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Estimating railway resilience curves: recovery duration and train traffic response to floods and tree fall

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Abstract

An important aspect of transport infrastructure resilience is recovery, i.e. the process of returning to original service levels after a disruption. In this paper, we estimate recovery trajectories of the German rail network for two specific types of natural hazards: floods and tree fall. Extensive traffic data on track segments of the Deutsche Bahn are matched to geospatial information on disruptive flood and tree-fall events between 2018-2020. We quantify mean resilience curves for flood and tree-fall events by taking average train counts for each day within a (–7, +14)-day window. Results suggest that traffic takes about three days on average to return to normal operations after a tree-fall disruption lasting longer than one day, while it takes five days on average to recover from a flood. Trajectories vary according to route type and are influenced by seasonal weather conditions.

Keywords: flood; tree fall; resilience; railway

1. Introduction

It is important to make rail operations more resilient to natural hazards, especially in the context of climate change, in order to enable the public and freight transport to function continuously and reliably. The United Nations Office for Disaster Risk Reduction (UNDRR) defines resilience as “the ability of a system, community or society exposed to hazards to resist, absorb, accommodate and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions” (UNDRR 2009). In terms of the transport sector, CEN (2021) defines resilience as the “ability to continue to provide service if a disruptive event occurs”. The resilience of an infrastructure to natural hazards therefore depends on at least two things: the ability to soak up the adverse effect of the natural hazard upon impact (absorption) and the process of returning to its original, pre-disruption service level (recovery). While absorption encompasses the robustness or vulnerability of the

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infrastructure, the second aspect, recovery, includes the rapidity and trajectory of the return to regular operations. Typically, resilience is measured as the deviation from a standard level of service and is presented in the form of a curve. For railway infrastructure, whose absorption capabilities are constrained by limited re-routing possibilities and the prevalence of single-line tracks (Mattson and Jenelius 2015), a swift post-hazard recovery is of vital importance. However, the quantitative study of railway recovery from natural hazards remains relatively unexplored. Prior studies have focused mainly on the absorption aspect, investigating the effect of natural hazards on economic or operational damages to the railway system (Chan and Schofer 2016; Kellerman et al. 2016; Xu, et al. 2016; Fabella and Szymczak 2021). While recent recovery research have proposed deterministic (Janic 2018) or network science-based (Bhatia, et al. 2015; Yadav, et al. 2020) quantifications of resilience, the results of these approaches remain limited to the specific disaster event which they simulate or analyse.

In this paper, we estimate average resilience curves and recovery trajectories of the German railway network with respect to two types of natural hazards: floods and tree fall. Tree-fall events are the most commonly occurring hazard along the German railway network, with more than 3,000 reported line disruptions every year (Fabella & Szymczak 2021). Meanwhile, compared to other natural hazards such as landslides and slope fires, floods have the largest adverse impact on railway operations. Fabella and Szymczak (2021) estimate that a flood disruption could reduce the daily train traffic by 19% on average. Indeed, the scope of damages a flood can cause to transportation infrastructure is most salient in the recent flooding disaster in Germany and central Europe in summer of 2021 (Fekete and Sandholz 2021; Koks et al. 2021; Szymczak et al. submitted).

To approximate resilience trajectories of tree-fall and flood hazards, we match historical traffic data of the Deutsche Bahn AG (henceforth DB) to geospatial information on disruptive flood and tree-fall events between 2018 and 2020. How these closures correspond to the resulting recovery duration in terms of train traffic restoration are examined descriptively by taking average train counts for each day within a (-7, +14)-day window around the disruption. This allows for an aggregate approximation of the mean post-disruption recovery duration and recovery trajectories for flood and tree-fall events along the railway network.

2. Data and Methods

Estimating average resilience curves of a transportation infrastructure network to natural hazards requires two types of information: (i) the service level of the infrastructure over time and (ii) the temporal and spatial incidence of natural hazard disruptions along the network. For (i) we use daily, track segment-level traffic data, while for (ii) we use disruption datasets for flood and tree fall events taken from the accident database of the DB. Both datasets were graciously provided by the DB Netz AG, Frankfurt, a fully owned subsidiary of the largest rail-transport operator in Germany, the Deutsche Bahn. In the following subsections, we elaborate on the two datasets and the methods used for matching and analysis.

2.1. Train traffic data

To represent the service level provided by the rail transport network, we use daily traffic data from the DB for the time period January 25, 2018 to December 31, 2020. For each segment of the railway network between two operating points (henceforth called track segments), the daily number of passing trains in both directions is provided. Train counts include freight trains as well as long- and short-distance passenger trains. The specific route number to which the track segment belongs is also included, allowing the identification of each track segment by its route number and the two operating points at both ends of the segment. The traffic data consists of 10767 track segments, of which 3720 experienced at least one disruptive flood or tree-fall event over the investigation period.

The distribution of daily train counts varies considerably across track segments (Figure 1). Close to one fourth of all segments have around 25 trains per day, yet some segments have an average daily traffic exceeding 200 trains. To make traffic levels comparable across track segments, train counts were standardized using segment-specific means and standard deviations. Furthermore, the transformation uses the first two moments of the distribution over a restricted sample of days where no natural hazard disruption takes place. This serves to provide an easy benchmark for “regular operations”, which is when the value of the standardized variable is equal to zero.

In order to filter out the variations in traffic caused by weekly or seasonal fluctuations and other confounding factors, we conduct an ordinary least squares (OLS) regression of the standardized train counts against dummy variables for the day of the week, the month and the year, as well control variables that correlate strongly with traffic, such as precipitation. The variables used for the regression and how much they correlate with traffic are discussed in detail by Fabella and Szymczak (2021). The R-squared of the regression is 0.21, meaning the seasonal and control variables explain only 21% of all the variation in train counts, and 79% of the variation remain in the residuals. The residuals from this regression, henceforth called *residual traffic*, represents the variations in standardized train counts caused by factors other than precipitation or week, month or year effects. From this point forward, residual traffic will be used as the primary measure of the level of service in the estimation of the resilience curves.

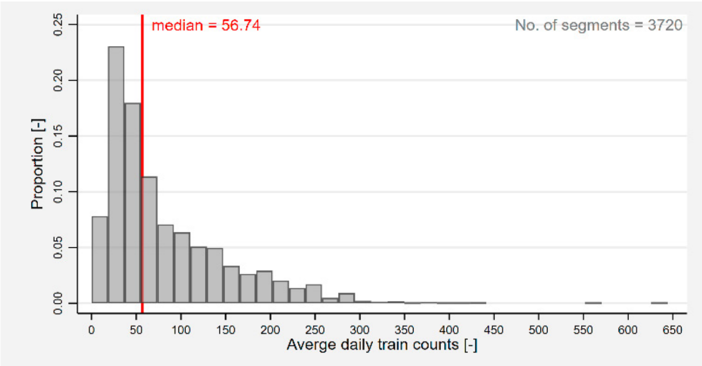

Fig. 1. Histogram of average daily train counts across track segments.

2.2. Disruption data

The second piece of information critical for resilience curve estimation is the occurrence of natural hazards. Reported tree-fall and flood disruptions along the German railway network (also referred to as *events*) were obtained from the accident database of DB Netz AG, which contain records of disruption reports submitted by train operators. Both datasets containing flood and tree-fall disruption reports provide information on the geographic location, date, time, and duration of every reported disruptive event that occurred along the railway network between 2018 and 2020. However, the flood and tree-fall datasets differ in the type of geographic information they provide. The tree-fall dataset includes the route number and kilometer location of the disruption, allowing the exact identification of the associated track section in the traffic dataset. There is therefore a one-to-one matching between tree-fall events and track segments in the traffic dataset. In contrast, the flood dataset only reports the closest operating point to the location of the disruption. This means that the exact track segment associated with the disruptive event could not be identified with precision. Instead, each flood event was matched to *all* track segments that have as an endpoint the closest operating point to the flood. Since operating points may belong to intersecting routes on the network, this strategy results in a one-to-many matching of flood events to track segments. This less-accurate matching could result in flatter resilience curves and wider confidence intervals due to the increased uncertainty in the location of the disruption. Nevertheless, estimated resilience curves using this data could still be useful when taken as an upper bound of the true recovery trajectory of the resilience curve.

Disruptions due to tree fall occur frequently along the German railway network, with 9862 reported events between 2018 and 2020. Of these, 8387 were successfully matched to track segments in the traffic data (90% match rate). In contrast, flood events occur much less frequently with only 98 reported disruptions in the same period. All flood events were successfully matched to 210 track segments in the traffic data (100% match rate).

Figure 2 plots the weekly distributions of tree fall and flood events over the investigation period. The 8387 tree fall events are distributed over a total of 991 days with a maximum of 363 events in a single day (February 10, 2020, storm Sabine). The events are fairly evenly distributed between spring, summer and winter, while a significantly lower number of events occurs in autumn. The 210 flood events are distributed over a total of only 47 days with a maximum of 29 events on one day (June 1, 2018). More than half of the floods occurred in summer, while floods in autumn and winter are rare in the three years included in the study. Tree-fall events tend to cluster around incidences of storms, as can be seen by the spikes in disruptions during the storms Bennet, Eberhard and Sabine, which all occurred early in the year. In contrast, the maximum peak of flood events occurred in summer 2018. No storm or hurricane occurred during this time, but constant thunderstorms and heavy rains ravaged Germany throughout May and June (DWD 2018).

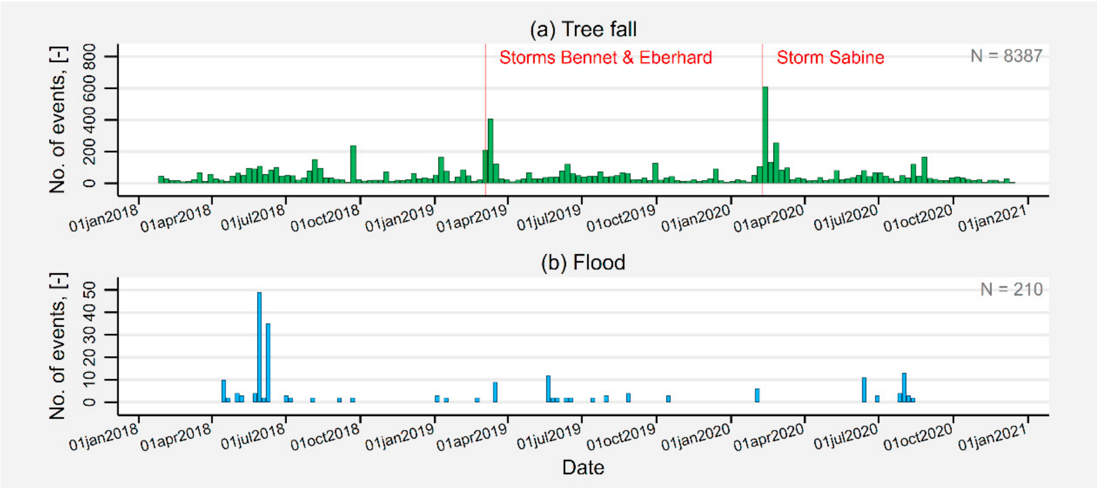

Fig. 2. Weekly distribution of tree fall (top) and flood (bottom) events.

Table 1 presents the summary statistics of disruption duration for tree fall and flood events. On average, tree fall disruptions last 4.4 hours, while flood disruptions are considerably longer with 68.8 hours or 2.9 days. For flood events, a larger proportion result in interruptions lasting longer than one day (32.9% versus 1.9% for tree fall). The average duration of interruptions longer than one day is 196 hours (8 days) for flood events and 119 hours (5 days) for tree fall. The number of events with interruptions lasting longer than a week are 18 for flood and 23 for tree-fall events, respectively.

Table 1. Distribution of disruption duration by natural hazard.

	Tree fall				Flood			
	No. of events	Duration (in hours)			No. of events	Duration (in hours)		
		Mean	Median	Std. Dev.		Mean	Median	Std. Dev.
Shorter than one day	8224	2.1	1.3	2.8	141	6.6	4.1	6.2
Longer than one day	163	119.7	41.5	260	69	195.9	55.8	310.2
Total	8387	4.4	1.3	39.7	210	68.8	10.9	198.2

2.3. Average resilience curves

To estimate the average trajectories of traffic around the tree-fall and flood events, we take the seven days before and 14 days after the start of each reported event and calculate the arithmetic mean of residual traffic for each individual day around the disruptive event. Given that tree fall and floods longer than 24 hours last on average five and eight days, respectively, a 14-day window after the recorded begin of the disruption was selected to capture the full recovery trajectory of the disruptions. Including the week *before* the event serves to give an impression of the prior traffic levels, which may already fall below the average, especially for disruptions that happen during and around storms.

Formally, for each disruption type $d \in$ (*tree fall*, *flood*) and day $t \in (-7, +14)$ we calculate the mean residual traffic, *MRT,* as

$$MRT_t^d = \frac{\sum_{i=1}^{N_t^d} RT_{it}}{N_t^d} \tag{1}$$

where RT_{it} is the residual traffic of event i on day t, and N_t^d is the total number of events for disruption type d on day t. Since train traffic data is only available in daily resolution, we divided the data set into disruptions with a duration shorter and longer than one day and present the resilience curves for each of these subsets separately. We then compare the resulting resilience curves across types of railway lines (main line vs. branch line), and explore the influence of temporally adjacent disruptions on the same track segment, i.e. disruptions occurring within 14 days of each other.

3. Results and discussion

Figure 3 plots the trajectory of the mean residual traffic for tree-fall and flood events, separating the curves according to disruption duration. For both tree fall and floods, short disruptions have a relatively flat curve with only a small decline on day zero that recovers immediately, as seen from the dashed lines. The brief dip in traffic is small but significant: –0.05 standard deviations for tree fall and close to –0.2 standard deviations for floods. In contrast to short disruptions, events lasting longer than one day, as depicted by the solid green or blue lines, exhibit a pronounced decline in traffic at day zero. Long-lasting tree-fall events reduce traffic by almost 0.75 standard deviations and take on average three days to get back to the normal level. Long-lasting floods cause an immediate decline in the number of trains by over one standard deviation and remains there for another two days before returning to the normal level on day five. That the immediate impact of the disruption is relatively larger on average for floods than for tree fall aligns with the findings of Fabella and Szymczak (2021).

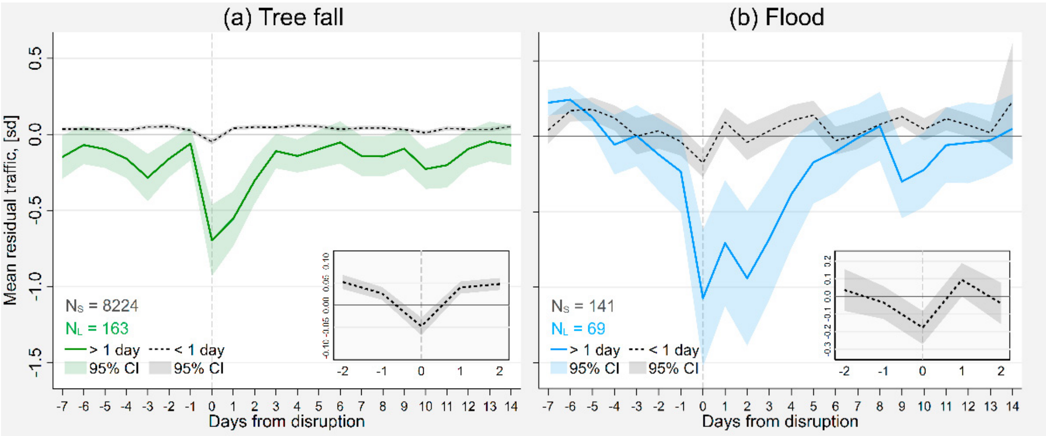

Fig. 3. Mean resilience curves for tree fall (left) and flood (right) events, separated by duration of the disruption.

Given that tree fall and floods tend to cluster around specific time periods (Figure 2), we check whether particular weather conditions associated with clustered disruptions influence the recovery trajectories. The mean resilience curves of tree-fall disruptions that occurred during a period in March 2019 with a series of storm events, most notably Bennet and Eberhard (Haeseler et al. 2019) is plotted in Figure 4(a). Since these two storms hit Germany within six days of each other, we analyse the resulting disruptions together. The tree fall events brought about by storm Sabine in March 2020 (Haeseler et al. 2020) is plotted in Figure 4(b). The solid lines show the mean resilience curves of disruptions longer than one day. These curves in (a) and (b) show similar trajectories, dropping by over one standard deviation, but recovering fairly quickly. In contrast to Bennet and Eberhard, however, the traffic during Sabine took a large hit even from short disruptions, as depicted by the dashed lines. Tree fall events shorter than one day reduced the number of trains by 0.5 standard deviations.

The resilience curve for floods during the heavy summer rains in 2018 (Figure 4(c)) exhibits a gradual decrease that begins seven days prior to the disruption, reaches its minimum at day two, and gradually rises all the way back up on day 14. The slow reduction and recovery could be traced back to the consistent rains that spanned several weeks, which likely caused traffic to go down before and after any one disruption (DWD 2018). Prior reductions in traffic could be due to reduced train speeds or pre-emptive cancellation of trips. The slow recovery could also be due to clearance and repair capacity limits being reached in the presence of temporally and spatially clustered disruptions. The variations in reported starting times of the disruption may also elucidate the differences in the curves. Reports submitted by train operators on disruptions due to fallen trees usually peak between 7:00 and 9:00 am. However, since reports are filed upon encountering a disruption, the time at which the tree actually fell may not necessarily be within these hours of the day. Given that train operations are minimal at night, trees in the tracks are often not sighted until the first run of the day. Therefore, the actual time of the event might be late at night the day before. Furthermore, when severe weather warnings are issued, operations are often reduced or even stopped altogether as a precautionary measure to avoid trains from getting stuck on an open track. This would prevent the timely discovery and report of a tree fall and could explain why train counts in Figure 4(b) begin to decline the day before the event. The situation is different for flood events. Here, the onset of the event is most often in the afternoon hours, i.e. one can assume a more direct temporal connection between the occurrence of the event and its subsequent report. More than half of the events occur during summer months, when local thunderstorms with heavy precipitation are one of the main causes of small-scale flooding. These thunderstorms often come in the afternoon and early evening, which correspond with the time of day in which most reports are filed. In fact, floods may even be reported at the very onset of the event, before it reaches its worst phase, potentially explaining the delayed trough in Figure 4(c).

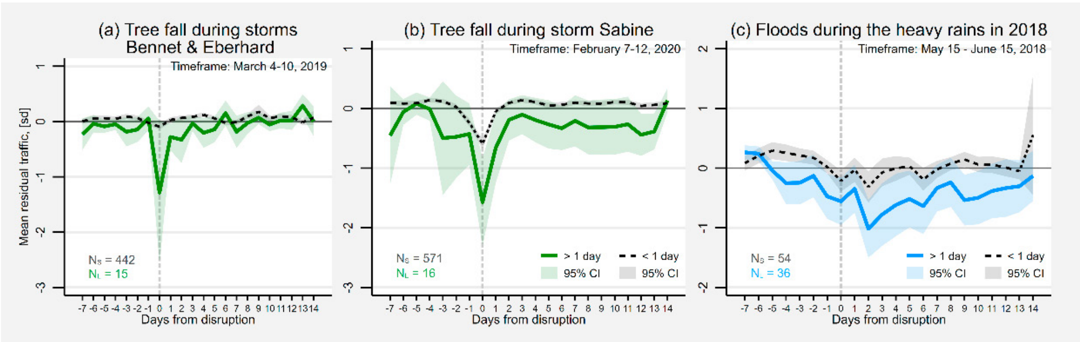

Fig. 4. Mean resilience curves for tree fall events during the storms Bennet and Eberhard (left), Sabine (middle), and floods during the heavy summer rains in 2018 (right).

A detailed analysis of the impact of events on spatially adjacent routes is beyond the scope of this study; however, it is sensible to expect that the closure of a particular track segment will have an impact on adjacent track segments and intersecting routes. The magnitude of this impact depends on several factors, including the type of the route, normal daily traffic volumes, and the availability of alternative routes. The triggering factors of natural hazards also play an important role. For instance, storm events, the main trigger for tree fall, are often large-scale events that affect the entire railway network. Within a short period of time, disruptions occur at many points in the network at the same time, making it necessary to prioritize clearance. In addition, personnel or infrastructural bottlenecks or poor accessibility of the disruption location can lead to a delay in clearance. This can result in the initial level of train numbers only being reached again with a time delay several days after the event, visible in Figure 4(a) and (b).

To further investigate the effect of temporally adjacent events, Figure 5 illustrates mean resilience curves for tree fall events by distance (in days) to adjacent disruptions. This analysis could only been conducted for tree fall as there are too few track segments with adjacent flood events in the data. In the majority of tree fall events (85%), no further disruptions occur on the same track segment within the (–7, +14)-day window. In 653 cases (7.8%), another event occurs after, in 591 (7.1%) cases before the event. If another event occurs 1-2 days later, this is clearly visible in the trajectory of the solid, green curve in 5(a). In this case, the recovery trajectory is rather flat and is slow to return to the initial level. In contrast, subsequent events that occur between 3-7 days manifest in narrow bursts that quickly returns to the initial level, as seen from the dashed, blue curve in Figure 5(a). For subsequent events that occur more than 8 days after, no significant decline in the curve can be perceived.

In Figure 5(b), on the other hand, one can observe the solid green curve that traffic already decreases at day –1 when tree-fall events occur 1-2 days prior. Any event preceding the disruption by more than two days does not have any discernable effect on average.

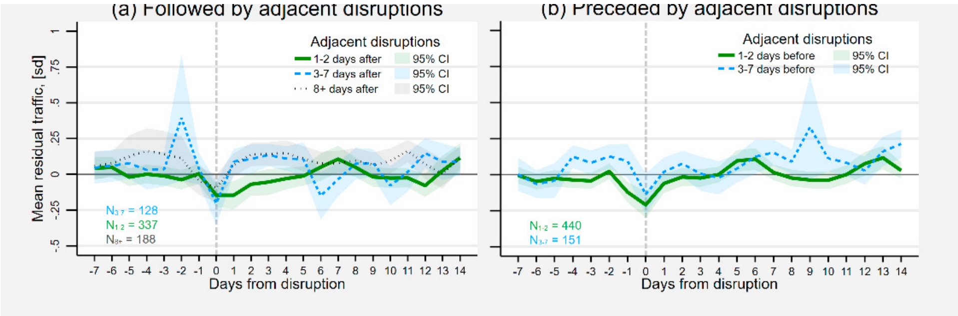

Fig. 5. Mean resilience curves for tree fall events, separated by distance (in days) from adjacent disruptions in the same track segment after (left) and before (right) the event under consideration. This analysis was conducted only for tree fall as the number of events with adjacent disruptions is too small for flood events (18 events only).

Another factor influencing the shape of the curves is the type of route (main line or branch line), which implies the degree of importance of a track segment relative to the rest in the network. Figure 6 plots the resilience curves according to the route type. Tree fall disruptions have only a discernable effect on traffic for disruptions lasting longer than one day. The stronger impact on main lines can be explained by the different degree of electrification. On the main lines, 66% are electrified, 31.8% not electrified and 2.2% partially electrified. By contrast, only 8.1% of the branch lines are electrified, while 88.8% are not electrified and 3.1% partially electrified. If a tree fall damages the overhead cables of an electrified route, it will take longer to restore the track back to regular operations.

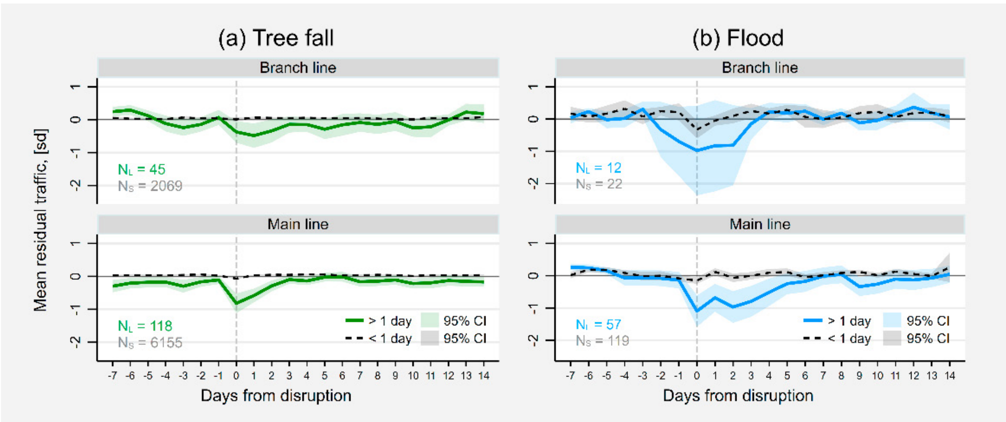

Fig. 6. Mean resilience curves for tree fall (left) and flood (right) events, separated by type of route and duration.

For flood events, both solid blue curves for main and branch lines show a decline on the day of the event, albeit only statistically significant for main lines. The recovery trajectory in the main line is flatter and takes longer to recover. However, the decline in traffic in the branch lines already begin two days prior to the reported start of the flood event. Branch lines can be more susceptible to small-scale flooding because they often follow the topography and frequently run along river valleys on the valley floor. This makes them vulnerable even at the onset of river flooding and rainwater accumulation. Hence, the early reduction in traffic in branch lines. In contrast, high-speed lines usually run straight via tunnels or bridges. A disruption that damages bridges or tunnels will take longer to repair, thereby flattening the recover trajectory on main lines.

4. Conclusions

In this paper we investigate the resilience curves and recovery trajectories for two types of natural hazards along the German railway network. This is the first study that attempts to quantify both the absorption and recovery phases of railway traffic resilience in a single framework. We find that for flood disruptions lasting of more than one day, it takes on average five days for traffic to return to its regular operations. For tree-fall disruptions, it takes three days on average. Trajectories vary by route type and the presence of adjacent disruptions, and are strongly influenced by weather or seasonal processes. The network-wide statistical approach employed here allows for a broad inspection of resilience of the German railway that is limited neither to a specific local infrastructure nor to specific natural hazard events. An extension would be to validate the descriptive results using an event study analysis. Infrastructure managers and the Deutsche Bahn can use the recovery duration estimates resulting from this study as a benchmark upon which to set resilience policies and post-disruption recovery strategies, in order to build a more reliable transport system in the event of floods or tree fall. When performed for more than these two processes, the estimated resilience curves can help the infrastructure manager determine which natural hazard their transportation system is least resilient to, allowing for a more specific prioritization of safety measures.

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