

1 **The influence of weather patterns and the**
2 **Madden-Julian Oscillation on extreme precipitation**
3 **over Sri Lanka**

4 **Akshay Deoras^{1,2}, Andrew G. Turner^{1,2}, Kieran M. R. Hunt^{1,2}, I. M.**
5 **Shiromani Priyanthika Jayawardena³**

6 ¹National Centre for Atmospheric Science, University of Reading, UK

7 ²Department of Meteorology, University of Reading, UK

8 ³Department of Meteorology, Colombo, Sri Lanka

9 **Key Points:**

- 10 • The association between weather patterns and extreme precipitation over Sri Lanka
11 is investigated
- 12 • Extreme precipitation in Sri Lanka occurs most frequently in weather patterns as-
13 sociated with the northeast and second intermonsoon seasons
- 14 • The frequency of extreme precipitation events is enhanced in phases 1–4 of the
15 Madden-Julian Oscillation

Corresponding author: Akshay Deoras, akshay.deoras@reading.ac.uk

Abstract

Sri Lanka is affected by extreme precipitation events every year, which cause floods, landslides and tremendous economic losses. In this study, we use the ERA5 reanalysis dataset to understand their association with 30 weather patterns, which were originally derived to represent the variability of the Indian climate during January–December 1979–2016. We find that weather patterns that are most common during the northeast monsoon (December–February) and second intermonsoon (October–November) seasons produce the highest number of extreme precipitation events. Furthermore, extreme precipitation events occurring during these two seasons are more persistent than those during the southwest monsoon (May–September) and first intermonsoon (March–April) seasons. We analyse the modulation of extreme precipitation events by the Madden-Julian Oscillation, and find that their frequency is enhanced (suppressed) in phases 1–4 (5–8) for most weather patterns.

Plain Language Summary

Extreme rainfall events affect Sri Lanka every year, causing floods, landslides and tremendous losses. Thus, it is important to identify weather patterns that are associated with these events. Furthermore, it is important to understand how the dominant modes of the tropical intraseasonal variability, such as the Madden-Julian Oscillation, modulate their occurrence. In this study, we use the ERA5 reanalysis dataset to understand the association between extreme precipitation events and a set of 30 weather patterns that were originally derived to understand the variability of the Indian climate. Our results suggest that weather patterns that are most common during winter and autumn seasons produce the highest number of extreme precipitation events in Sri Lanka, and these events are more persistent than those occurring during summer and spring seasons. The frequency of extreme precipitation events is enhanced when the Madden-Julian Oscillation is active over the Indian Ocean.

1 Introduction

Sri Lanka is a compact island in the tropics which witnesses two monsoon seasons each year. The southwest monsoon brings rainfall between May and September, contributing to around 30% of the total annual rainfall, whereas the northeast monsoon (December–February) contributes around 26% of the total rainfall for the country as a whole (e.g., Jayawardena et al. 2020). The bimodal rainfall pattern (Figure 1b) is associated with the movement of the intertropical convergence zone (ITCZ) over Sri Lanka (e.g., Suppiah 1996), with the two rainfall peaks occurring in April and November. Sri Lanka receives around 14% and 30% of the total annual rainfall during the first (March–April) and second (October–November) intermonsoon seasons, respectively. The spatial distribution of rainfall is skewed since the mountainous region in the south-central part (Figure 1a) results in considerable orographic rainfall.

Sri Lanka is vulnerable to devastating floods and landslides every year (Askman et al., 2018), particularly during the October–December period when the frequency of extreme precipitation events (here defined as the number of days on which daily rainfall averaged over the whole country exceeds the 95th percentile on all days between 1979 and 2016) is high (Figure 1b). For example, many parts of the country received over 200 mm rainfall on 15th May 2016, causing more than 200 fatalities and about USD 2 billion in economic losses (Samantha, 2018; Koralegedara et al., 2019). Jayawardena et al. (2020) found that rainfall in Sri Lanka is enhanced (suppressed) in phases 2–3 (6–7) of the Madden-Julian Oscillation (MJO), and the occurrence of extreme rainfall events is enhanced in MJO phases 2–3. Deoras et al. (2021) found that low-pressure systems forming over southern parts of the Bay of Bengal during June–September produce substantial rainfall in Sri Lanka, and the frequency of these weather systems is enhanced in MJO

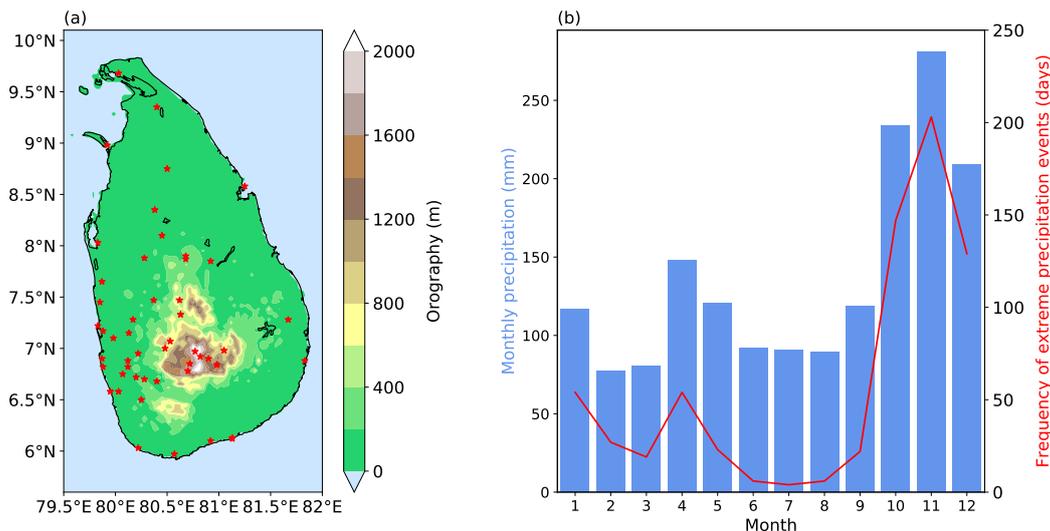


Figure 1. (a) The orography of Sri Lanka (m) obtained from the National Center for Atmospheric Research TerrainBase dataset (National Geophysical Data Center, NESDIS, NOAA, U.S. Department of Commerce, 1995). Red stars show locations of 51 meteorological stations that are managed by the Department of Meteorology, Sri Lanka. (b) Monthly precipitation (mm; blue bars) and the frequency of extreme precipitation events (days; solid red curve) in Sri Lanka during January–December 1979–2016, computed using the ERA5 reanalysis dataset. Extreme precipitation events are defined as events with area-mean daily rainfall over Sri Lanka exceeding the 95th percentile of daily rainfall on all days in the analysis period.

66 phases 1–2. In fact, low-pressure systems can trigger extreme precipitation events in the
 67 country (e.g., Koralegedara et al. 2019). However, unlike for other countries in the re-
 68 gion such as India, there has been a limited investigation of weather patterns associated
 69 with extreme precipitation events in Sri Lanka. It is therefore important to identify such
 70 weather patterns and analyse their modulation by the MJO. This analysis is important
 71 since the MJO can be well predicted on the sub-seasonal time scale (Vitart, 2017), which
 72 could help meteorologists issue warnings to weather-dependent stakeholders such as farm-
 73 ers.

74 The identification of weather patterns and their applications in weather forecast-
 75 ing are becoming increasingly popular. Their applications rely on the repeated appear-
 76 ance of certain large-scale flow patterns, which persist beyond the lifetime of individual
 77 synoptic-systems at fixed geographical locations and thus influence the intraseasonal vari-
 78 ability (Robertson and Ghil, 1999). Weather patterns are identified using different tech-
 79 niques such as the empirical orthogonal function (EOF) analysis and cluster analysis.
 80 For the Indian subcontinent, Neal et al. (2020) identified a set of 30 weather patterns
 81 that are the most representative of the variability of the Indian climate. They applied
 82 a k -means clustering technique (MacQueen et al., 1967) to mean sea-level pressure, u and
 83 v winds at 925 hPa and 850 hPa at 12 UTC during January–December 1979–2016, for
 84 which they used the European Centre for Medium-Range Weather Forecasts (ECMWF)
 85 Interim reanalysis data (ERA-I; Dee et al. 2011). They generated a total of 192 sets of
 86 weather patterns at 10 geographically varying locations across India, of which 30 pat-
 87 terns based on 850 hPa winds were selected. The application of these 30 weather pat-
 88 terns need not be confined to India since they also represent the observed large-scale cir-
 89 culation features over Sri Lanka (see Figure 4 of Neal et al. 2020).

In this study, our primary aim is to understand the association between weather patterns and extreme precipitation over Sri Lanka, for which we analyse the 30 weather clusters derived by Neal et al. (2020); our objective is to answer the following questions:

- How do the 30 weather patterns modulate mean precipitation and the frequency of extreme precipitation events in Sri Lanka?
- How persistent is extreme precipitation in Sri Lanka?
- To what extent does the presiding weather pattern play a role in the relationship between the MJO and extreme precipitation over Sri Lanka?

We present an outline of the data and methodology in Section 2. We look at mean precipitation, the frequency and persistence of extreme precipitation events, and the modulation of their occurrence by the MJO in Section 3, and conclude in Section 4.

2 Data and Methods

2.1 ERA5 reanalysis

We use data from the ECMWF ERA5 reanalysis (Hersbach et al., 2020) to investigate 850 hPa winds and precipitation in the 30 weather patterns during January–December 1979–2016. The ERA5 data is available globally from 1950 at an hourly resolution and on a $0.25^\circ \times 0.25^\circ$ grid. We use a land-sea mask to consider precipitation over the land area of Sri Lanka. If the daily rainfall over Sri Lanka exceeds the 95th percentile of daily rainfall on all days during January–December 1979–2016, we consider that event as an extreme precipitation event. Thus, the precipitation threshold for an extreme precipitation event is 15.6 mm day^{-1} , and extreme precipitation events occurred on 694 of 13,880 days in the analysis period.

Bandara et al. (2022) compared nine gridded precipitation datasets from reanalysis and remote sensing products for meteorological and hydrological applications in Sri Lanka. They inferred that ERA5 had the best performance since it replicated the observed precipitation climatology of Sri Lanka very well. We therefore select ERA5 as the primary dataset in this study to analyse rainfall.

2.2 Station rainfall

We use daily rainfall data from 51 meteorological stations (see Figure 1a) in Sri Lanka to take some account of the observational uncertainty. These stations are operated by the Department of Meteorology, Sri Lanka. The data is available from January 1981, and has been used in many previous studies (e.g., Hapuarachchi and Jayawardena 2015; Jayawardena et al. 2020). Since these stations are not uniformly distributed across Sri Lanka, including being particularly sparse in the north, we interpolate rainfall to a grid using the inverse distance-weighted method. It is commonly used to estimate rainfall at a location using observations from nearby meteorological stations (e.g., Chen and Liu 2012). The unknown rainfall R at the location of interest is estimated as follows:

$$R = \sum_{i=1}^N w_i R_i \quad (1)$$

$$w_i = \frac{d_i^{-\alpha}}{\sum_{i=1}^N d_i^{-\alpha}} \quad (2)$$

where R_i is rainfall at known meteorological stations, w_i is the weight corresponding to the i^{th} meteorological station, d_i is the distance of the location of interest to each

129 meteorological station, N is the total number of meteorological stations, and α is the power,
 130 which we set to two following previous studies (e.g., Chen and Liu 2012).

131 Figure S1a shows a comparison between the station rainfall dataset and the ERA5
 132 dataset during January–December 1981–2016. The daily mean rainfall over Sri Lanka
 133 in the station rainfall dataset is more than in ERA5. In fact, the difference is most promi-
 134 nent during the southwest monsoon season (not shown). The two datasets are highly cor-
 135 related (Pearson correlation coefficient of 0.8) and have a root mean square error of 1.4
 136 mm day⁻¹. We follow the same method discussed in the previous subsection to identify
 137 an extreme precipitation event. The threshold value for an extreme precipitation event
 138 is 21.2 mm day⁻¹, and extreme precipitation events occurred on 658 of 13,149 days in
 139 the analysis period.

140 2.3 MJO index

141 We use the MJO dataset maintained by the Bureau of Meteorology, Australia. The
 142 MJO index is based on a pair of combined EOFs of the outgoing longwave radiation data
 143 and near-equatorially averaged zonal winds at 850 hPa and 200 hPa (Wheeler and Hen-
 144 don, 2004). The index has a daily temporal resolution, and is separated into eight phases
 145 that represent different geographical locations. From the common period of January–December
 146 1979–2016, only those days on which the amplitude of the index exceeds one standard
 147 deviation have been considered (i.e., 8471 days), in order to identify the MJO phase at
 148 a given instant.

149 3 Results

150 3.1 Mean precipitation

151 Figure 2 shows a composite of mean 850 hPa winds and daily precipitation in the
 152 30 weather patterns (hereafter referred to as clusters) during January–December 1979–2016.
 153 The heaviest rainfall in Sri Lanka occurs in cluster 18 in which there is a cyclonic cir-
 154 culation and convergence over the country in the lower troposphere. The western slopes
 155 receive approximately 16 mm day⁻¹ rainfall, with similar rainfall magnitude off the south-
 156 eastern coast of India. The second heaviest rainfall occurs in cluster 1, where there are
 157 easterly winds of the northeast monsoon over Sri Lanka. The magnitude of rainfall over
 158 the western slopes in cluster 1 is more than in cluster 18, whereas northern parts of Sri
 159 Lanka receive more rainfall in cluster 18. These two clusters are most common during
 160 October–December (see Figure 7 of Neal et al. 2020). For the sake of simplicity, we re-
 161 name clusters 18 and 1 as *sl-heavy* and *sl-moderate*, respectively. There are northeast-
 162 erly winds over Sri Lanka in clusters 2, 3, 8, 9, 20 and 27, but the magnitude of rainfall
 163 is much smaller than in the *sl-heavy* and *sl-moderate* clusters. This is because these clus-
 164 ters are uncommon in November when monthly rainfall over Sri Lanka is the highest.

165 The magnitude of precipitation is smallest in cluster 16, which is most common dur-
 166 ing March. We call this cluster as *sl-light*. This is followed by cluster 10, which is asso-
 167 ciated with active southwest monsoon conditions over the Himalayan foothills, eastern
 168 and northeastern parts of India. The southern coast of India receives a lot more rain-
 169 fall than Sri Lanka in clusters with westerly winds over Sri Lanka (i.e., clusters 4, 11,
 170 13–17, 19, 21, 22, 25, 26 and 28–30) when moisture flux convergence in the lower tro-
 171 posphere is enhanced. These clusters are mostly associated with the southwest monsoon
 172 (*swm*) season, and in all of them, the western slopes receive more rainfall than other ar-
 173 eas of Sri Lanka. We collectively rename these clusters as the *swm* cluster. Clusters 5
 174 and 23, which are associated with the first intermonsoon season, have weak 850 hPa winds.
 175 The magnitude of rainfall across most of Sri Lanka is small, but the western slopes re-
 176 ceive a lot of rainfall. We collectively rename these two clusters as the *first-intermonsoon*

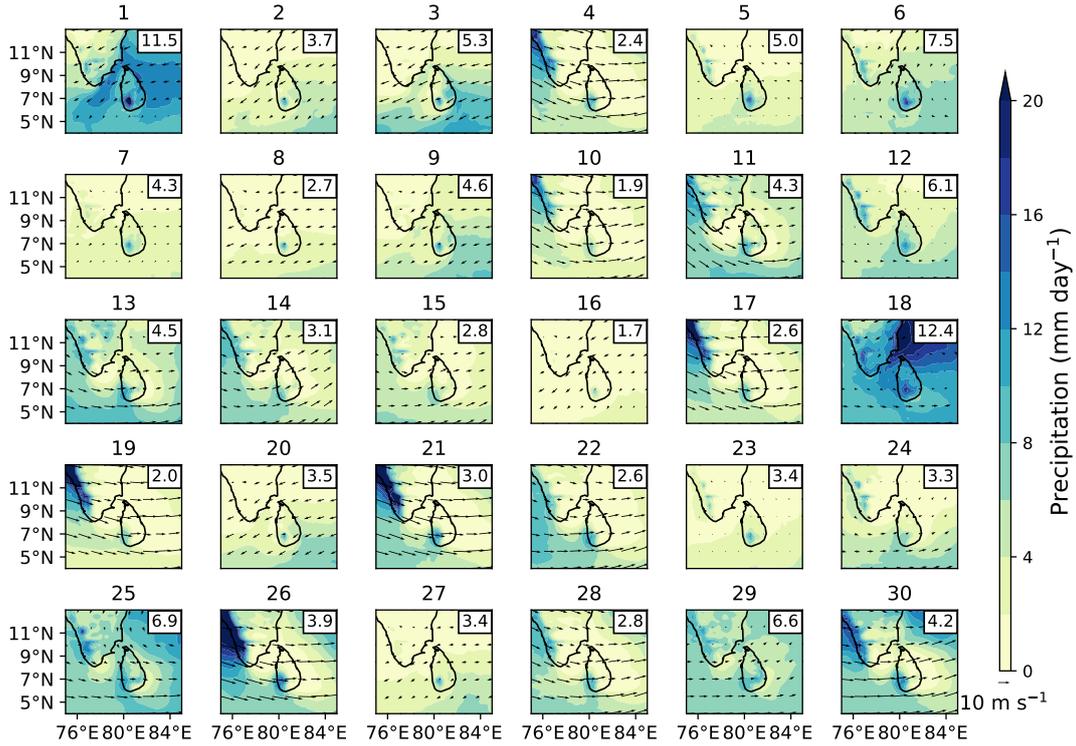


Figure 2. Mean precipitation (shading; mm day^{-1}) from ERA5 in the 30 clusters during January–December 1979–2016. These clusters were originally derived by Neal et al. (2020). Wind vectors show 850 hPa winds from ERA5. Numbers in each subfigure show the mean precipitation over Sri Lanka (mm day^{-1}).

177 cluster. We get similar results for mean precipitation in the 30 clusters when the sta-
 178 tion rainfall dataset is considered (Figure S1b), indicating the robustness of our results.

179 **3.2 Frequency of extreme precipitation events**

180 We now examine the frequency of extreme precipitation events in the 30 clusters
 181 during January–December 1979–2016. This analysis will help in identifying clusters that
 182 are most important for disaster management in Sri Lanka. In Figure 3, we group the fre-
 183 quency according to the four meteorological seasons in Sri Lanka. According to Neal et al.
 184 (2020), the sl-moderate cluster is the most common cluster among the 30 clusters. The
 185 frequency of extreme precipitation events is the largest in the sl-moderate cluster (179
 186 events), and they are most common during the second intermonsoon season. This is fol-
 187 lowed by the sl-heavy cluster (133 events) and cluster 6 (73 events) in which the high-
 188 est number of extreme precipitation events also occur during the second intermonsoon
 189 season. Interestingly, extreme precipitation events do not occur in most swm clusters,
 190 and even if they occur (e.g., clusters 11–13, 21 and 24), their frequency in each cluster
 191 remains small (<20 days), generally agreeing with Figure 1b.

192 Compared to the second intermonsoon season, the frequency of extreme precipi-
 193 tation events is much smaller in the first intermonsoon season. Cluster 5 contains the

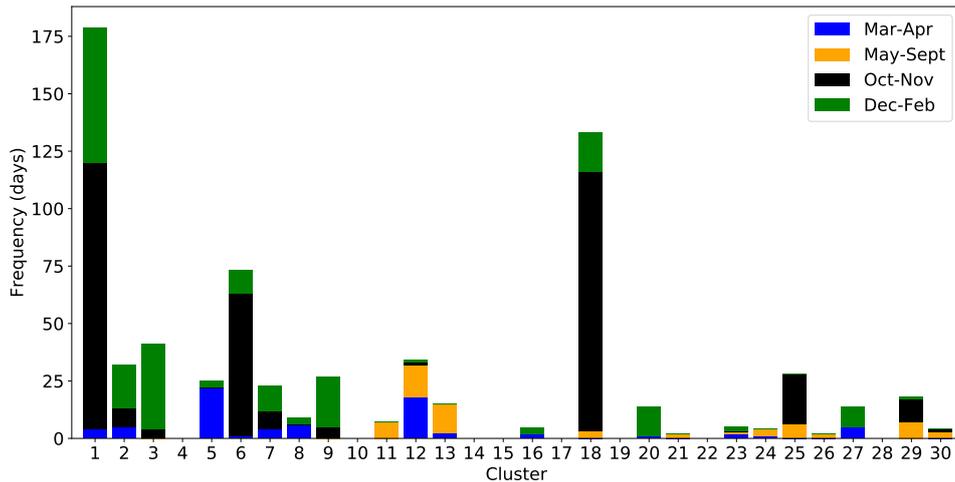


Figure 3. Frequency of extreme precipitation events (days) in Sri Lanka in the 30 clusters during January–December 1979–2016, calculated using the ERA5 precipitation dataset. The bars are stacked according to the following four meteorological seasons in Sri Lanka: first intermonsoon (March–April), southwest monsoon (May–September), second intermonsoon (October–November) and northeast monsoon (December–February).

194 majority of extreme precipitation events that occur during the first intermonsoon sea-
 195 son (22 events). The frequency of extreme precipitation events continues to remain the
 196 highest in the sl-high cluster when the station rainfall dataset is considered (Figure S2),
 197 suggesting that this result is not sensitive to the choice of precipitation dataset. How-
 198 ever, unlike for ERA5, extreme precipitation events occur in all 30 clusters when the sta-
 199 tion rainfall dataset is considered. In fact, the frequency of extreme precipitation events
 200 in the swm cluster increases using the station rainfall dataset. This could be related to
 201 the larger magnitude of rainfall in this dataset than in ERA5 (see Section 2.2). Never-
 202 theless, extreme precipitation events are most frequent in clusters associated with the
 203 second intermonsoon and northeast monsoon seasons, and this result is independent of
 204 the choice of rainfall dataset.

205 3.3 Persistence of extreme precipitation

206 The possibility of flooding and damages due to persistent extreme rainfall is ex-
 207 pected to be higher than due to non-persistent extreme rainfall. So it is important to
 208 understand the persistence of extreme precipitation. We centralise the average rainfall
 209 over the whole country during each extreme precipitation event to day zero and then com-
 210 pute a lead-lag composite of rainfall for a period of three days that precede and succeed
 211 these events.

212 Figure 4 shows a lead-lag plot of ERA5 precipitation averaged over Sri Lanka for
 213 30 clusters during January–December 1979–2016. Whilst the frequency of extreme pre-
 214 cipitation events is the largest in the sl-high and sl-moderate clusters (Figure 3), the mag-
 215 nitude of extreme precipitation is the largest in cluster 24 (30 mm day^{-1}) and, on av-
 216 erage, extreme precipitation occurs a day before and a day after the day-zero event. This
 217 cluster is most common in May, during which there is an increased frequency of tropi-
 218 cal cyclones (TCs) over the Bay of Bengal (e.g., Bhardwaj and Singh 2020). These TCs,
 219 especially those that have a long lifespan over the BoB, could intensify the lower-tropospheric
 220 winds of the southwest monsoon, enhancing moisture incursion and the magnitude of ex-
 221 treme precipitation over Sri Lanka. Furthermore, the ITCZ crosses Sri Lanka in May (e.g.,

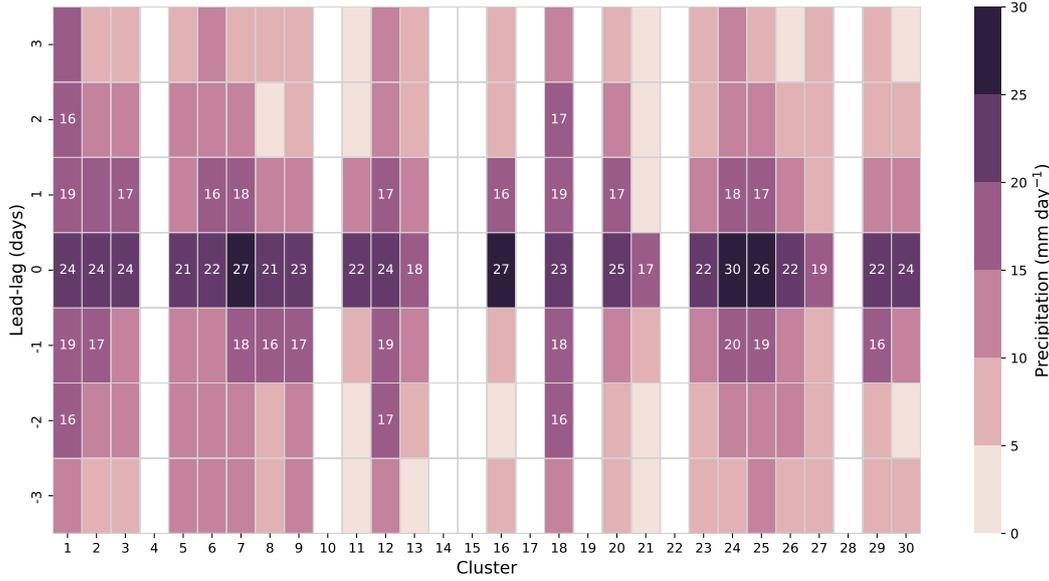


Figure 4. Lead-lag composite of precipitation (mm day^{-1}) averaged over Sri Lanka during January–December 1979–2016, computed using the ERA5 precipitation dataset. Precipitation recorded during all extreme precipitation events is centred on day zero. Positive numbers on the y -axis indicate lead, whereas negative numbers indicate lag. A white rectangle at the day-zero grid box of a cluster indicates that an extreme precipitation event did not occur and hence the lead-lag composite is not computed for the entire cluster. Grid boxes are annotated with the respective composite rainfall values (mm day^{-1}) only when the extreme precipitation threshold is met.

222 Waliser and Gautier 1993), which enhances convergence in the lower troposphere for the
 223 occurrence of extreme precipitation. The BoB witnesses a second peak in the frequency
 224 of TCs during October and November; this could influence the occurrence of extreme
 225 precipitation in cluster 25, which is most common in October.

226 For the sl-high and sl-moderate clusters, extreme precipitation persists for 5 con-
 227 secutive days, whereas for the swm and first-intermonsoon clusters, it persists for an av-
 228 erage of 1–2 consecutive days. This suggests that the sl-high, sl-moderate, and cluster
 229 24 might have a larger potential to cause flooding, landslides and other related damage
 230 than other clusters. Whilst the magnitude of extreme precipitation in these three clus-
 231 ters remains large when the station rainfall data is considered (Figure S3), cluster 8 has
 232 the largest magnitude of precipitation. Moreover, extreme precipitation does not typ-
 233 ically occur before and after the day-zero events in most clusters. However, the mag-
 234 nitude of precipitation in many clusters on the preceding and following day of the day-zero
 235 event is close to the extreme precipitation threshold. Thus, this analysis could help me-
 236 teorologists and researchers in designing forecasting products for weather-dependent stake-
 237 holders.

238 3.4 Modulation of the occurrence of extreme precipitation by the MJO

239 We now analyse the modulation of the occurrence of extreme precipitation events
 240 by the MJO to determine whether MJO behaviour at the large scale adds any predictabil-
 241 ity to extreme events. Figure 5 shows a heatmap of the frequency of extreme precipi-
 242 tation events in the eight MJO phases for all clusters during January–December 1979–2016.

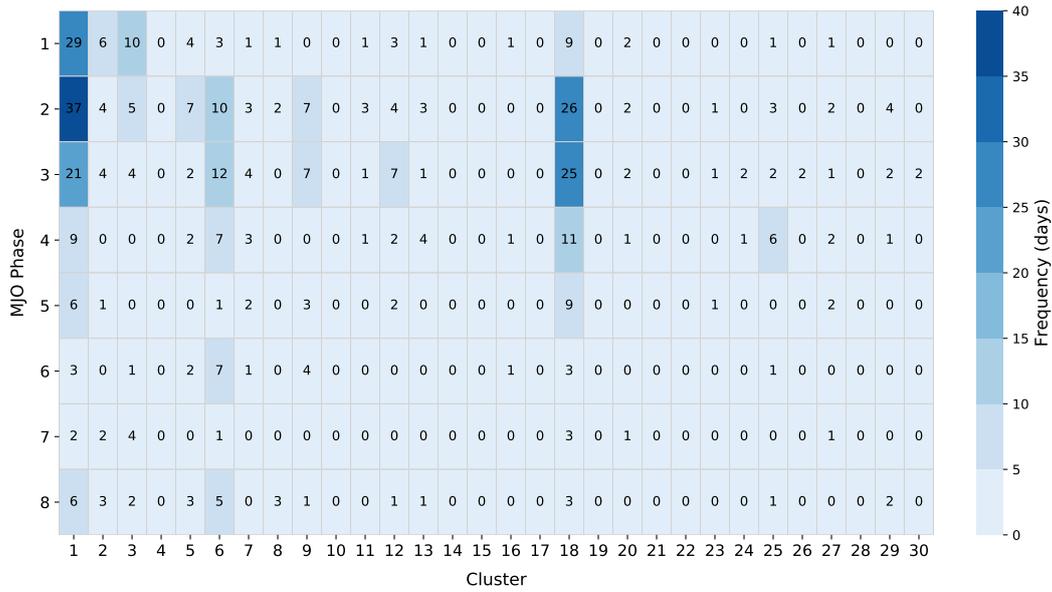


Figure 5. Heatmap showing the frequency of extreme precipitation events (numbers in each grid box; days) in the eight phases of the Madden-Julian Oscillation (MJO) for 30 clusters during January–December 1979–2016. Only those MJO phases when the amplitude exceeds one standard deviation have been retained. The source of precipitation is the ERA5 reanalysis dataset.

243 The frequency of occurrence of extreme precipitation events in most clusters is en-
 244 hanced in MJO phases 1–4 and suppressed in phases 5–8, in general agreement with pre-
 245 vious studies (e.g., Jayawardena et al. 2020). The enhancement of frequency is most promi-
 246 nent in the sl-high and sl-moderate clusters, and there is a prominent variation between
 247 various clusters. For example, 37 extreme precipitation events occurred in MJO phase
 248 2 of the sl-moderate cluster as opposed to 0 in the same phase of the sl-light cluster. Thus,
 249 only five combinations are responsible for the majority of extreme precipitation events
 250 (i.e., MJO phases 1–3 and 2–3 for the sl-moderate and sl-high clusters, respectively). This
 251 result could help meteorologists in developing forecasting products, which could improve
 252 planning and disaster preparedness in Sri Lanka.

253 The results are similar for the sl-high and sl-moderate clusters when the station
 254 rainfall dataset is considered (Figure S4), but there are prominent variations in other clus-
 255 ters. For example, extreme precipitation occurs in all MJO phases in cluster 14, differ-
 256 ing from the result obtained from analysing the ERA5 precipitation dataset (Figure 5).

257 4 Conclusions

258 Despite being prone to floods and landslides every year, there has been a limited
 259 investigation of weather patterns associated with extreme precipitation events in Sri Lanka.
 260 In this study, we analysed the 30 weather patterns derived by Neal et al. (2020) in or-
 261 der to understand their role in causing extreme precipitation events in Sri Lanka dur-
 262 ing January–December 1979–2016. We also analysed the modulation of these events by
 263 the Madden-Julian Oscillation (MJO). We defined extreme precipitation events as those
 264 with daily rainfall over Sri Lanka exceeding the 95th percentile of daily rainfall on all days
 265 in the analysis period.

We found that the magnitude of rainfall over Sri Lanka was the largest (12.4 mm day⁻¹) when there was a cyclonic circulation centred to the east of the country (cluster 18), which caused increased moisture flux convergence in the lower troposphere. This pattern was most common during October–December. In contrast, the magnitude of rainfall was very small in weather patterns associated with the southwest monsoon season (May–September). This is because Sri Lanka receives much less rainfall in this season. The magnitude of rainfall was the smallest in a weather cluster (cluster 16) associated with a weak northeast monsoon circulation over the country during December–February. We hypothesise this to be due to reduced moisture incursion over the country.

We found that extreme precipitation events mostly occurred in clusters associated with the northeast monsoon and second intermonsoon seasons (October–November). They did not occur in clusters associated with the southwest monsoon season when the ERA5 precipitation dataset was considered. Furthermore, their frequency during the first intermonsoon season (March–April) was much smaller than during the second intermonsoon season.

We then analysed the persistence of extreme precipitation over Sri Lanka, and found that it persisted for 5 consecutive days in clusters associated with the largest frequency of extreme precipitation events (i.e., clusters 1 and 18). Its magnitude was the largest in the cluster associated with tropical cyclones over the Bay of Bengal (cluster 24).

We finally examined the modulation of the occurrence of extreme precipitation events by the MJO. We found that their frequency was enhanced (suppressed) in phases 1–4 (5–8) of the MJO in general, which was similar to the results of previous studies (e.g., Jayawardena et al. 2020). The impact of the MJO was not prominent in clusters associated with the southwest monsoon season.

In summary, MJO phases 1–4 and clusters 1, 18 and 24 are most important for disaster management in Sri Lanka given the enhanced frequency, intensity and duration of extreme precipitation. The results of this study could benefit meteorologists, hydrologists and researchers in developing forecasting products (e.g., probabilistic forecasts of extreme precipitation) based on the identification of these weather patterns and MJO phases in numerical weather prediction and the subseasonal-to-seasonal prediction models, envisaging improved disaster preparedness in Sri Lanka.

A limitation of this study is that despite different climatic regions, we analysed the mean and extreme precipitation over Sri Lanka as a whole. This might have caused a loss of important fine details related to these different climatic regions. Researchers could therefore analyse the association between weather patterns and extreme precipitation over different climatic regions in a future study.

5 Acknowledgements

AD is funded through the Weather and Climate Science for Service Partnership (WCSSP) India, a collaborative initiative between the Met Office, supported by the UK Government’s Newton Fund and the Indian Ministry of Earth Sciences (MoES). AGT is supported by the National Centre for Atmospheric Science through the NERC National Capability International Programmes Award (NE/X006263/1). KMRH is supported by a NERC Independent Research Fellowship (MITRE; NE/W007924/1).

6 Data availability

The ERA5 hourly data on pressure levels is available at <https://doi.org/10.24381/cds.bd0915c6>. The catalogue of the 30 weather patterns identified by Neal et al., (2020) is available at <https://doi.pangaea.de/10.1594/PANGAEA.902030>. The MJO indices from the Bureau of Meteorology, Australia can be accessed at <http://www.bom>

314 .gov.au/climate/mjo/graphics/rmm.74toRealtime.txt. The Sri Lanka station rain-
 315 fall dataset was provided by Dr I. M. Shiromani Priyanthika Jayawardena from the De-
 316 partment of Meteorology, Sri Lanka. It can be requested from the Department’s weather
 317 and climate data store ([http://www.meteo.gov.lk/index.php?option=com_content&view=](http://www.meteo.gov.lk/index.php?option=com_content&view=article&id=100&catid=21&lang=en&Itemid=321)
 318 [article&id=100&catid=21&lang=en&Itemid=321](http://www.meteo.gov.lk/index.php?option=com_content&view=article&id=100&catid=21&lang=en&Itemid=321)) by contacting the Data Process-
 319 ing and Archival Division (metdpa@meteo.gov.lk) or Dr Jayawardena (shirojaya2000@yahoo.com).
 320 For review purposes, the data has been temporarily provided (i.e., temporary private link)
 321 at [https://gws-access.jasmin.ac.uk/public/incompass/akshay/sri_lanka_station](https://gws-access.jasmin.ac.uk/public/incompass/akshay/sri_lanka_station_rainfall_data.xlsx)
 322 [_rainfall_data.xlsx](https://gws-access.jasmin.ac.uk/public/incompass/akshay/sri_lanka_station_rainfall_data.xlsx).

323 7 References

- 324 Askman, J., Nilsson, O. and Becker, P. (2018) Why people live in flood-prone ar-
 325 eas in Akuressa, Sri Lanka. *International Journal of Disaster Risk Science*, **9**,
 326 143–156. <https://doi.org/10.1007/s13753-018-0167-8>.
- 327 Bandara, U., Agarwal, A., Srinivasan, G., Shanmugasundaram, J. and Jayawardena,
 328 I. M. S. P. (2022) Intercomparison of gridded precipitation datasets for prospec-
 329 tive hydrological applications in Sri Lanka. *International Journal of Climatology*,
 330 **42**, 3378–3396. <https://doi.org/10.1002/joc.7421>.
- 331 Bhardwaj, P. and Singh, O. (2020) Climatological characteristics of Bay of Bengal
 332 tropical cyclones: 1972–2017. *Theoretical and Applied Climatology*, **139**, 615–629.
 333 <https://doi.org/10.1007/s00704-019-02989-4>.
- 334 Chen, F.-W. and Liu, C.-W. (2012) Estimation of the spatial rainfall distribution us-
 335 ing inverse distance weighting (IDW) in the middle of Taiwan. *Paddy and Water*
 336 *Environment*, **10**, 209–222. <https://doi.org/10.1007/s10333-012-0319-1>.
- 337 Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S.,
 338 Andrae, U., Balmaseda, M., Balsamo, G., Bauer, D. et al. (2011) The ERA-
 339 Interim reanalysis: Configuration and performance of the data assimilation
 340 system. *Quarterly Journal of the Royal Meteorological Society*, **137**, 553–597.
 341 <https://doi.org/10.1002/qj.828>.
- 342 Deoras, A., Hunt, K. M. R. and Turner, A. G. (2021) The four regional varieties of
 343 South Asian monsoon low-pressure systems and their modulation by tropical in-
 344 traseasonal variability. *Weather*, **76**, 194–200. <http://dx.doi.org/10.1002/wea.3997>.
- 345 Hapuarachchi, H. and Jayawardena, I. M. S. P. (2015) Modulation of seasonal rain-
 346 fall in Sri Lanka by ENSO extremes. *Sri Lanka J Meteorol*, **1**, 3–11.
- 347 Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater,
 348 J., Nicolas, J., Peubey, C., Radu, R., Schepers, D. et al. (2020) The ERA5 global
 349 reanalysis. *Quarterly Journal of the Royal Meteorological Society*, **146**, 1999–2049.
 350 <https://doi.org/10.1002/qj.3803>.
- 351 Jayawardena, I. M. S. P., Wheeler, M. C., Sumathipala, W. and Basnayake, B.
 352 (2020) Impacts of the Madden-Julian Oscillation (MJO) on rainfall in Sri Lanka.
 353 *Mausam*, **71**, 405–422.
- 354 Koralegedara, S. B., Lin, C.-Y. and Sheng, Y.-F. (2019) Numerical analy-
 355 sis of the mesoscale dynamics of an extreme rainfall and flood event in Sri
 356 Lanka in May 2016. *Journal of the Meteorological Society of Japan. Ser. II*.
 357 <https://doi.org/10.2151/jmsj.2019-046>.
- 358 MacQueen, J. et al. (1967) Some methods for classification and analysis of multivari-
 359 ate observations. In *Proceedings of the fifth Berkeley symposium on mathematical*
 360 *statistics and probability*, vol. 1, 281–297.
- 361 National Geophysical Data Center, NESDIS, NOAA, U.S. Department of
 362 Commerce (1995) TerrainBase, Global 5 Arc-minute Ocean Depth and
 363 Land Elevation from the US National Geophysical Data Center (NGDC).
 364 <https://doi.org/10.5065/E08M-4482>.

- 365 Neal, R., Robbins, J., Dankers, R., Mitra, A., Jayakumar, A., Rajagopal, E. and
366 Adamson, G. (2020) Deriving optimal weather pattern definitions for the represen-
367 tation of precipitation variability over India. *International Journal of Climatology*,
368 **40**, 342–360. <https://doi.org/10.1002/joc.6215>.
- 369 Robertson, A. W. and Ghil, M. (1999) Large-scale weather regimes and local
370 climate over the western United States. *Journal of Climate*, **12**, 1796–1813.
371 [https://doi.org/10.1175/1520-0442\(1999\)012%3C1796:LSWRAL%3E2.0.CO;2](https://doi.org/10.1175/1520-0442(1999)012%3C1796:LSWRAL%3E2.0.CO;2).
- 372 Samantha, G. (2018) The impact of natural disasters on micro, small and medium
373 enterprises (MSMEs): A case study on 2016 flood event in Western Sri Lanka.
374 *Procedia engineering*, **212**, 744–751. <https://doi.org/10.1016/j.proeng.2018.01.096>.
- 375 Suppiah, R. (1996) Spatial and temporal variations in the relationships between the
376 Southern Oscillation phenomenon and the rainfall of Sri Lanka. *International*
377 *Journal of Climatology*, **16**, 1391–1407. [https://doi.org/10.1002/\(SICI\)1097-0088\(199612\)16:12%3C1391::AID-JOC94%3E3.0.CO;2-X](https://doi.org/10.1002/(SICI)1097-0088(199612)16:12%3C1391::AID-JOC94%3E3.0.CO;2-X).
- 379 Vitart, F. (2017) Madden—Julian Oscillation prediction and teleconnections in
380 the S2S database. *Quarterly Journal of the Royal Meteorological Society*, **143**,
381 2210–2220. <https://doi.org/10.1002/qj.3079>.
- 382 Waliser, D. E. and Gautier, C. (1993) A satellite-derived climatology of the
383 ITCZ. *Journal of Climate*, **6**, 2162–2174. [https://doi.org/10.1175/1520-0442\(1993\)006%3C2162:ASDCOT%3E2.0.CO;2](https://doi.org/10.1175/1520-0442(1993)006%3C2162:ASDCOT%3E2.0.CO;2).
- 385 Wheeler, M. C. and Hendon, H. H. (2004) An All-Season Real-Time Multivari-
386 ate MJO index: Development of an Index for Monitoring and Prediction.
387 *Monthly Weather Review*, **132**, 1917–1932. [https://doi.org/10.1175/1520-0493\(2004\)132%3C1917:AARMMI%3E2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132%3C1917:AARMMI%3E2.0.CO;2).
- 388