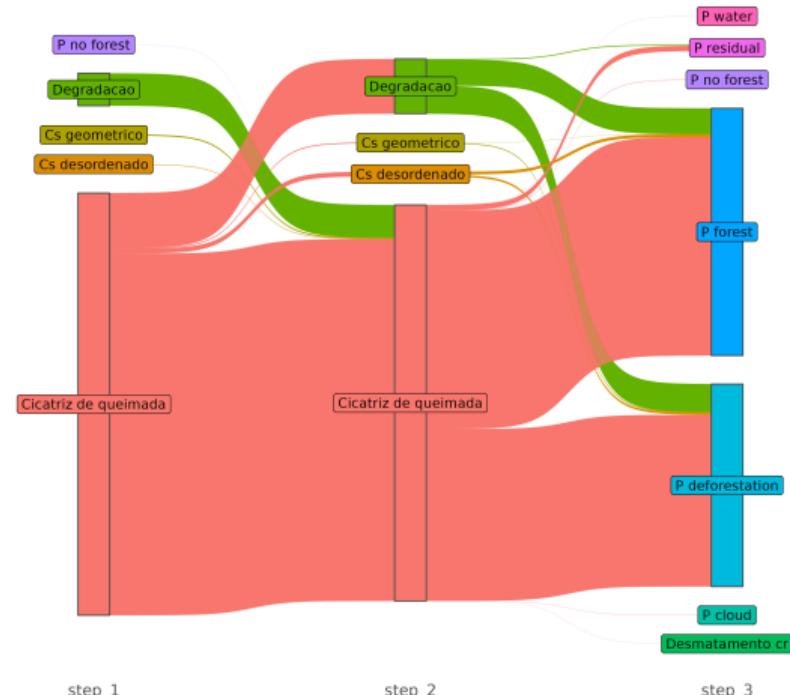
## Analysis 2

- ▶ Same as Analysis 1, but only using DETER's burn scars.

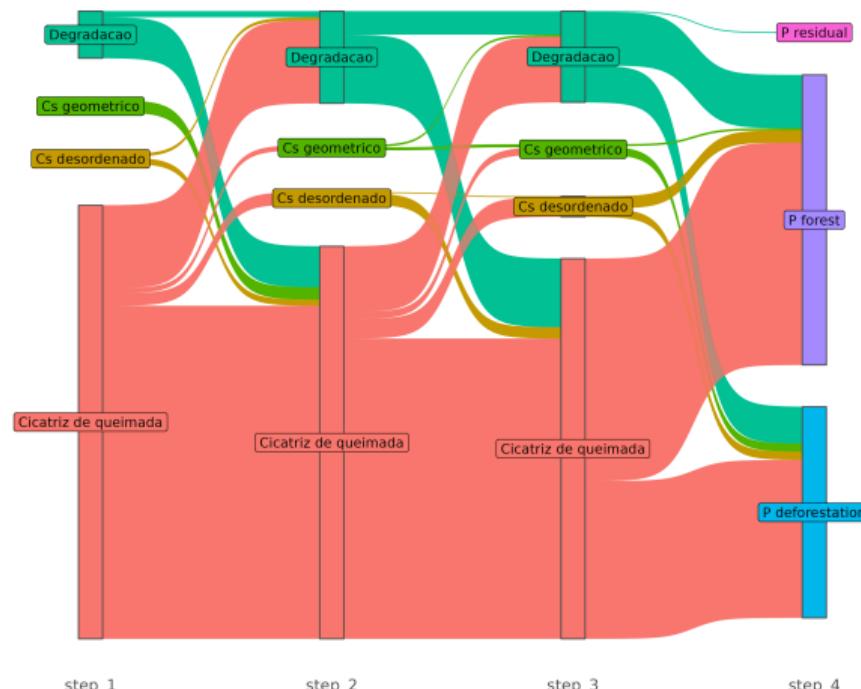
## Analysis 2 (2 warnings)



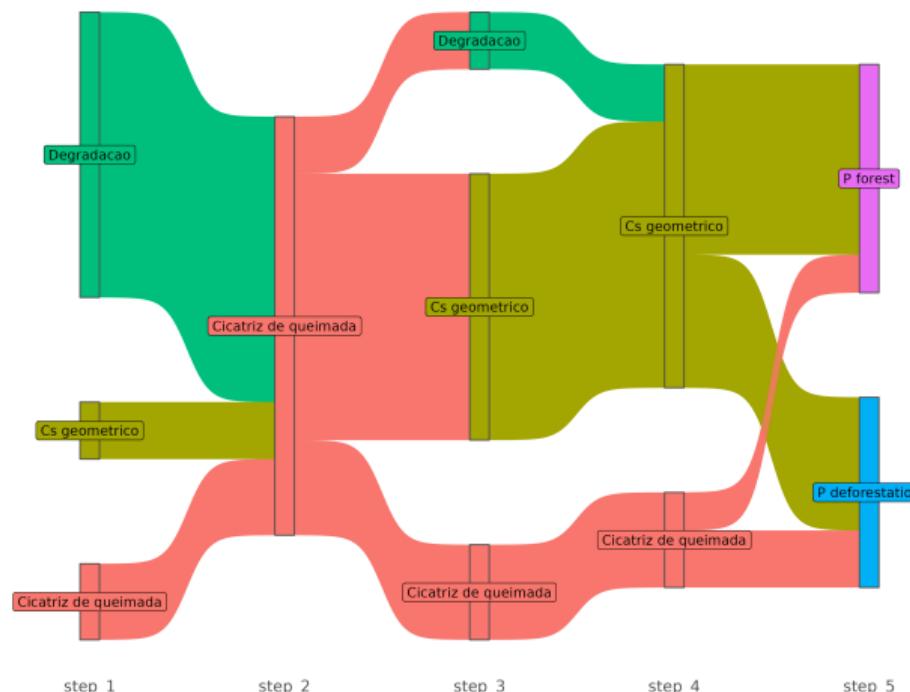
## Analysis 2 (3 warnings)



## Analysis 2 (4 warnings)



## Analysis 2 (5 warnings)



## Analysis 2 (6 warnings)



## Final remarks

- ▶ The analysis of DETER warning subareas along time could improve the characterization of forest degradation along time.
- ▶ Potential applications of our work are:
  - ▶ Improve estimation of emissions of greenhouse gases, i.e. our data could help avoiding double counting.
  - ▶ Identify spatio-temporal areas which could help training Machine-Learning algorithms for automatic identification of forest degradation.
- ▶ Code available at <https://github.com/albhasan/treesburnareas>

## References I

-  Claudio Aparecido De Almeida, Luis Maurano, Dalton M. Valeriano, Gilberto Câmara, Lúbia Vinhas, Marisa Da Motta, Alessandra Rodrigues Gomes, Antonio Miguel Vieira Monteiro, Arlesson Antônio De Almeida Souza, Cassiano Gustavo Messias, Camilo Daleles Rennó, Marcos Adami, Maria Isabel Sobral Escada, Luciana De Souza Soler, and Silvana Amaral, *Metodologia Utilizada nos Sistemas PRODES e DETER - 2a Edição (atualizada)*, Tech. report, Instituto Nacional de Pesquisas Espaciais (INPE), 2022.
-  Yosio Shimabukuro, Valdete Duarte, Liana Anderson, Dalton Valeriano, Egídio Arai, Ramon Freitas, Bernardo Rudorff, and Maurício Moreira, *Near real time detection of deforestation in the Brazilian Amazon using MODIS imagery*, Ambiente e Água - An Interdisciplinary Journal of Applied Science **1** (2006), no. 1, 37–47.