Extreme precipitation induced concurrent events trigger prolonged disruptions in regional road networks

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Abstract
Concurrency in extreme precipitation-induced events including flooding, landslides and associated debris flow result in massive loss of life, damage to infrastructures, and widespread disruption to socioeconomic activities. Despite recent advances in field of risk hazard modeling, we lack a systematic framework to model and assess the impact of extreme precipitation induced concurrent hazards on infrastructure lifelines including road networks. Here we develop an integrated framework to study the effect of concurrent hazards i.e. landslide, debris flow, and flood on regional road networks. Our spatiotemporal 1D simulations of shallow landslides and debris flows in combination with the 2D hydrodynamic model for floods indicate that even highly localized concurrent events have potential to induce widespread and prolonged disruptions to the regional road networks. We illustrate the proposed framework’s application to assess the functionality loss from the individual and concurrent events induced by extreme precipitation. Our results show that not accounting for concurrence in these correlated hazards could result in underestimation of functionality losses by 71%, which in turn can undermine the pre-disaster preparedness and post-disaster recovery efforts.

1. Introduction
Extreme-precipitation-induced hydrological hazards cause devastating damages to lives, infrastructure, and the economy across the globe (Ávila et al 2016, Lin and Emanuel 2016, Winter et al 2016, Pregnolato et al 2017, Kirschbaum et al 2020, Tellman et al 2021). In changing climate scenarios, there is an increasing likelihood of independent as well as cascading and correlated hazards (Dankers and Feyen 2008, Whitfield 2012, Hirabayashi et al 2013, AghaKouchak et al 2020, Raymond et al 2020, Emberson et al 2021, Upadhyay et al 2021). Densely populated regions across the globe such as India, Brazil, China, and Europe have witnessed rapid urbanization and population growth even in the remote areas away from established urban clusters (Goldewijk 2005, Tan 2017, Sun et al 2020). The unprecedented growth in human footprints is typically accompanied by the tremendous development of complex and interconnected infrastructure systems, including transportation, water, power and energy distribution networks (Graham and McFarlane 2014), which further enhance the risk, given the increased exposure of assets and population (Wagner 2007, Bonachea et al 2009, Postance et al 2017, Pregnolato et al 2017, Kasmalkar et al 2020). Moreover, hydrological hazards rarely occur in isolation, mainly when triggered by extreme precipitation within a region (Moftakhari et al 2017, Fan et al 2019, Ruiter et al 2020). The poignant examples are flash floods and landslides events in Rio de Janeiro, Brazil (2011); Typhoon Lionrock triggered debris flow and flash flood in Hokkaido, Japan (2016); and the 2018 precipitation-induced landslide and debris flow events in Kerala, India. The 2011 events in Brazil resulted in 916 casualties and rendered 35 000 people homeless (Marengo et al 2013). The 2016 events in Japan resulted in property losses of $260 Million, damage to agricultural lands over 40 258 hectares, and disruption to rail and road transportation as a consequence of simultaneous debris flows (Furuichi et al 2018, Zhu et al 2020).
In this study, we move beyond modeling isolated events and their associated impacts. We develop an integrated hydrodynamical, geomechanical, and network science-based framework to model and analyze the effect of concurrent extreme precipitation-induced floods and landslides (shallow landslides and debris flow) on transportation systems (figure 1). For our analysis, we choose the 2018 extreme precipitation events of Kerala, India (Hao et al 2020, Yunus et al 2021). Precisely, we quantify the far-reaching perturbations to the road network associated with the extreme precipitation events, which triggered numerous shallow landslides and debris flows. To identify the spatial location of these events over an extended period, we use the indigenously developed catchment-scale 1D shallow landslide and debris flow models (Van Asch et al 2014, Siva Subramanian et al 2020). To represent fluvial flooding, we use 2D hydrodynamic model based on unsteady flow and shallow water equations (Brunner 1995). Using these models, we perform numerical simulations of landslides, debris flows and flood within the Periyar river basin, Kerala; the severely affected basin during 2018 monsoons (figure 1). We validate the results using satellite derived metadata and remotely sensed flood extent maps. We identify the spatiotemporal overlapping of hydrological hazards with regional road networks and analyze connectivity losses within the basin. We analyze the road network disruptions and recovery using mathematical models developed by Bhatia et al (2015), Bhatia (2019), and later used by Yadav et al (2020).

We organize the rest of the manuscript as follows: in section 2, first, we discuss the details of the study area and data sets used in this research. Then, we present the overview of the integrated framework, the 2D hydrodynamic model for flood, 1D shallow landslide, and debris flow models. After this, we brief the mathematical model analyzing perturbations in the regional road network. Section 3 presents the results. Finally, in section 4, we discuss the spatiotemporal concurrency of extreme events.

2. Materials and methods

2.1. Study area

To illustrate the applicability of the proposed framework, we choose the Periyar river basin (hereafter referred to as Periyar basin), which was affected severely during 2018 extreme events. The Periyar basin is the longest (244 km) river basin in Kerala, with a catchment area of 5398 km² (figure 1(a)). The basin runs from the South to the Northwest with many west draining tributaries such as Mullayar, Cheruthoni, Muthirapuzha, Perinjankutty, and Idamalayar, most of the tributaries find their origin in the deep gorges and steep valleys at elevations above 2000 m above mean sea level. The maximum
elevation of the basin is approximately 2685 m above sea level. The dendritic drainage pattern is prominent all through the basin. All the tributaries converge into the main Periyar river and drain in the Arabian Sea through the estuaries of Kochi. The entire basin experience a humid tropical climate with dry rainfall deficit seasons and wet monsoon seasons. Mean annual rainfall of the upstream and downstream parts of the basins are 3677 and 3233 mm respectively (Sudheer et al. 2019). The mean monthly temperature ranges from minimum of 14°C–19°C to a maximum of 25°C–32°C in upstream and a minimum of 23°C–26°C to a maximum of 28°C–32°C in downstream. There are three predominant geological formations present within the Periyar basin. First, the Precambrian formation with crystalline rocks charnockite and migmatite groups. Second, Tertiary formations with intrusive rocks, and third Quaternary formations of sedimentary rocks (Kumar et al. 2015). The Periyar basin covers two administrative districts of Kerala, i.e., Idukki and Ernakulam, with a population of 1 million with 251 km\(^2\) density, and 3 million with 277 km\(^{-2}\) density respectively (Tatem 2017).

2.2. Data
We obtain the daily precipitation data at 0.25° × 0.25° spatial resolution from India Meteorological Department (IMD). Daily precipitation data is available for six locations within the study area (figure 1(a)), (Pai et al. 2014). To identify the locations of shallow landslides and debris flows, we refer to an open-source metadata (Hao et al. 2020). This metadata is an event-based complete landslide inventory for the 2018 extreme precipitation-induced landslide events that occurred in the state of Kerala, India. The open dataset can be found in van Westen (2020). The data consists of locations and attributes of 4728 landslides, including 1760 shallow landslides, 2816 debris flows, and 152 rockfalls. Within the Periyar basin, a total of 1202 shallow landslides and 751 debris flows occurred during 2018. In this study, we restrict our analysis to 492 shallow landslides, 211 debris flow that caused damages to roads. For all three models, i.e., shallow landslides, debris flows, and floods, a high-accuracy digital elevation model (DEM) in this study is critical. Here we use the 30 m spatial resolution shuttle radar topography mission DEM, which has a vertical accuracy
of 9.73 m. We use demographics data to visualize the population exposed to individual and concurrent hazards (figure 1(b)). The latest demographic data is available from the 2011 census, which may not precisely depict the present demographics. To address this issue, we use modeled population data for 2018 provided by the Worldpop with a spatial resolution of 30 arc-second (approximately 100 m) (Tatem 2017). Further, for the shallow landslide and debris flow modeling, the depth of soil layers is essential. For this, we use the global soil depth data from SoilGrids250 (Shangguan et al 2014, Hengl et al 2017). The soil parameters required for the modeling are obtained from Kuriakose et al (2009) and Abraham et al (2021). Further, to perform flood inundation modeling, we use the observed discharge data obtained from gauge stations at Neeleeswaram and Arangali provided by India-WRIS. The discharge data is available at https://indiawris.gov.in/wris/#/. We obtain the road network data for the Periyar basin from OpenStreetMap http://download.geofabrik.de/asia/india.html.

2.3. Overview of the framework
We develop a unified framework to model the road network disruptions caused by fluvial floods, shallow landslides, and debris flows. Here, extreme precipitation is the common triggering event for all the three hazards. The landslide model accounts for extreme precipitation-induced changes in soil moisture and simulates the onset of failure based on the degree of saturation. Similarly, the debris flow model considers extreme-precipitation induced soil moisture and run-off (using a similar hydrological model as the landslide model) to propagate debris flows. In summary, the framework consists of a hydrodynamic model, a slope stability model, a debris flow model, and a mathematical model of network functionality. The constituting components of the framework are shown in figure 2 with detailed equations in SI (available online at stacks.iop.org/ERL/16/104050/mmedia).

To analyze the impacts of fluvial flooding caused by extreme precipitation-induced excess river discharge, we use state-of-the-art 2D hydrodynamic model Hydrological Engineering Centre—River Analysis System (HEC-RAS) (Brunner 1995). By definition, a fluvial flood is the inundation of river banks, shores and land surrounding a river which occur due to an increase in water levels in rivers caused by extreme precipitation (Merz et al 2010, Dingman 2015). In this study, we do not account for pluvial and coastal flooding. In HEC-RAS, we use an unsteady flow model assuming shallow water flow under variable discharge for the period of 1 July 2018 to 31 August 2018. To account for realistic flow depth, we run an initial flow analysis from 1 January 2018 to 30 June 2018. For the flood extent simulation, we use the observed discharge data from India-WRIS as input. The two gauged discharge data at Neeleeswaram and Arangali are input into the numerical model as upstream boundary conditions. The analysis is performed for daily timesteps considering the available daily discharge data. Spatial extents of flood inundated areas are obtained as outputs from the numerical model. We validate the flood model results through microwave remote sensing synthetic aperture radar (SAR) imagery by extracting the waterbody pixels during the flood duration. Specifically, we run time-series extraction of Sentinel-1 satellite images through Google Earth Engine. The code used for the satellite image analysis can be accessed from the link in Code availability section. We use three different statistical measures, i.e., Accuracy, Cohen’s Kappa, and F1 score, to validate the spatial accuracy of the model results compared with the satellite imagery (table 1).

To simulate the flooding in 2D, we choose the simplified set of shallow water equations in HEC-RAS. The single differential vector form of the momentum equation is:

\[
\frac{\partial V}{\partial t} + V \cdot \nabla V = -g \nabla H + \nu \nabla^2 V - \epsilon_f V + f_k V \times V,
\]

(1)

where \( V \) is the velocity, differential operator \( \nabla \) is the vector of the partial derivative operators \( \nabla = (\partial/\partial x, \partial/\partial y) \), \( g \) is gravity, \( H \) is the elevation of water (m), \( \nu \) is the horizontal eddy viscosity coefficient, \( \epsilon_f \) is the bottom friction coefficient, \( f \) is the Coriolis parameter, and \( k \) is the unit vector in vertical direction. Further theoretical details of the model can be found in Brunner (1995).

Multiple numerical models are available to assess the susceptibility of precipitation-induced shallow landslides at regional (basin/catchment) scale (Burton and Bathurst 1998, Brunsden 1999, Van Asch et al 1999, Iverson 2000, Borgia et al 2002, van Beek 2002, Casadei et al 2003, Crosta and Frattini 2003, Frattini et al 2004, Chen and Young 2006, Rosso et al 2006, Claessens et al 2007, Baum et al 2008, 2010, Godt et al 2008, Lu and Godt 2008, Arnone et al 2011, Zhuang et al 2017, Bout et al 2018). The SINMAP—Stability Index Mapping (Pack et al 1998), SHALSTAB—Shallow Landslide STABILITY (Montgomery and Dietrich 1994), TRIGRS—Transient Rainfall Infiltration and Grid-based Regional Slope-Stability (Baum et al 2002, 2008, Raia et al 2014, Alvioli and Baum 2016), STARWARS+PROBSTAB (van Beek 2002, Malet et al 2005, Kuriakose et al 2009), and r.slope stability (Mergili et al 2014) are some of the widely used models. While these models have been widely used to understand the mechanisms of landslides, their applications to quantify the impact on critical infrastructure systems (e.g. transportation, water distribution systems, and power distribution) are limited. Studies that model the impact of shallow landslides on road networks often use probabilistic
risk assessment frameworks and pre-established hazard maps (Nelson et al 2019, Rose Santos et al 2021). Such approaches are beneficial only to understand the spatial extent events and they do not account for temporal probability. On the other hand, remote-sensing derived metadata (point or polygon based inventory) of shallow landslides do not always record the occurrence time of individual landslides, which are critical to understand spatiotemporal evolution of disruption and recovery of the impacted systems (Soeters and van Westen 1996, van Westen et al 2006, Guzzetti et al 2012, Samia et al 2017, Lin and Wang 2018).

To analyze the stability of slopes at basin scale, we use an ingeniously developed shallow landslide model that accounts for antecedent moisture conditions and infiltration characteristics within a variably saturated soil zone. Specifically, the model uses daily precipitation, antecedent moisture conditions and slope characteristics from the DEM as inputs. To account for heterogeneity in the soil stratum, the user can specify up to three soil layers. The numerical model further consists of a hydrological module (to simulate the seepage) and a slope stability module (to calculate the factor of safety (FoS) of slopes). The FoS is then defined as,

$$
FoS = c' + \Delta c' + \left[ (Z - WL) \gamma + WL_s \right] \cos \beta \tan \phi' \left[ (Z - WL) \gamma + WL_s \right] \sin \beta \cos \beta
$$

$$
\text{Eq. (2)}
$$
where $c'$ and $\Delta c'$ are respectively the effective and apparent cohesion, $Z$ is the depth of shear plane (slip surface), $WL$ is the water level above the shear plane, $\gamma$ and $\gamma_s$ are the 'dry' and 'saturated' bulk densities of the soil, and $\beta$ is the slope angle (equal to the angle of sliding surface). Further details of the model can be found in supplementary information (SI) and Siva Subramanian et al. (2020).

All the required spatial data, topographic data (the DEM, the soil depth, and slope), hydrological and geotechnical parameters of the model are given as input. To account for the heterogeneity of soil types within the basin, we use a Gaussian distribution for both the cohesive strength and angle of internal friction (Tobutt 1982, Griffiths et al. 2011). Precipitation data from 1 January 2018 to 31 August 2018, is given as the boundary condition. We calculate the factor of safety (FoS), defined as the ratio between inducing shear stresses and resisting shear stresses for each pixel on a given day. For each timestep, the numerical model provides both the spatial extents of the unstable pixels (30 m) and the temporal data of FoS. When FoS falls below one at a given pixel, we classify that event as a shallow landslide.

While our landslide model helps us identify the location and time of onset of shallow landslides, it does not account for the associated propagation of debris flow (runout). While multiple models exist to simulate the onset and propagation of debris flow (Takahashi 2007, Begueria et al. 2009, Ouyang et al. 2013, 2015, Van Asch et al. 2014, Bout et al. 2018a, Domènech et al. 2019), these models may not be suitable for basin-scale analysis where varying intensities of precipitation occur over an extended period (Hu et al. 2014, 2018, Van Asch et al. 2018, Zhu et al. 2020). We adapt a 1D infinite slope debris flow model to address this limitation that accounts for the runoff-induced erosion based on Coulomb-viscous rheology. The debris flow model used here is an adaptation of Van Asch et al. (2014) and Domènech et al. (2019), which did not consider the antecedent moisture conditions, and hydrological characteristics of the basin. We calculate the initiation of debris flows based on the rate of erosion ($e_r$) following Takahashi et al. (1992):

$$e_r = \delta_s \frac{dR}{dt} \frac{\alpha_L}{U} = \delta_s \frac{V - V_c}{V_c - V_w} \frac{q_t}{d_L},$$

where $\delta_s$ is the coefficient of erosion rate a non-dimensional and calibrated value, $\alpha_L$ (m) is the depth within the sediment layer under the condition $\tau_L = \tau$, $d_L$ is $d_{50}$ mean diameter of the grain, $U$ (m s$^{-1}$) is the velocity of the flow-through an infinite vertical section, $q_t$ (m$^2$ s$^{-1}$) is the routed total discharge of the sum of sediments and water per unit width (m). Further details of the model can be found in supplementary information (SI) and Van Asch et al. (2014).

To identify the runout distance of debris flows across road networks within the Periyar basin, we perform three numerical simulations considering constant precipitation intensities, i.e., 93, 153, and 211 mm d$^{-1}$. Unlike the shallow landslide model, the debris flow model can only consider time-step in hours. Due to the non-availability of hourly precipitation data, we used constant precipitation intensities. All three numerical simulations are run for 24 h with an hourly time step to obtain the time-series of debris flow within the basin.

The materials transported by shallow landslides and debris flows to rivers may impact the flooding. However, the meta-data by (Hao et al. 2020) clearly distinguishes the type of event in Kerala as shallow landslides and debris flow. Hence, there is no evidence of a shallow landslide evolving into debris flows. Also, there is no data available regarding the transport of landslide materials to rivers and their impacts on flooding. Due to these reasons, we do not explicitly account for the interactions between shallow landslides, debris flows, and rivers in our analysis. Nevertheless, future research directions need to consider the interplay among various hazards more realistically.

Finally, to quantify the (loss of) connectivity of road network, we measure the state of critical functionality (SCF) on each day. SCF is defined as the ratio of number of nodes in the largest connected cluster (LCC) at given instance to number of nodes in the LCC in unperturbed network. The choice of this metric is guided by the fact that SCF has been widely used in network science and engineering literature to assess the robustness and resilience characteristics of the networked systems.

3. Results

3.1. Extent of flood area

In the Periyar basin, the extreme precipitation events occurred between 1 July 2018 to 31 August 2018 (Mishra and Shah 2018, Anandakrishmi et al. 2019, Viswanadhapalli et al. 2019). During this period, heavy to very heavy rainfall events (as per the IMD glossary) were reported on 17 July, 9 August, and 15 August (figure 3) that triggered multiple flooding, landslides, and debris flow events.

Our 2D hydrodynamic modeling of flood suggests that peak flood inundation occurred thrice between 1 July 2018 and 31 August 2018 (figure 3). On 18 July, a day after heavy rainfall, inundation of over 250 km$^2$ occurred at the downstream (figure 3). The maximum discharge from Neelamangalam was 3000 m$^3$ s$^{-1}$ on 17 July. After this event, the inundation area reduces due to the retreat of the floodwater. However, on 12 August, due to another episode of heavy precipitation, the next flooding event inundated over 250 km$^2$ area. The flood receded to 200 km$^2$ area on 14 August. However, another extreme precipitation event occurred on 15 August, which resulted in the maximum discharge of 6000 m$^3$ s$^{-1}$.
Figure 3. Hyetograph of daily precipitation at the six gridded locations within the basin shows the timestamp of occurrence of heavy, and very heavy rainfall (as per IMD terminology). The discharge hydrograph of Neeleeswaram and Arangali show the peak discharges on 17 July, 12 August, and 16 August. Simulated flood area peaks as obtained from the hydrodynamic model coincides with the extreme precipitation and high discharge events.

3.2. Simulating landslides and debris flow modeling

The metadata used in this study only provides information about the location of landslides and debris flow events without any timestamp of occurrence and prevalence (Hao et al 2020). To fill in the missing information, we set up separate numerical models for (shallow) landslides and debris flow to identify the prevalence time within the basin. Specifically, the output of our landslide model yields a time series of the FoS at each pixel (figure 4(a)). As discussed in section 2, When FoS falls below one at a given pixel, we classify that event as a shallow landslide. Our simulations show that the first set of shallow landslides occurred between 10 July and 17 July, followed by multiple landslide events between 12 August and 16 August. Given the high sensitivity of our landslide model to antecedent moisture conditions and precipitation rates, it is not surprising that these events are generally triggered after the onset of the precipitation events in our simulations. Disruptions caused by shallow landslides further increase the risk of debris flows under upcoming rainfall episodes. The collapsed soil from shallow landslides could transform into debris flows under extreme runoff. From the analysis of shallow landslides, we observe that areas with FoS less than one can be precursors of debris flows (see figure 4(a)). We use a hydrological model coupled rheological erosion model to simulate the debris flow at the hourly timescale. We use following three precipitation conditions in our debris flow model: (a) 211; (b) 153; and (c) 93 mm d⁻¹. These precipitation values correspond to the maximum daily precipitation intensities observed at three locations within the basin (figure 4(a)). Our simulations for debris flow (figure 4(b)) indicate that while 211 mm d⁻¹ precipitation event would result in the onset of debris flow after 8 h of the onset of precipitation, the 93 mm d⁻¹ precipitation event would result in the onset after 22 h. Further, we note that 153 mm d⁻¹ precipitation event will result in 1 million square meters of debris flow at its peak, with the mean value of 750,000 m² occurring within 4 h after the onset, which is comparable to the observed area of debris flows of 755,938 m².

3.3. Modeling disruption on road networks

Finally, to understand the impact of flooding, landslides, and debris flow events on the connectivity of regional road networks, we use complex network representation where road segments represent the
Table 1. Error matrix of accuracy assessment for 2D hydrodynamic modeling with Cohen’s Kappa value and F1 score.

|                  | Non-flooded region | Flooded region | Total | User’s accuracy |
|------------------|--------------------|----------------|-------|-----------------|
| Non-flooded region | 3399               | 210            | 3609  | 0.941 (94.1%)   |
| Flooded region   | 605                | 786            | 1391  | 0.565 (56.5%)   |
| Total            | 4004               | 996            |       |                 |
| Producer’s accuracy | 0.848 (84.8%)       | 0.789 (78.9%) |       | Overall accuracy = 0.837 (83.7%) |
|                  |                    |                |       | F1 score = 0.658 |

Sample size = 5000

Figure 4. (a) Time-series of factor of safety of slopes at 492 pixels in landslide-prone area shows dip in FoS immediately after heavy and very heavy precipitation events. FoS lower than 1 are typical precursors of debris flow events. (b) Simulated area of debris flows for three rainfall intensities 93, 153 and 211 mm d$^{-1}$ as estimated from our 1D erosion models.

links and the junctions of two road segments (identified by the change in geometry) represent the nodes. Then, we superimpose the hazard maps generated from our modeling outputs to identify the location of potential disruptions (see conceptual figure 5). Figure 6 shows the spatiotemporal evolution of the events along with the disruptions on the road network. The road network disruptions started with a 150 km$^2$ area of flood that occurred on 1 July 2018, (see figure 3). The flooding event resulted in the inundation of 16% of junctions and 10% of road segments (figure 6(a)). Again, on 16 July, 2908 m$^3$ s$^{-1}$ discharge occurred from Neeleeswaram which (see figure 3) triggered flooding from 17 to 19 July. Simultaneous occurrence of landslides are also observed on 17 July (figure 4(a)). These events together disrupted 26% of road junctions and 19% of road segments (figure 6(b)). On 12 August, due to concurrent shallow landslides and flood, 31% of road junctions and 23% of road segments (figure 6(c)) were disrupted. Maximum inundation of road junctions and road segments, 47% and 39%, respectively occurred on 16 August 2018 (figure 6(d)) when shallow landslides, debris flows and flood occur together. Disruptions caused by road junctions and road segments increase with time along with the concurrency of events.

Figure 7 shows the SCF of the entire road network impacted by the flood, shallow landslides, debris flows, and concurrent events. SCF 1 means the GCC in the road network is fully connected. Flooding reduces the SCF from 1 to 0.8 between 1 July and 5 July. This loss in functionality is caused by 16% disruptions at road junctions and 10% at road segments (figure 6). Throughout the analysis, these certain fraction of initial disruptions never recovered. Interestingly, the SCF under flood impact not decreases after 5 July. Though peak floods occurred on 18 July, 12 August, and 16 August (figure 3), these events do not affect the road network functionality. The network topology may help to reason the cause. We find road junctions (i.e. nodes) in the flooded area exhibit fringe patterns with low betweenness centrality which affects the criticality (SCF) of the entire road network (see figure 7 and figure S3 in SI). The impact of shallow landslides on road networks started on 17 July with a SCF drop from 1 to 0.97. After that, a drastic drop in functionality from 0.97 to 0.41 occurs on 15 August. Debris flows impacted the functionality on 16 July with a drop in SCF from 1 to 0.35. Under concurrent events, the SCF drops sequentially from 1 to 0.8, 0.8 to 0.79, 0.79 to 0.76, 0.76 to 0.4, and 0.4 to 0.31. These impacts occurred on 1 July, 10 July, 17 July, 15 August, and 16 August. Compared to all independent events, concurrent events induce maximum loss of network functionality up to 71%.
Figure 5. Conceptual diagram of road network nodes and edges disrupted disparate, and concurrent events. (a) Disruption by flood, (b) disruption by shallow landslide within a 500 m buffer, (c) disruptions by debris flow within a 1000 m buffer, and (d) disruptions by concurrent events.

Figure 6. Visualization of road network failures caused by floods, shallow landslides and debris flows on (a) 1 July 2018, (b) 17 July 2018, (c) 12 August 2018, (d) 16 August 2018, and (e) 31 August 2018. Pie charts show the percentage of damaged road junctions and road segments.
Discussion

High-impact weather events, including precipitation extremes, trigger hydrological hazards like floods, shallow landslides, and debris flows. These events’ potential impacts may result in loss of lives and damage to infrastructure systems over prolonged periods due to the simultaneous or delayed onset of various events in sequence. Adverse effects worsen when disruptions occur in critical infrastructure and lifeline networks, including transportation systems, power distribution networks, water distribution and wastewater systems. Thus, maintaining the essential functionality of such systems is crucial for disaster preparedness and response. Hence, to predict the impact of spatially and temporally overlapping concurrent hazards, understanding the interlinks between individual events is essential (Moftakhari et al. 2017, AghaKouchak et al. 2020, Raymond et al. 2020). This study presents a new way to analyze the effects of precipitation extremes-induced simultaneous hazards (floods, shallow landslides, and debris flows) on the connectivity of the road transportation network at the basin scale. Specifically, we illustrate the proposed framework’s application to assess the functionality loss from the individual and concurrent events during the Monsoon season of 2018 in the Periyar Basin of Kerala, India.

Our analysis enables us to correlate topographical variability and network topological properties with the spatiotemporal characteristics of the hazards. We note that high variability in topography in our study area increases the damage susceptibility of road networks to disparate hazards. Our analysis revealed that flooding events during the study period were primarily concentrated in the western part of the basin, a low elevation area. Interestingly, road junctions in this area exhibit a typical fringe pattern (i.e., high concentration of nodes with low betweenness centrality). Hence, we do not observe drastic losses in functionality solely due to flooding. On the other hand, central regions in the basin are predominantly mountainous with an average elevation of 1830 m above sea level and steeper slopes. Our landslide model suggests high susceptibility of landslides and debris flow events in this area after precipitation events (figures 4(a) and (b)). However, we observe a large number of high importance nodes (i.e., nodes with a large degree and betweenness centrality) are also situated within the buffer zones of identified landslide and debris flow sites. Hence, we observe sharp transition points in the functionality curves during the landslide and debris flow events.

We note the following limitations in our framework that future extension of this work would attempt to address:
The shallow landslides and debris flow models do not consider the multi-phase nature of the soil. The hydrodynamic model does not account for the 3D nature of flood in urban settings. Consideration of spatial variability and heterogeneity in hydrological and geomechanical properties. Missing bathymetry and inconsistencies in the DEM data typically introduces error in the spatial extent and depth of flood inundation. Cascading nature of one hazard triggering two or more sequential hazards, i.e., shallow landslides evolving into debris flow and debris flow converging into floods is not considered (AghaKouchak et al. 2020, Fan et al. 2020).

In the absence of station-based weather data, we used daily gridded precipitation data with the resolution of 25 km × 25 km. Given the coarse spatiotemporal resolution of the gridded data, the actual peak is generally attenuated as a consequence of spatial smoothing. Moreover, future works in this direction should consider the realistic fragilities of impacted systems and actual recovery times to assess these systems’ resilience characteristics comprehensively.

Disruption to the critical infrastructure systems during disasters often translates to slow and suboptimal resource allocation, which undermines the efficient recovery of impacted socioeconomic systems. Despite the growing stakeholders’ interest in enhancing the resilience of critical infrastructure systems, few quantitative integrated impact assessment tools are available to guide the informed decision making. Our study offers novel insights into the interaction of networked systems with disparate hazards, which can be generalized to networked systems of varying complexities (both built and natural), and aid in informing efficient pre-disaster preparedness and swift post-disruption responses.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Data and code availability

The data sets and codes used in this study are publicly available and can be accessed online through the links given in section 2. The Python script for network functionality, Java script for SAR image analysis using Google Earth Engine, and PCRaster scripts for shallow landslides and debris flows are available at our GitHub repository: https://github.com/raviraj-dave96/concurrent_event_infrastructure_perturbation.git.

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Author contributions

U B, S S, and R D designed the experiments. R D and S S performed the analysis. U B and S S wrote the manuscript with inputs from R D. R D and S S contributed equally.

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