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On the use of disdrometer data for characterization of precipitation episodes in the Basque Country

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1. Introduction



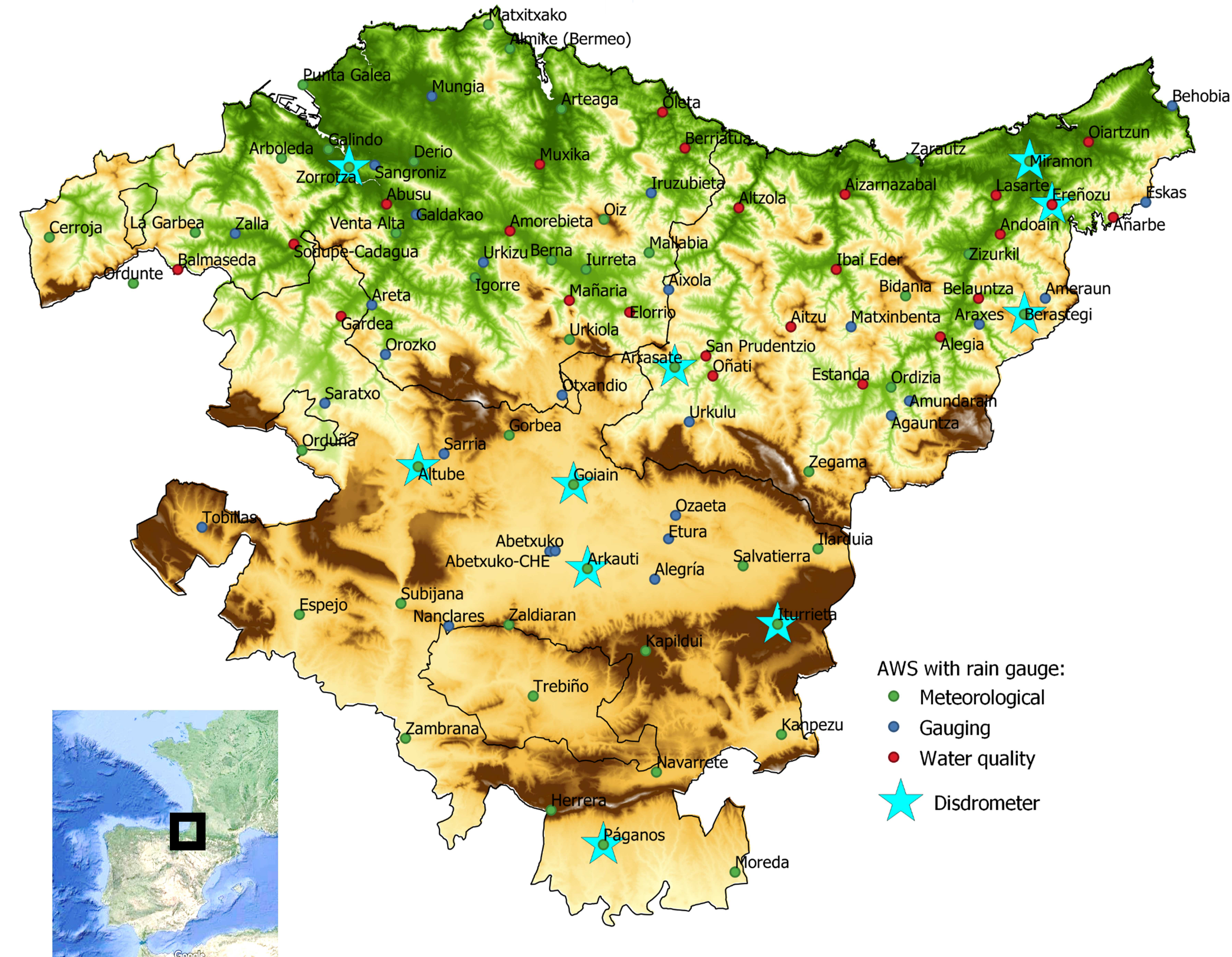
- The ultimate goal of this work is the characterization of precipitation episodes, that is, to identify patterns and common characteristics of precipitation episodes using 1-minute data from disdrometers.
- Such instrumentation, among other parameters, provides information on precipitation intensity and hydrometeor classification (Drizzle, Drizzle with rain, Rain, Rain with snow, Freezing rain, Snow, Hail).
- Aggregating precipitation data into episodes is a more natural way to understand how showers are structured and how they affect a specific location.



1. Introduction

The Basque disdrometer network

- Deployed by the Basque Government, this network comprises several **Parsivel OTT-2** disdrometers installed in various locations across the Basque Country.
- Optical disdrometers operate by measuring the degree of light obstruction caused by particles passing through a laser beam.
- When raindrops intercept the beam, a sensor detects a reduction in light intensity, which is then converted into an electric signal by a photodiode.
- This reduction in intensity corresponds to the size of the raindrops blocking the beam.
- Additionally, by analyzing the duration of reduced intensity, the falling velocity of the particles can be estimated.
- This instrumentation provides both raw data, such as **raindrop size and velocity distribution**, and derived data, including **rain intensity, hydrometeor classification, reflectivity, and visibility**, recorded every minute.

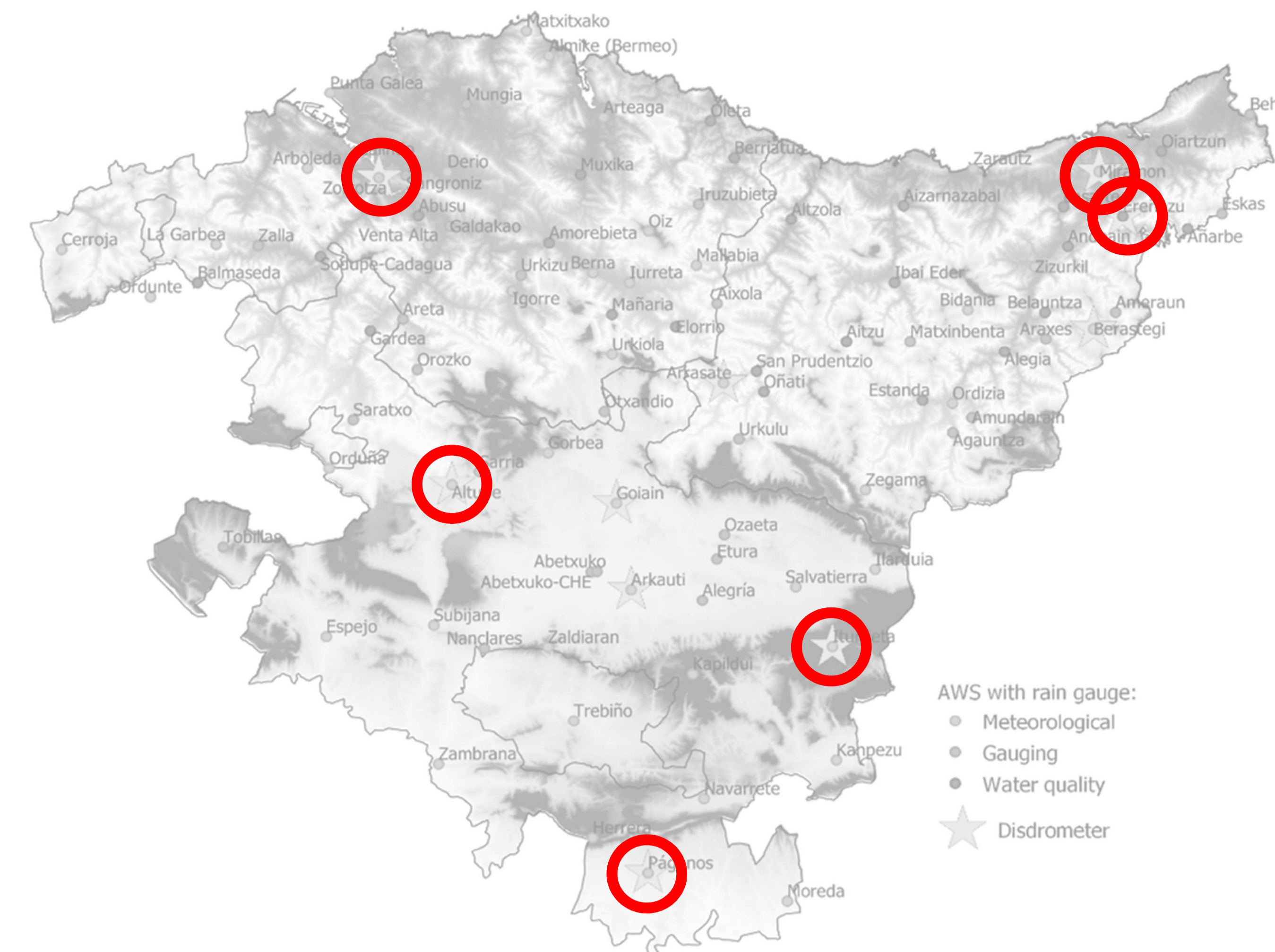


Tipping bucket rain-gauges and disdrometers



1. Data

- We selected 6 locations with complete observations (from disdrometers and pluviometers) during the three years study period (from 2021 to 2023).
- **DIS:** A dataset is created from raw 1-minute disdrometer telegrams containing different key variables, primarily Rain Intensity (**RI**), Number of Particles (**NP**), and **Type** (**HC-Hydrometeor Classification**).
- We filtered out some 1-minute events with $NP < 10$ or $RI < 0.01$ mm/h. This resulted in 2023 events (0.2%) with a total precipitation amount of 12 mm (0.06%).
 - TBG: 10-minute precipitation data set from heated tipping-bucket rain gauges are prepared



Selected locations used in this study

Name	alt (m)	lat	lon
Altube	618	42,9661	-2,86795
Ereñozu	25	43,242	-1,93922
Iturrieta	987	42,7935	-2,34575
Miramón	113	43,2868	-1,97121
Páganos	577	42,5605	-2,60055
Zorroza	5	43,2849	-2,96845

DIS dataset
disdrometer 1-min data

TBG dataset
tipping-bucket 10 min
rain gauge data



An example of disdrometer (**dis**) and tipping bucket rain-gauge (**tbg**)



1. Methodology

- We considered 1-minute **event variables**, **numerical** (rain intensity, rain amount, number of particles) and **nominal** (precipitation type).
- Event data (1-minute) **was aggregated into precipitation episodes** based on selected criteria for temporal aggregation (see next slide).
- **New episode variables** were generated by applying mathematical operations (depending on numerical or nominal nature), such as count, sum, maximum, minimum, mean, median, mode, standard deviation, or percentiles.
- We analyzed episode characteristics based on **segmentation** by different factors, such as duration, predominant precipitation type, total precipitation amount, maximum intensity, or season/month.



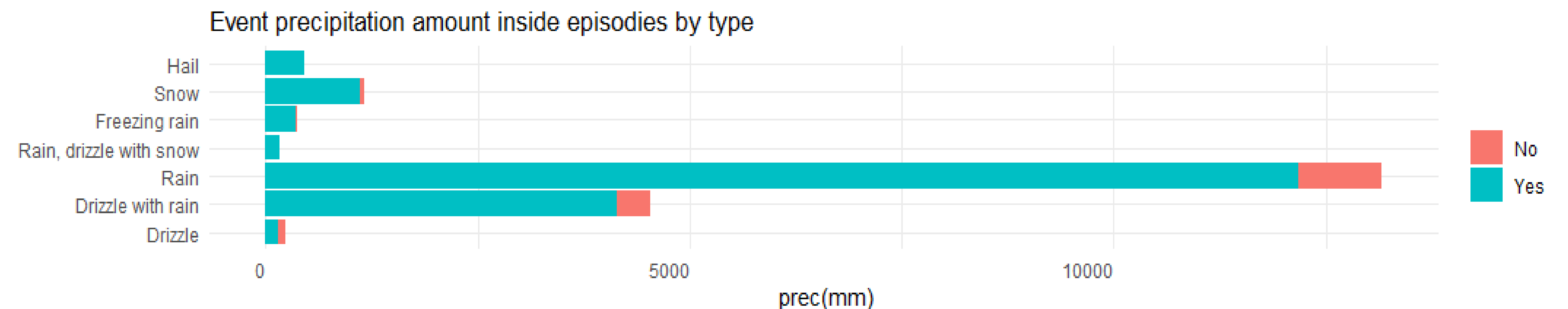
- Various exploratory data analysis (**EDA**) and visual data analytics (**VDA**) techniques were applied to characterize and identify patterns and common characteristics.
- Some **ad-hoc R scripts** were implemented to manage data, simplify complexity, and extract conclusions.
- We used different libraries like **tidyr** for data manipulation and transformation, **dplyr** for data transformation and analysis, and **ggplot2** for data visualization and analysis. **Facets** were used to generate multiple plot panels based on factors, grouping, and summarizing.



2.1. Results and discussion: Episodes generation

- Episodes generation are based on the **USGS-Rainmaker** methodology.
- Ad-hoc functional implementation in **R**, modified for 1-minute intervals and multiple stations.
- Episodes are generated considering:
 - Minimum Inter-episode Time (**MIT**): the minimum time difference between episodes.
 - Minimum Episode Rain Threshold (**MRT**): the minimum accumulated precipitation required to define an episode.
- A higher IET results in fewer episodes, longer duration, and higher mean precipitation (though not always true for high-intensity episodes).
- A lower MRT results in more episodes, as more minor events are included, but similar behavior is observed in high-intensity episodes.
- After sensitivity tests, **MIT = 30 minutes** and **MRT = 1 mm** were selected.

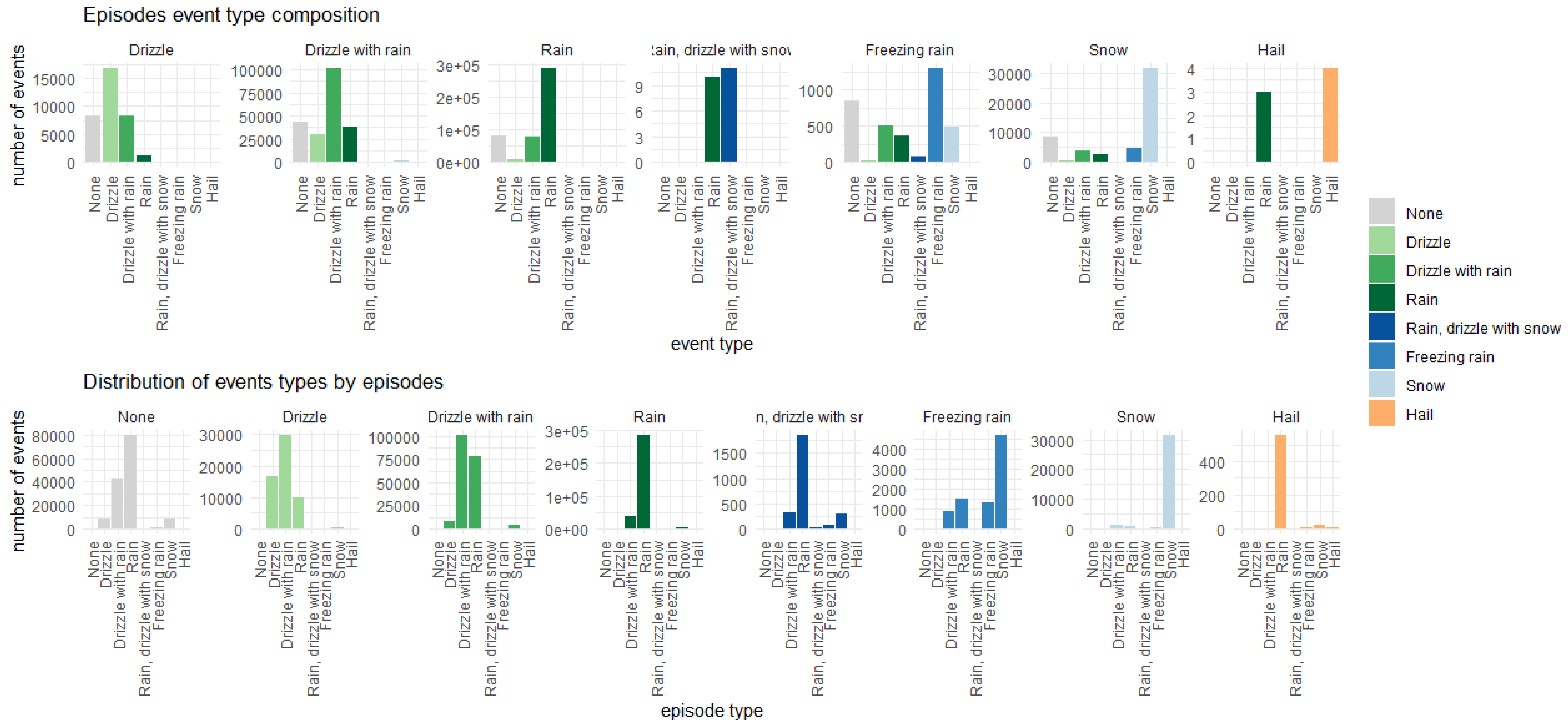
8% of total event precipitation remain outside episodes (34% Drizzle, 9% Drizzle with rain, 7% Rain, 4% Snow, and less in other cases).



2.2. Results and discussion. Episodes and events types

Note that for "type" (nominal data), the mode is used to calculate the most representative "type" during an episode, and that we include "None" as an episode can have no-rain events inside

The figure shows the composition of types within episodes and the distribution of events types into episodes



- Different hydrometeor types can coexist within an episode.

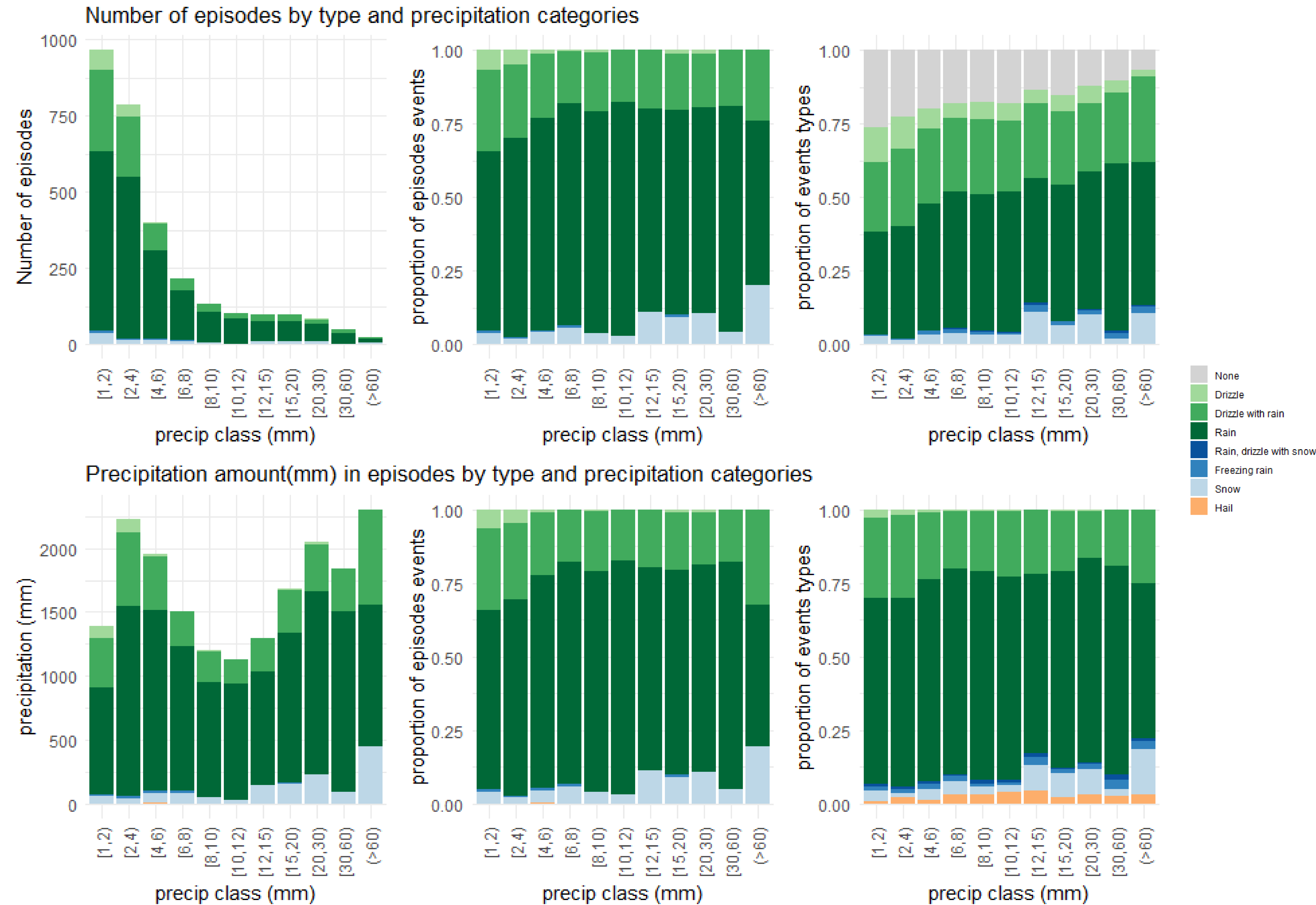
- Note that most hail events or freezing rain events are included in "rain" episodes.



2.3. Results and discussion. Total precipitation

Focusing on episodes' total precipitation segmentation:

- There is a decrease in the number of episodes for higher precipitation classes and an increase in accumulated precipitation for higher precipitation classes (first column).
- The relative proportion of episode types per precipitation class shows a higher proportion of snow in higher classes and drizzle in lower classes for both the number of episodes and accumulated precipitation (second column).
- Focusing on the details of event-type composition within episodes (third column):
 - Drizzle events are present in all classes, and freezing rain events appear in higher classes.
 - Non precipitation events are less relevant as total precipitation increase
 - Pure drizzle events contribute insignificantly to total precipitation.
 - Hail events contribute to total episode precipitation across all classes.
 - Snow events contribute more for higher classes



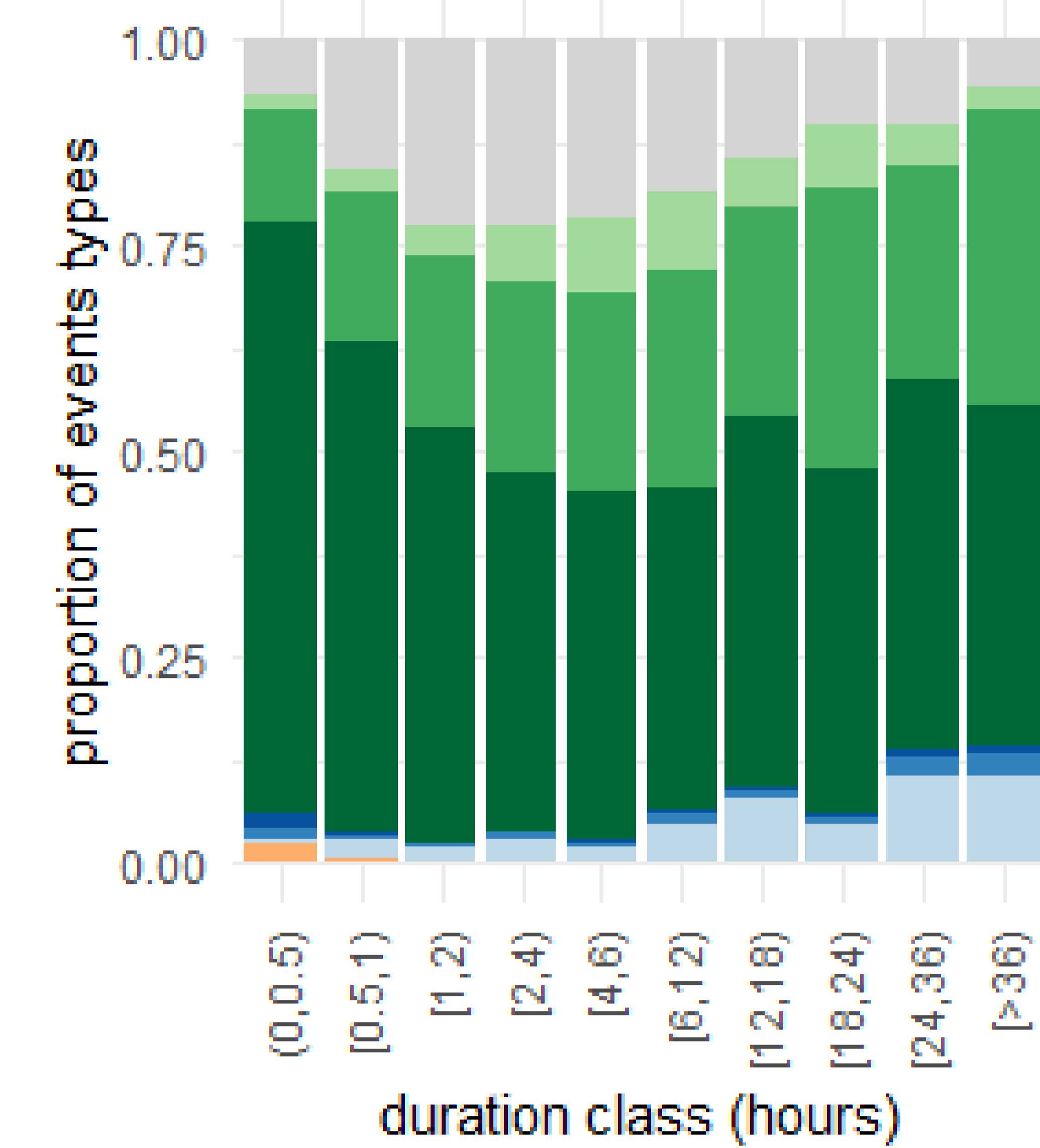
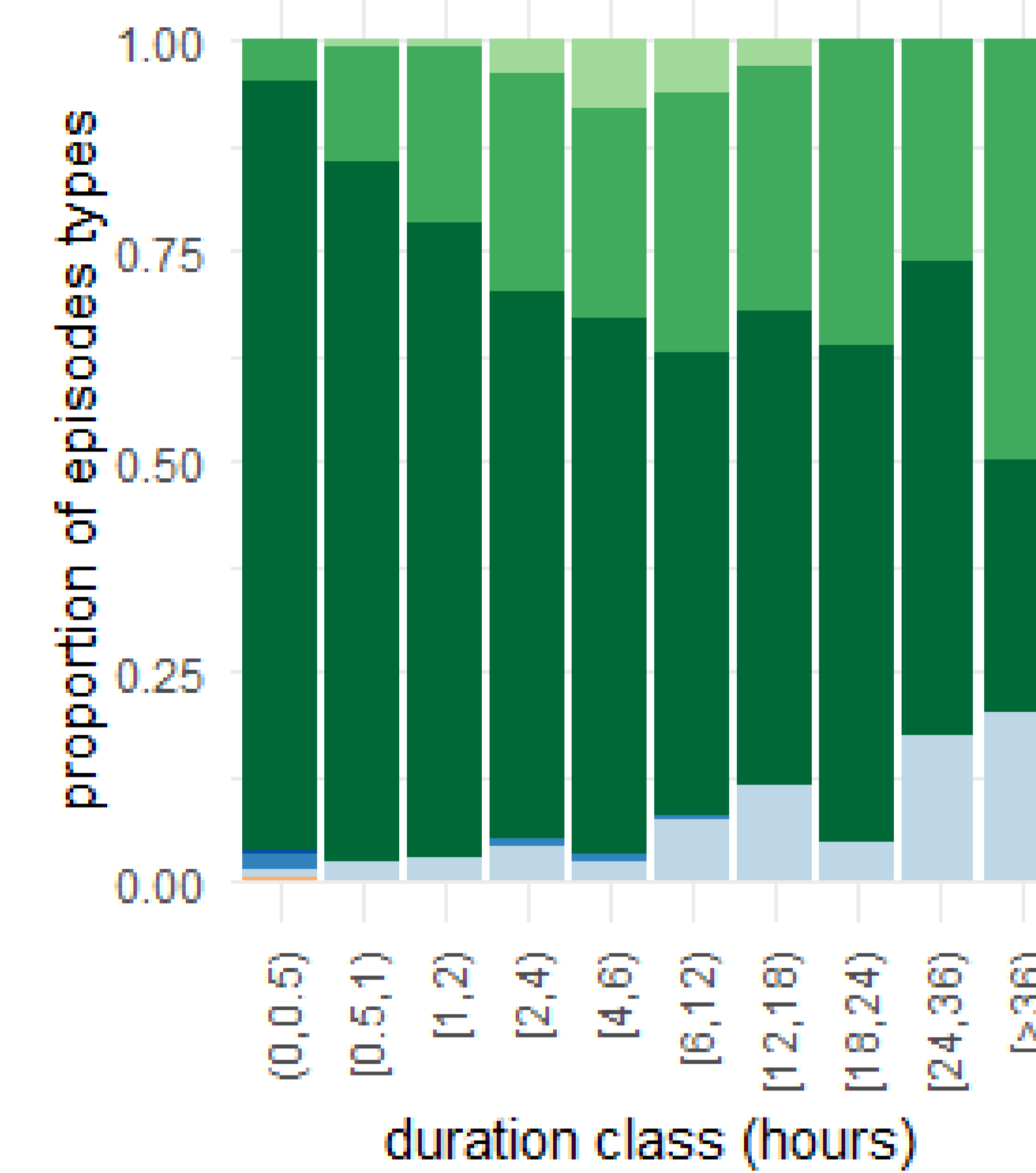
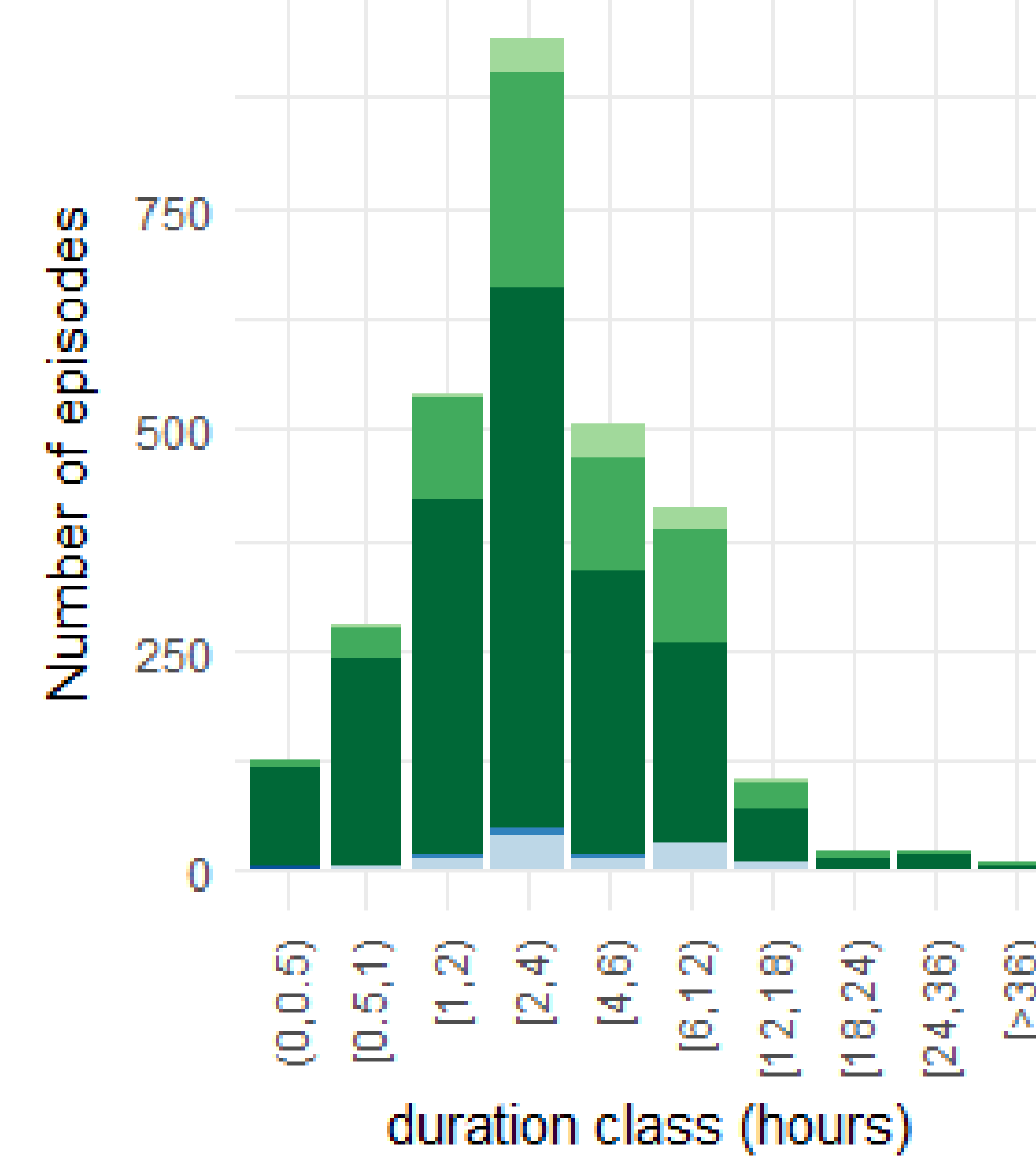
2.4. Results and discussion. Duration



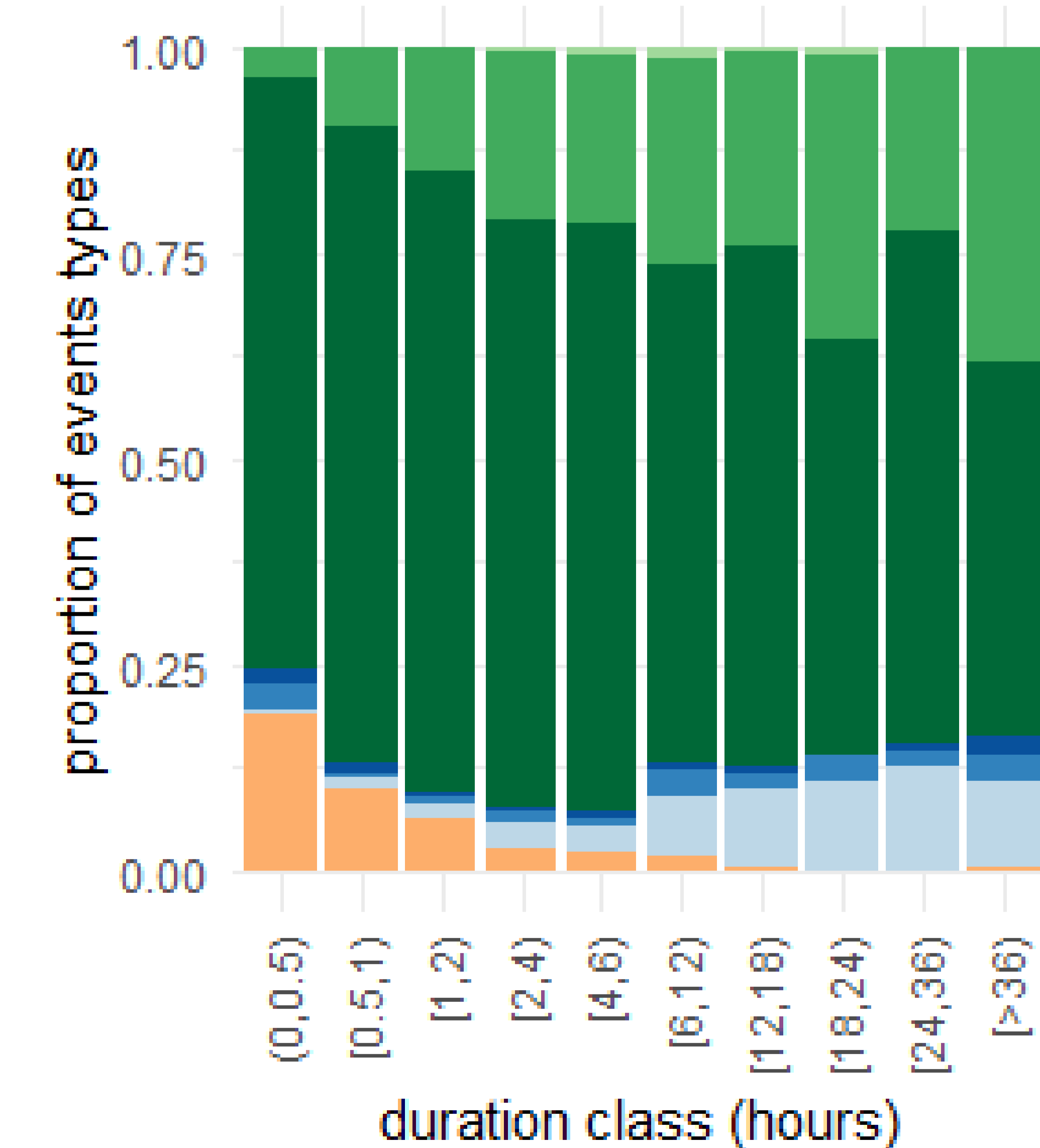
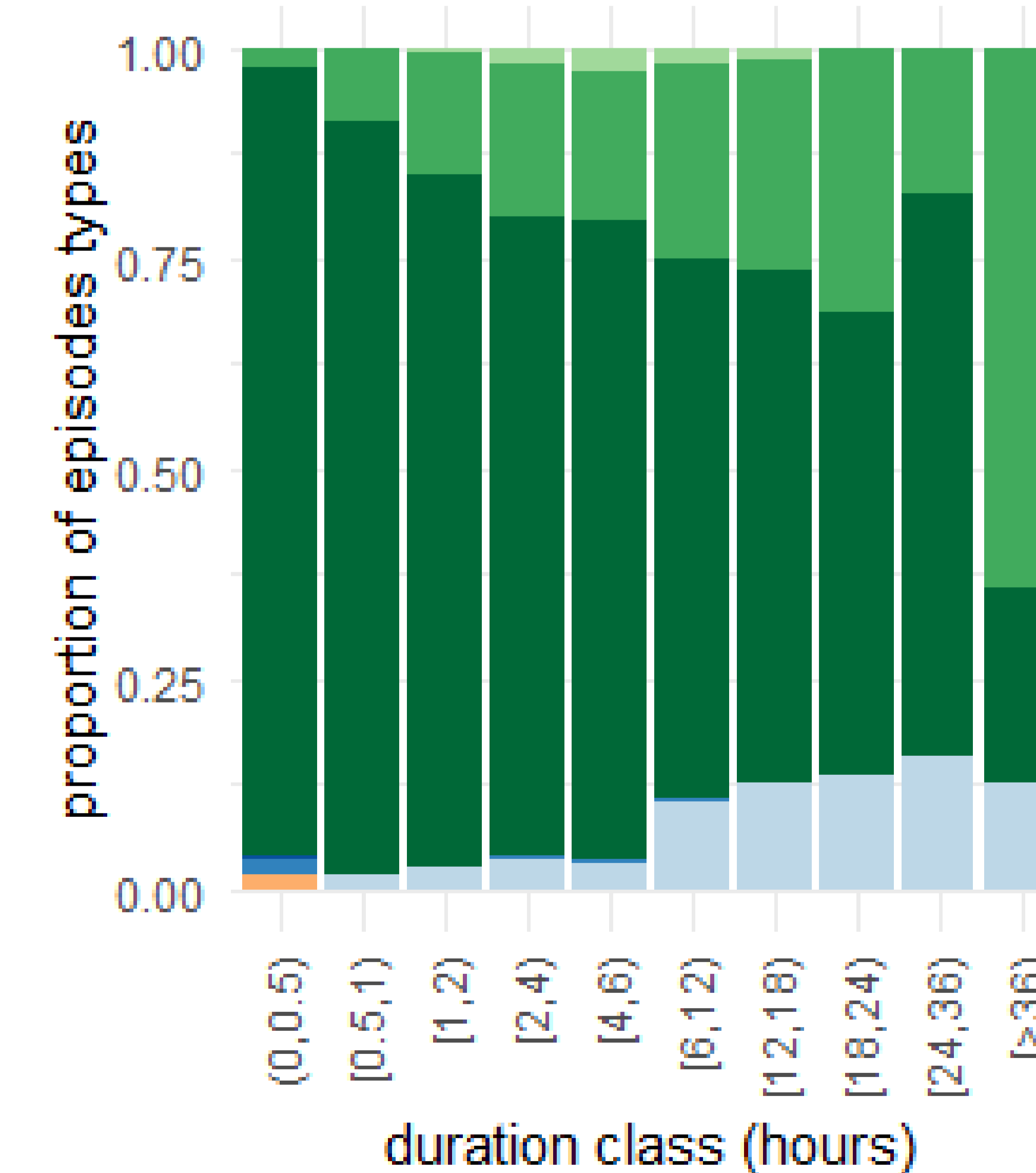
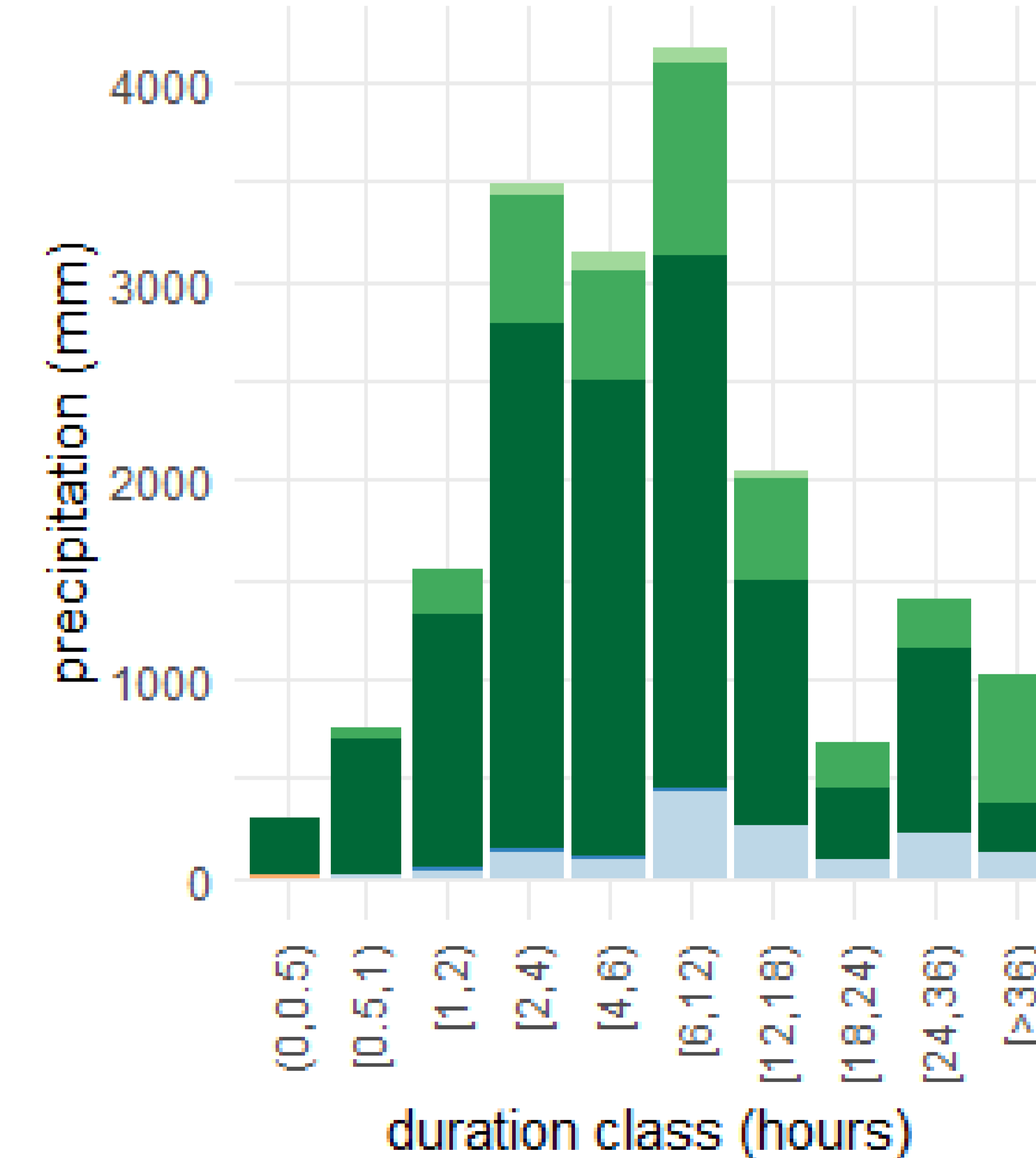
Focusing on episodes' duration segmentation:

- The majority of episodes are distributed around the 2-4 hour class. The contribution to total precipitation from events over 18 hours is significant, despite their low number (first column)
- Examining the proportions per episode type, we see an increasing contribution of drizzle with rain and snow episodes as the duration class increases, while hail and freezing rain episodes last for less than half an hour (second column)
- Focusing on details from events type composition of episodes (third column), we see that:
 - Drizzle events and associated precipitation become more significant as duration increases.
 - Hail events are mostly present in low-duration classes and are relevant in terms of precipitation amount.
 - Snow events become more relevant as the duration increases.

Number of episodes by type and duration categories



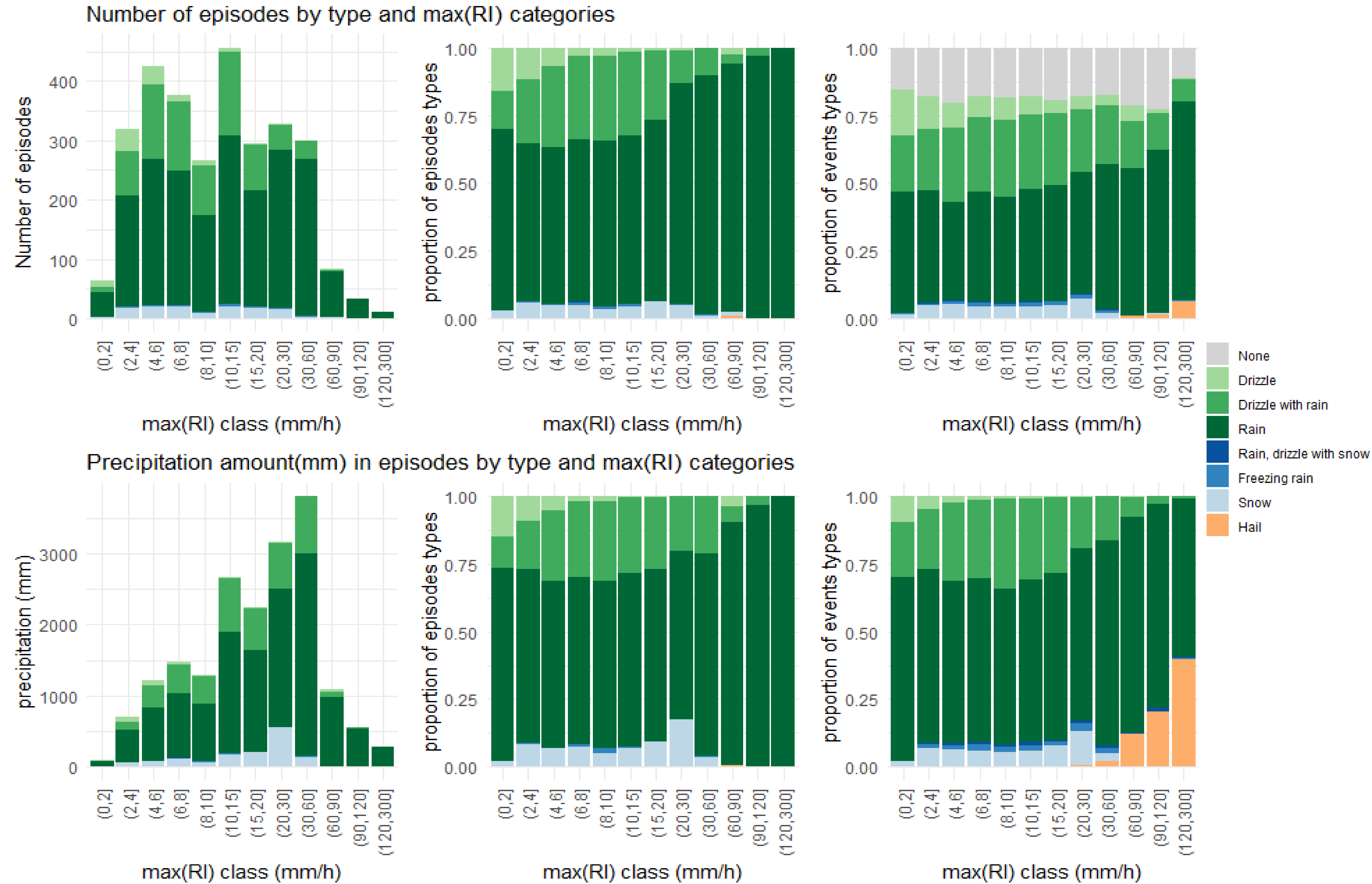
Precipitation amount (mm) in episodes by type and duration categories



2.5. Results and discussion. Precipitation intensity

Focusing on episodes' maximum rain intensity segmentation:

- The number of episodes is quite similar between 2 and 60 mm/h. The contribution to total precipitation mainly comes from episodes between 10 and 60 mm/h. (first column)
- Pure snow events are limited to 1-30 mm/h. **No snow events are observed over 60 mm/h.** Over 30 mm/h, episodes are mainly classified as rain. Drizzle episodes have a maximum RI of less than 10 mm/h. (second column)
- Focusing on details from event type composition of episodes (third column):
 - Freezing rain and snow does not occur with RI over 60 mm/h.
 - Hail events are limited to episodes with a maximum RI over 60 mm/h.

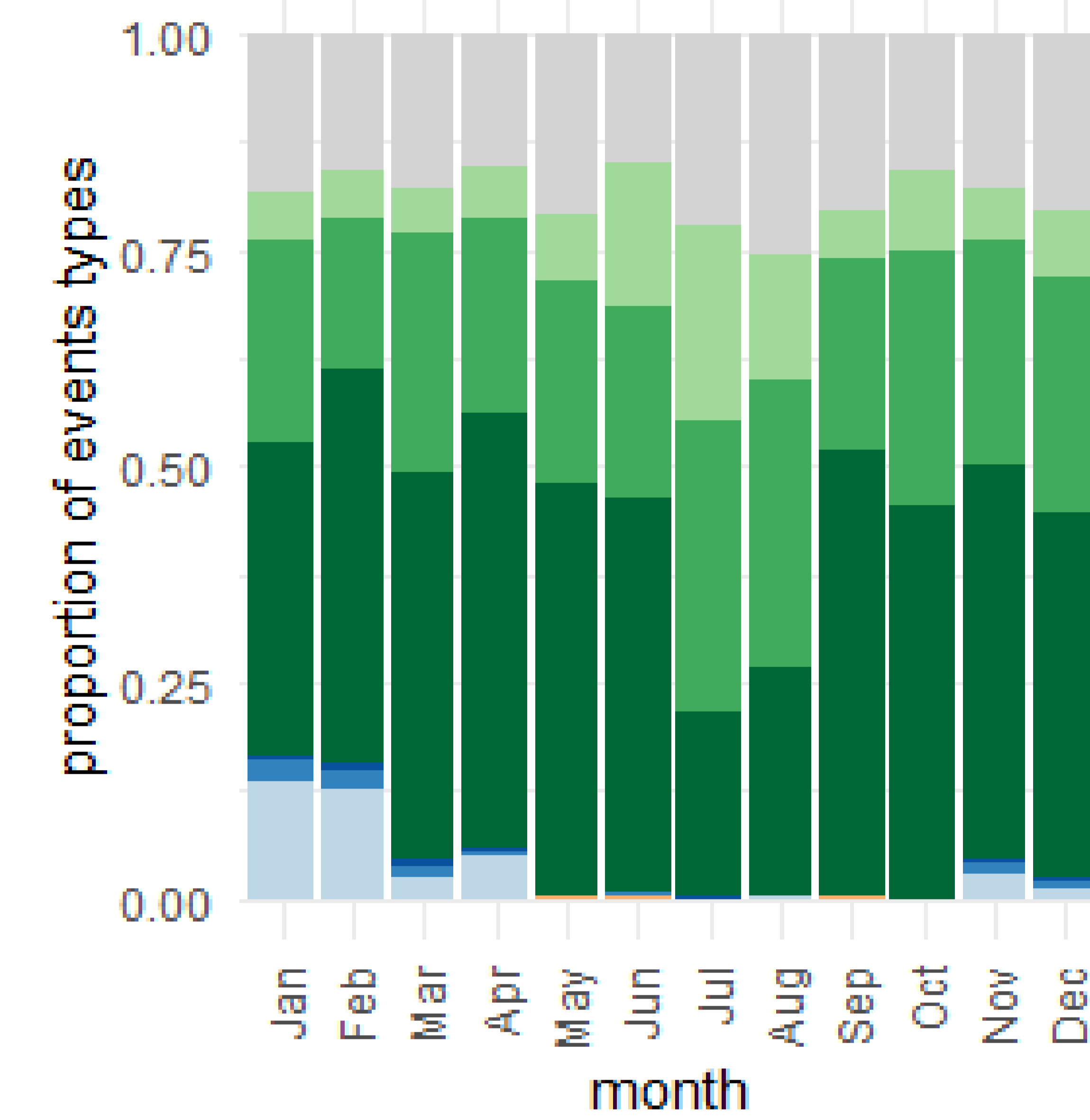
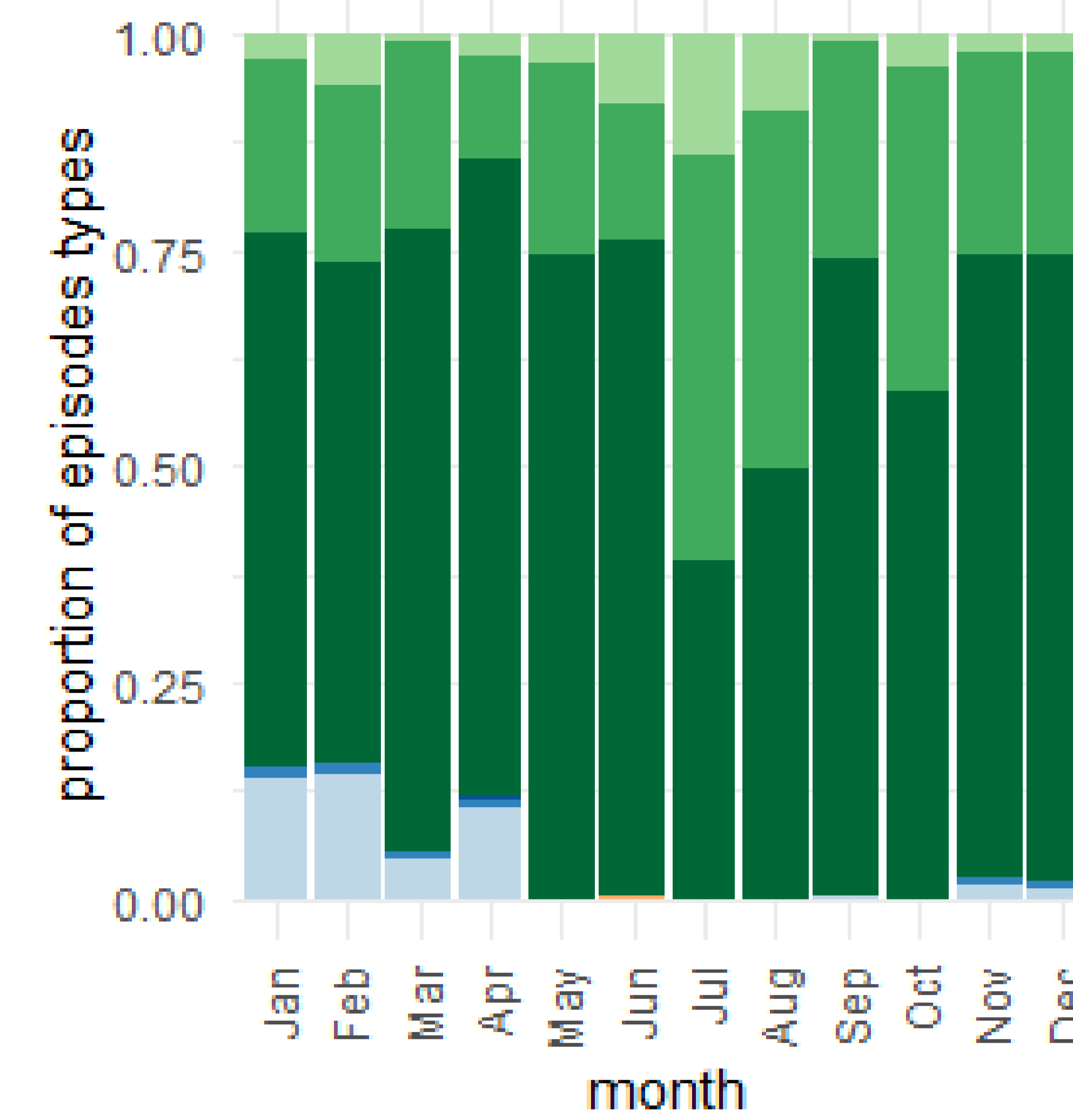
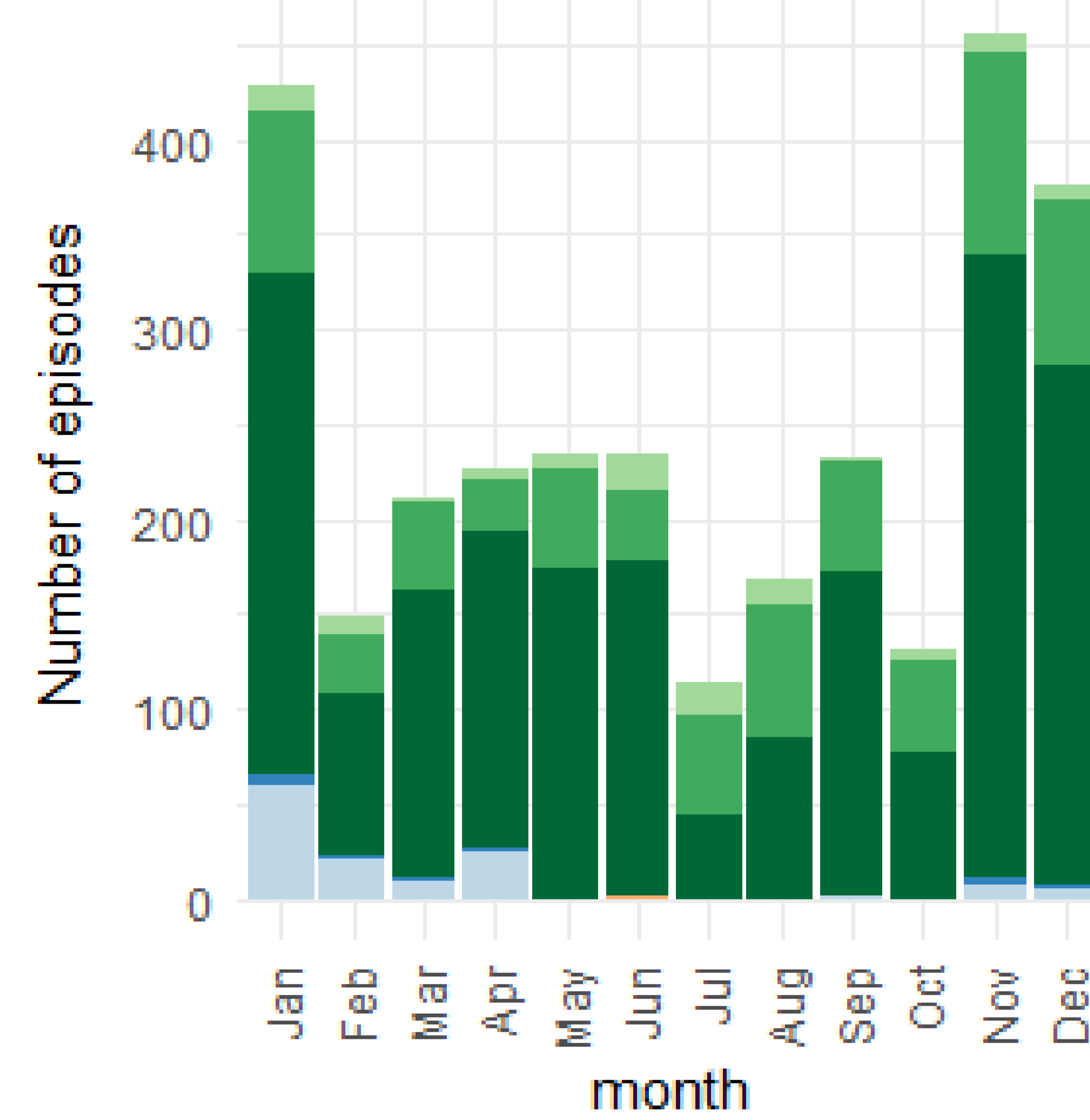


2.6. Results and discussion. Monthly segmentation

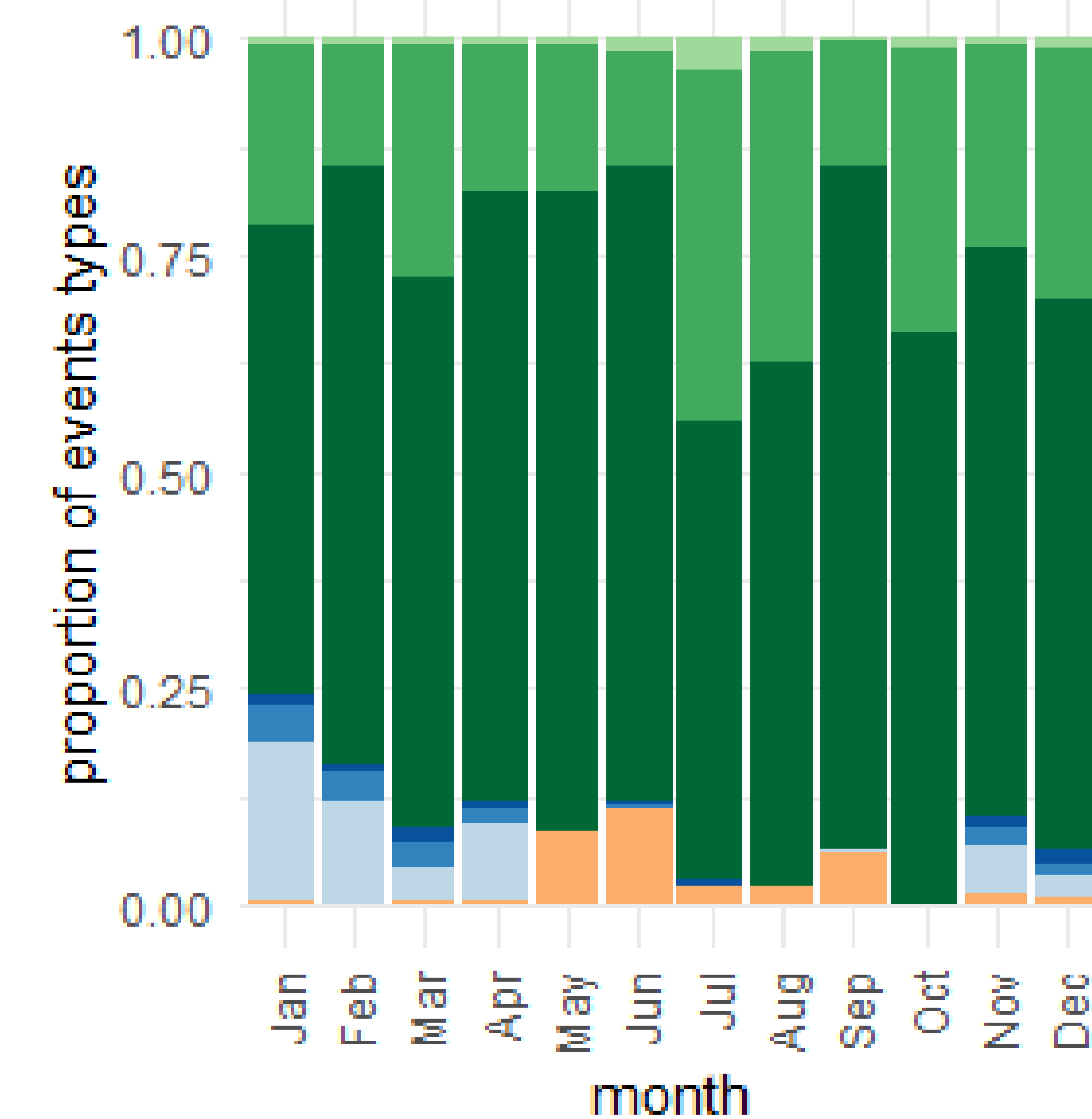
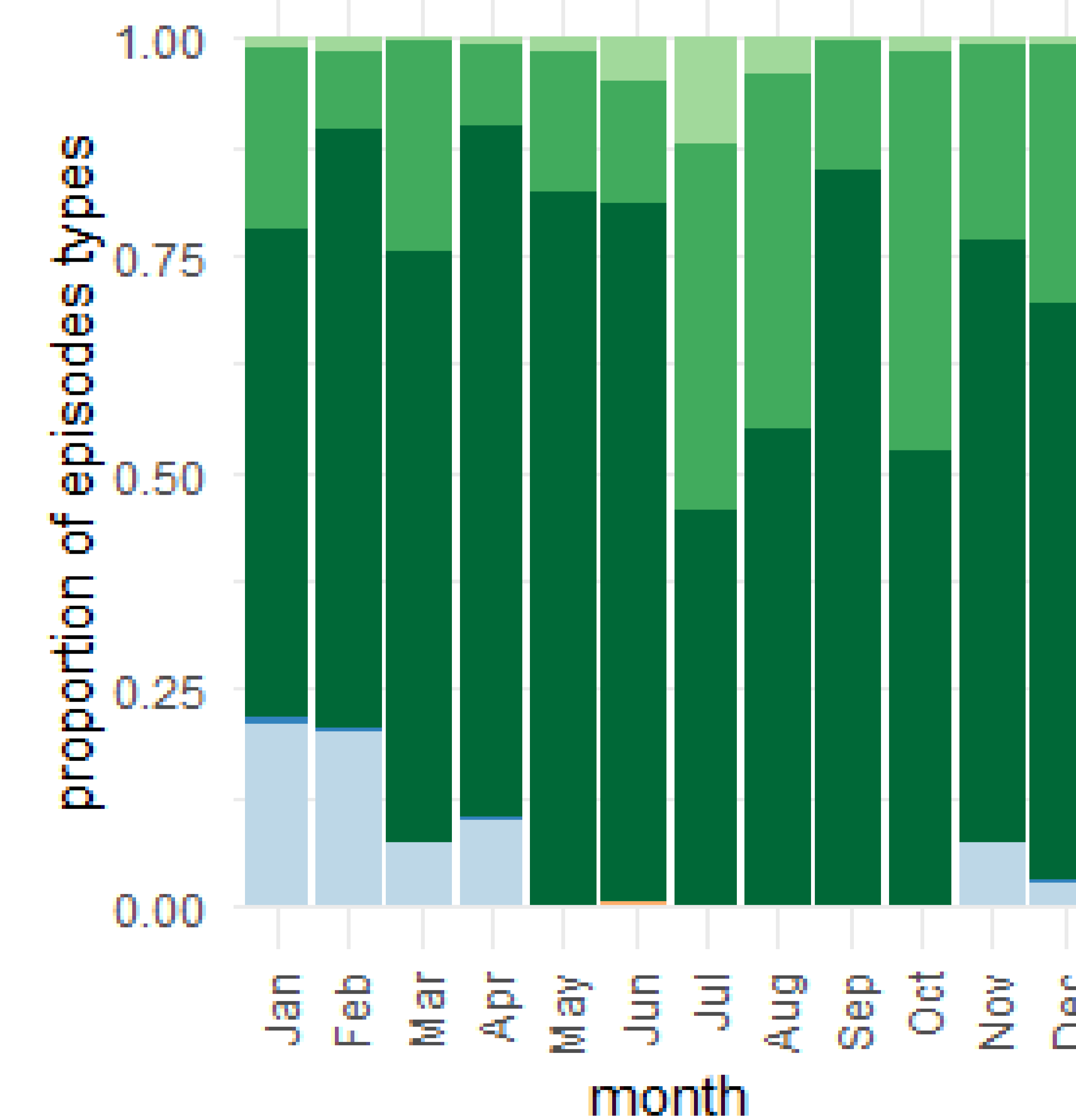
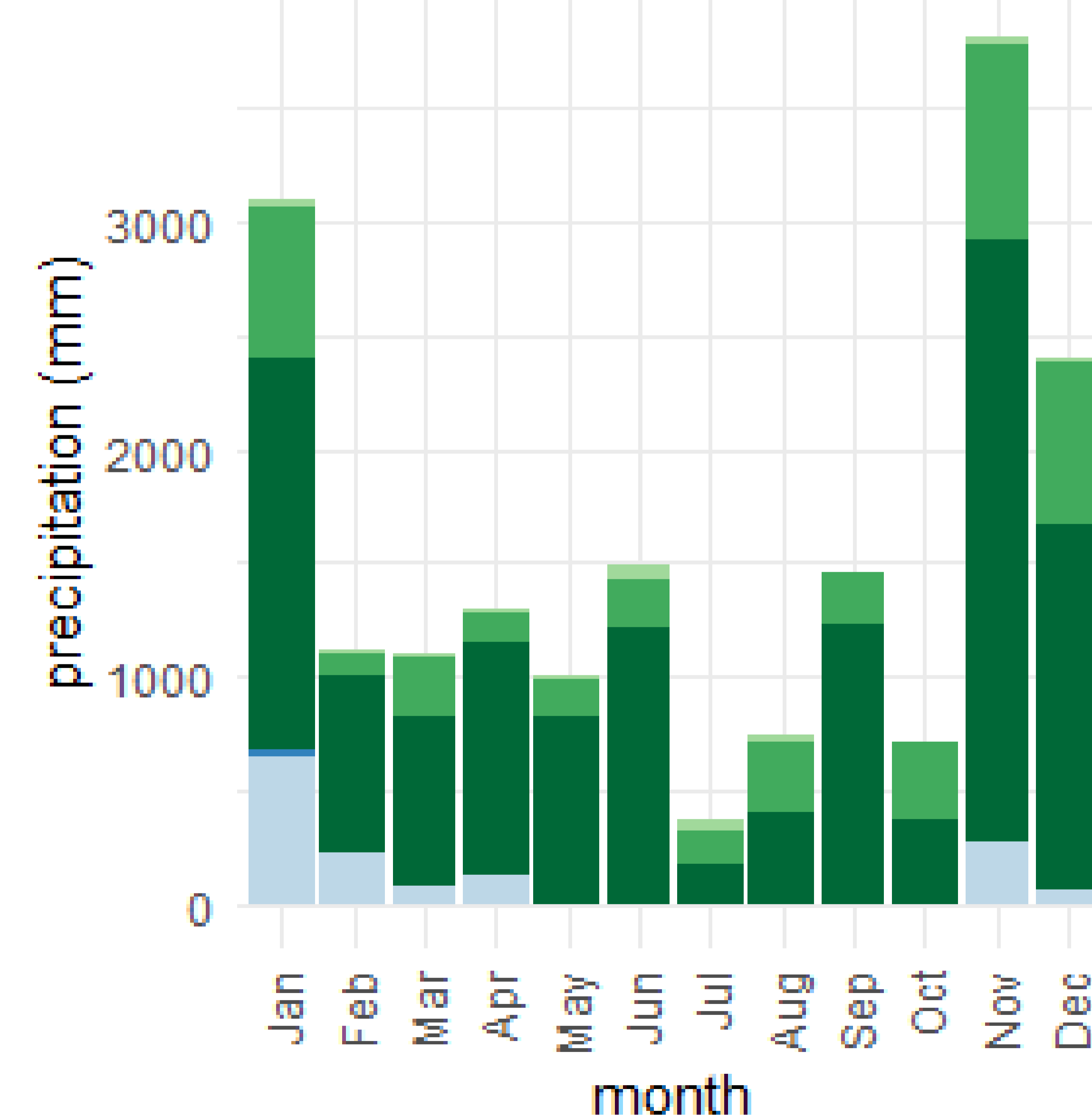
Focusing on episodes' monthly segmentation:

- The number of episodes is greater during November, December, and January. More accumulated precipitation occurs in November, December, and January. (first column)
- Snow episodes occur from November to April. Drizzle and Drizzle with rain are predominant in July and August. (second column)
- Focusing on details from event type composition of episodes (third column):
 - Residual hail occurs throughout the year.
 - Significant hail presence is observed from May to September.
 - Freezing rain occurs from November to April.

Number of episodes by type and month



Precipitation amount (mm) in episodes by type and month



2.7. Results and discussion. Mean episodes.



Characteristics of a typical precipitation episode by predominant type of precipitation

HC	TYPE	epis (num)	epis (%)	Mode (month)	Mean Dur (hour)	Mean Prec (mm)	Mode(type)	Mean Rimax (mm/h)	Mean NP (thous.)	Mean prec/dur	Mean num. Events	% Mean HC1	% Mean HC2	% Mean HC3	% Mean HC4	% Mean HC5	% Mean HC6	% Mean HC7	% Mean (P=0)
1	Drizzle	112	3,8	Jun	5,2	2,5	Drizzle	7	131	0,5	310	48,5	23,9	3,2	0	0	0	0	24,4
2	Drizzle with rain	701	23,7	Nov	5,1	5,9	Drizzle with rain	11,4	157	1,1	306	13,9	47,2	17,9	0,2	0,4	0,5	0	19,9
3	Rain	1996	67,5	Nov	3,8	6,4	Rain	20,1	59	2,2	231	2,1	17	62,4	0,4	0,3	0,2	0,1	17,4
4	Rain, drizzle with snow	1	0	Apr	0,3	1,4	Rain, drizzle with snow	7,9	12	4,1	21	0	0	47,6	52,4	0	0	0	0
5	Freezing rain	18	0,6	Jan	3,3	3,8	Freezing rain	11,6	50	1,6	199	0,4	14	10	2	36	13,7	0,2	23,8
6	Snow	127	4,3	Jan	6,8	11	Snow	11,8	210	1,5	411	0,8	7,5	5	0,6	9	60,7	0	16,4
7	Hail	1	0	Jun	0,1	4,3	Hail	84,1	2	42,9	7	0	0	42,9	0	0	0	57,1	0

HC5 and especially HC4 and HC7 are not representative

- Rain (HC3) episodes account for 70% of total episodes, typically occurring in November, with a duration of 3.8 hours, a total rain of 6.4 mm, a maximum RI of 20 mm/h, 59,000 particles, a mean precipitation/duration ratio of 2.2 mm/h, and mainly consisting of HC3 and 17.4% of no-precipitation events.
- Snow (HC6) episodes account for 4% of all episodes, typically occurring in January, with an average duration of 6.8 hours, a total precipitation of 11 mm, and a maximum rain intensity (RI) of 11.8 mm/h. These episodes feature approximately 210,000 particles, with a mean precipitation-to-duration ratio of 1.5 mm/h. They are primarily composed of HC6, HC5, and HC3 types, with 16% of events showing no precipitation

2.1. Results and discussion. Mean episodes.



Characteristics of a typical precipitation episode by season

SEASON	epis (num)	epis (%)	Mode (month)	Mean Dur (hour)	Mean Prec (mm)	Mode(type)	Mean Rimax (mm/h)	Mean NP (thous.)	Mean prec/dur	Mean num. Events	% Mean HC1	% Mean HC2	% Mean HC3	% Mean HC4	% Mean HC5	% Mean HC6	% Mean HC7	% Mean (P=0)
Winter	951	32,2	Jan	5,1	6,9	Rain	13,2	113	1,5	308	6,2	24	40,1	0,5	1,9	8,7	0	18,7
Spring	670	22,7	May	4,2	5,1	Rain	14,4	72	1,6	255	6	24,7	47,9	0,3	0,7	2,8	0,1	17,5
Summer	516	17,5	Jun	2,9	5,1	Rain	24,4	71	2,7	173	17,3	28,1	34,6	0	0	0	0,3	19,7
Fall	819	27,7	Nov	4,3	7,3	Rain	19,3	95	2,1	260	6,2	25,7	46,9	0,4	0,8	1,8	0,1	18,1

- Winter Episodes account for **32%** of the total episodes. These are typically rain episodes occurring in January (or December), lasting for **5 hours** with an average accumulated precipitation of **7 mm**, an average precipitation rate of **1.5 mm/h**, and a maximum minute rain intensity RI of **13 mm/h**. There are approximately **113,000 particles** in **308 events**, with 71% being liquid phase precipitation, 10% snow, mixed or freezing rain, and 19% with no precipitation.
- Spring Episodes make up 23% of the total episodes, typically characterized by rain lasting for 4 hours with an average accumulated precipitation of 5 mm, an average precipitation rate of 1.6 mm/h, and a maximum minute RI of 14.4 mm/h. These episodes involve around 72,000 particles in 255 events, with 95% being rain and drizzle, 5% snow, mixed or freezing rain, and 17% without precipitation.
- Summer Episodes represent **17%** of the total episodes, usually as rain episodes lasting for **3 hours** with an average accumulated precipitation of 5 mm, an average precipitation rate of **2.7 mm/h**, and a maximum minute RI of **24.4 mm/h**. These episodes include approximately **71,000 particles** in **173 events**, with 80% being rain and drizzle and 20% having no precipitation.
- Fall Episodes comprise 28% of the total episodes, typically rain episodes lasting for 4 hours with an average accumulated precipitation of **7 mm**, an average precipitation rate of 2.1 mm/h, and a maximum minute RI of 19.3 mm/h. These episodes feature about 95,000 particles in 260 events, with 80% being rain and drizzle, 3% snow, mixed or freezing rain, and 18% with no precipitation.

2.1. Results and discussion. DIS vs TBG

A comparison of results between episodes constructed from **TBG** and **DIS** data using the same methodology shows that the duration of the episodes is almost double in DIS compared to TBG or the Mean RI is very superior in DIS that in TBG. This differences are due to the combination of a higher number of minor events and the aggregation methodology used, which accounts for a higher presence of smaller events.

ALL DATA	epis (num)	epis (%)	Mode (month)	Mean Dur (hour)	Mean Prec (mm)	Mode(type)	Mean Rimax (mm/h)	Mean NP (thous.)	Mean prec/dur	Mean num. Events	% Mean HC1	% Mean HC2	% Mean HC3	% Mean HC4	% Mean HC5	% Mean HC6	% Mean HC7	% Mean (P=0)
DISDROMETER	2956	100	Nov	4,3	6,3	Rain	17,1	91	1,9	259	7,4	25,1	43,1	0,3	1,1	4,4	0,1	18,4
TIPPING BUCKET	3336	100	Nov	2	4,8		6,9		2,8	121								7,7

DISDROMETERS	SEASON	epis (num)	epis (%)	Mode (month)	Mean Dur (hour)	Mean Prec (mm)	Mode(type)	Mean Rimax (mm/h)	Mean NP (thous.)	Mean prec/dur	Mean num. Events	% Mean HC1	% Mean HC2	% Mean HC3	% Mean HC4	% Mean HC5	% Mean HC6	% Mean HC7	% Mean (P=0)
	Winter	951	32,2	Jan	5,1	6,9	Rain	13,2	113	1,5	308	6,2	24	40,1	0,5	1,9	8,7	0	18,7
	Spring	670	22,7	May	4,2	5,1	Rain	14,4	72	1,6	255	6	24,7	47,9	0,3	0,7	2,8	0,1	17,5
	Summer	516	17,5	Jun	2,9	5,1	Rain	24,4	71	2,7	173	17,3	28,1	34,6	0	0	0	0,3	19,7
	Fall	819	27,7	Nov	4,3	7,3	Rain	19,3	95	2,1	260	6,2	25,7	46,9	0,4	0,8	1,8	0,1	18,1

TB RAIN GAUGES	SEASON	epis (num)	epis (%)	Mode (month)	Mean Dur (hour)	Mean Prec (mm)	Mode(type)	Mean Rimax (mm/h)	Mean NP (thous.)	Mean prec/dur	Mean num. Events	% Mean HC1	% Mean HC2	% Mean HC3	% Mean HC4	% Mean HC5	% Mean HC6	% Mean HC7	% Mean (P=0)	
	Winter	1132	33,9	Jan	2,2	4,8		5,6		2,3	133									7,8
	Spring	678	20,3	May	1,9	4,1		5,9		2,5	116									7,9
	Summer	559	16,8	Jun	1,5	4,4		9,2		3,7	90									8,5
	Fall	967	29	Nov	2,1	5,6		7,8		3	127									7,3



3. Remarks and future work

- An analysis of precipitation episodes derived from disdrometer data provides a comprehensive understanding of precipitation patterns, both on an event and episode level.
- The Basque Disdrometer Network effectively captures detailed precipitation characteristics, enabling more nuanced analyses of precipitation types and their behaviors across various durations, intensities, and seasonal distributions.
- Disdrometer and pluviometer data discrepancies must be acknowledged, considering both instrumental and methodological differences.
- Further research is needed to refine episodes aggregation, depuration of known errors in event type classification and to exploit full spectral available data.

Details:

- This study focuses on the use of the Basque disdrometer network, a novel and evolving network with operational purposes that seeks to improve our understanding of the complexity of precipitation distribution and characteristics at the surface.
- The results are conditioned by only three years of data (around one million data points), the locations, and the characteristics of the six sites used, as well as the initial decision on how to group them into episodes.
- Although the characteristics of the disdrometer model and internal processes influence the values and quality of NP, RI, and HC data, when properly processed, these data can serve as valuable repositories in the context of climate monitoring and extreme weather surveillance.
- It is important to note that this is a study with an Eulerian perspective (from the point of view of the interaction of the rain event with a rain gauge at a specific location). In the future, it will be complemented with a Lagrangian perspective using radar records, allowing for a complete observation of the characteristics of the rain event and its temporal evolution.
- There is a need to deepen the methodologies for constructing episodes, conducting a complete battery of tests related to the selection of parameters, and applying the most appropriate methodologies with minute data.
- Further study and characterization of non-precipitation events within the episodes are needed.
- It is essential to complement statistical studies with representative case studies.
- The work on episode characterization will be completed by exploiting the available particle spectrum information.

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5. Acknowledgments

- ✓ Our thanks to Basque Government for maintain and supports research and operational services in the hydro-ocean-meteo-climatic field essential for the Basque community, and particularly to the Department of Security and the Directorate of Emergencies and Meteorology (DAEM) for Euskalmet support.



- ✓ Likewise, our recognition the open-software community and R contributors.





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Thank you for your attention : QUESTIONS ?



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