Supporting robust and climate-sensitive adaptation strategies for infrastructure networks: A multi-hazard case study on Mozambique's healthcare sector

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ABSTRACT: As climate change causes more intense and frequent natural hazard events, decision makers are tasked to climate-proof vital infrastructure systems against these challenges. Adaptation studies often evaluate benefits of different options in face of single types of natural hazards, and on their damage aversion potential to individual infrastructure components. In a proof of concept, we use the healthcare sector in Mozambique, which is highly affected by tropical cyclone winds and concurrent flooding, to showcase how packages of adaptation measures may be evaluated in their effectiveness on a systemic level, to mitigate basic service disruptions from multiple hazards, across various interdependent infrastructure networks. Using the open-source risk modeling platform CLIMADA on 2019's tropical cyclone Idai, we simulate five stylized adaptation strategies and their effects in reducing direct damages from wind and flooding to roads, power lines and healthcare facilities, their overall aversion of people's healthcare access losses, and synergies or trade-offs with other basic service supplies. Results illustrate the importance of considering multi-hazard phenomena and interdependencies between infrastructure systems in adaptation appraisals. We further provide an outlook on how to integrate probabilistic and climate-scenario driven hazard modeling into robust adaptation planning.

1. INTRODUCTION

Mozambique is among the countries most affected by weather extremes, and in 2019 suffered from two category 4 tropical cyclones (TC) Idai and Kenneth. Healthcare facilities were strongly damaged by wind and flooding and access was further hindered due to interrupted roads (Petricola et al. 2022). Since critical infrastructure components are usually embedded in a network of supporting infrastructure systems, structural damages can have unexpected and significant cascading impacts on the service levels provided by these infrastructures, as studies have shown in several countries on the African continent (Hallegatte et al. 2019). Despite this, healthcare infrastructures, their exposure to natural hazards, and their dependence on other critical infrastructure, have long been under-researched. This is in spite of the fact that resilient healthcare infrastructure is a critical component in achieving many health-related sustainable development goals (e.g. SDG indicators 1.4.1 and 3)(Thacker et al. 2019), and that reducing damages to critical infrastructures and avoiding disruptions to basic services in general, is also a key goal of the Sendai Framework for Disaster Risk Reduction (*UNDRR,* 2015). Adaptation strategies towards resilient infrastructure are shown to have multiple co-benefits, making them cost-effective in many cases (Hallegatte et al. 2019). To create robust adaptation strategies, it is however necessary to consider the effects and trade-offs on the entire interdependent infrastructure system and the service levels they maintain, as well as their effectiveness in mitigating threats from multiple hazard types.

While some studies have assessed the structural impacts caused by tropical cyclones on healthcare facilities (Deltares 2021), few have considered the potential for indirect impacts to lead to cascading failures (Petricola et al. 2022). Additionally, previous adaptation studies focused on the costs and benefits of different measures, yet only for mitigating structural impacts, neglecting the synergies and trade-offs across infrastructure systems. Furthermore, it is common for adaptation studies to look at single hazards, without accounting for the influence of compound events or sub-hazards (cf. Eilander et al. 2022b for a rare counter-example).

In this study on 2019's tropical cyclone Idai in Mozambique, we provide a proof-of-concept on how to simulate wind and flood-induced disruptions to the healthcare infrastructure, due to direct impacts and due to cascading failures from supporting infrastructure systems, taking on a service-level centered, multi-hazard perspective. We explore the mitigation potential of a set of stylized structural and system-changing adaptation measures aimed at reducing healthcare access disruptions. We discuss how to refine this end-to-end, generically applicable framework, which is based on open-source software and data. Finally, we provide insights on the challenges and ways forward for incorporating probabilistic event scenarios and climate change signals into more robust and systemic adaptation strategy planning.

2. METHODS AND DATA

2.1. Risk Modeling Framework

The open-source and -access software CLIMADA is a globally consistent and spatially explicit tool to assess the risks of natural hazards and to support the appraisal of adaptation options (Bresch and Aznar-Siguan 2021). Its event-based modeling approach allows for a fully probabilistic risk assessment based on the IPCC risk definition as a function of hazard, exposure and vulnerability.

'Hazard' is a spatial representation of an intensity measure for the respective physical event. In this study, track data of Tropical Cyclone Idai was obtained from IBTrACS and wind fields were computed over Mozambique using CLIMADA's TropCyclone module based on the wind-field algorithm of Holland et al. (2008) at a resolution of 150 arcsec. The flood footprint of the event, including the contributions from storm surge as well as fluvial and pluvial flooding, was modeled based on Sentinel-1 SAR imagery. An automated-threshold classification (Otsu 1979) was applied to retrieve a binary surface water extent (flooded or not flooded) at a resolution of 10m. Hazard footprints are displayed in Figure 1, left.

'Exposure' represents the geo-located critical infrastructures at component level which are potentially at risk, and their associated value (see Fig. 1, left). Data was obtained from OpenStreetMap for healthcare facilities, main roads, power plants, cell towers and school facilities. High-and medium voltage power lines were obtained from the gridfinder project (Arderne et al. 2020); cell towers from an OpenCellID based rasterized map from the World Bank open data platform. Power towers were inferred and substation-locations were inferred along power lines. Gridded population count data was obtained from the WorldPop project (WorldPop 2020).

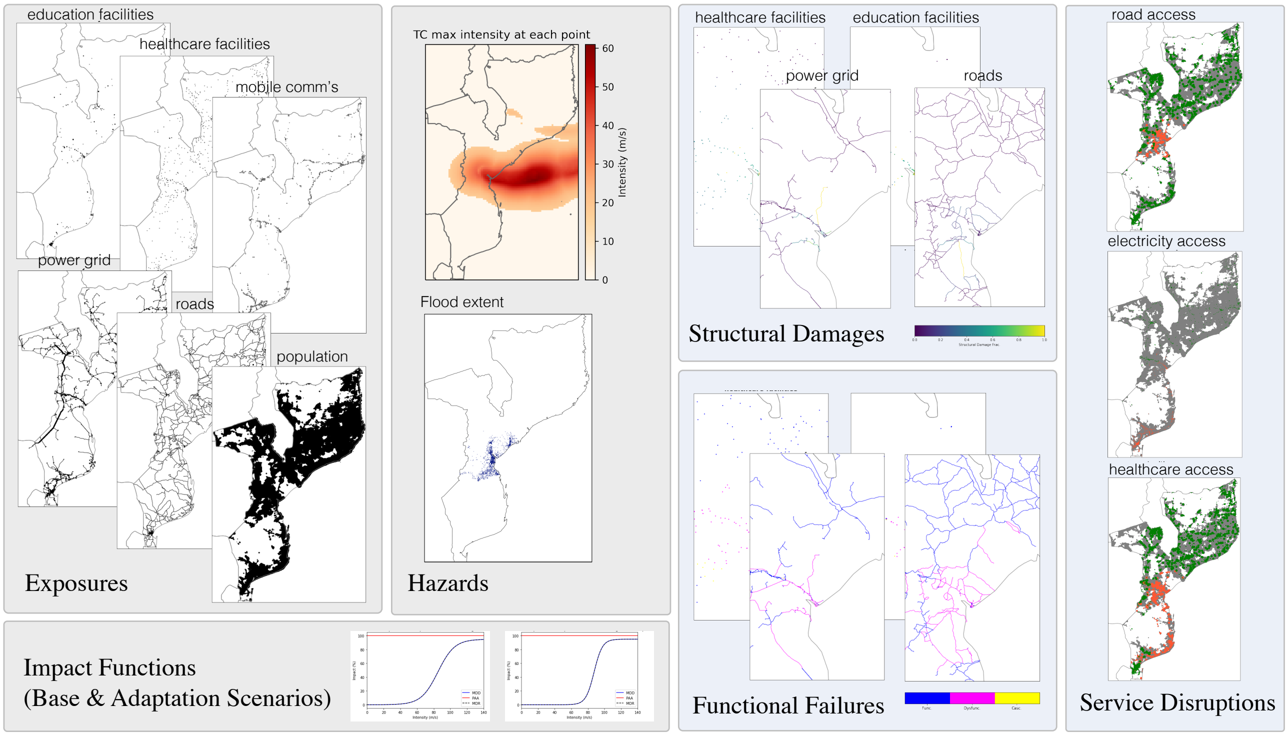

Figure 1: Schematic of the computation chain within CLIMADA. Gray - inputs to the systemic risk assessment and adaptation appraisal for Mozambique's healthcare sector, including six infrastructure and population exposure layers, flood and wind hazards from TC Idai, and various adaptation option parametrizations. Light blue - outputs metrics are structural damages to infrastructure components, functional infrastructure failures, and spatially explicit patterns service disruptions to the Mozambican population.

'Vulnerability' is a hazard- and infrastructure component specific function, relating hazard intensity to the degree of expectable structural damage. Vulnerability curves were obtained from literature for wind stress impacts on roads, power lines, power towers, cell towers, healthcare facilities and schools. Vulnerability curves for flood are constructed as binary step functions (damaged when flooded), and were applied to roads, substations, healthcare facilities and schools. Power plants are not designed to fail and hence not modeled as susceptible to either hazard.

The product thereof, 'direct risk' or 'impact', is measured in terms of the structural damages incurred by the infrastructure components. Direct impacts were computed for all exposures under three base scenarios (referring to the settings without adaptation assumptions): two single-hazard events, i.e. only flood and only wind, and one compound hazard event, where impacts from both flood and wind were summed on each exposure and capped at 100% of the respective values.

2.2. Failure Cascades and Service Disruptions Module

Indirect impacts - functional failures of infrastructure systems, failure cascades, and basic service disruptions - were computed using an interdependent infrastructure network model (Mühlhofer et al. 2022). The graph-based approach transforms spatial data of above-mentioned infrastructures and population clusters into directed edges and nodes. A set of rule-based and data-supported heuristics infer functional dependency links between components of different infrastructure systems, and service provision links between end-users and infrastructures. Qualitative examples of these link types and their generation approach are given below.

Functional infrastructure dependences

- **power supply -** A targeted edge is placed from the nearest substation node to hospital and school nodes**.** Functionality is upheld if the power grid runs at 60% or more of its normal capacity, else the dependent nodes fail. Not applicable to major hospitals (we assume generators to be available).

Service access dependences

- **access to healthcare** - Targeted edges are placed from healthcare facility nodes to population cluster nodes if they are reachable via functioning roads within one hour of driving at average speed, or if they are reachable by walking as the crow flies, at terrain-dependent speed, for less than one hour. Healthcare access is disrupted if no functioning facility is accessible according to those rules.
- **access to mobile communication** → Targeted edges are placed from cell tower nodes to population cluster nodes if they are located within a distance representative of typical rural cell site ranges. The service is disrupted if no single functioning link remains.

Structural damages from the previous risk computation stage introduce disruptions into the interdependent network, which may hence lead to functional infrastructure component failures upon surpassing design thresholds, which can cascade further across the systems along dependency links, leading to eventual service disruptions at population nodes.

2.3. Adaptation Appraisal

Adaptation measure packages for the healthcare sector were conceptualized in two categories: Structural adaptation measures (SAMs), reinforcing existing infrastructure components to withstand higher hazard intensities; and network adaptation measures (NAMs), reconfiguring the topology of the interdependent infrastructure network. Five different packages were parameterized.

Structural Adaptation Measures (SAMs):

- **SAM1 -** Wind-and flood proofing of healthcare facilities (through roof-reinforcements and flood protections). This package acts only on the healthcare infrastructure itself, and is parametrized by shifting healthcare impact functions for flood and wind towards higher intensities in the Sofala province.
- **SAM2 -** Flood proofing of primary and secondary roads, hardening of power infrastructure. This package acts only on supporting infrastructures, and is parametrized by shifting road, power line, power tower and substation impact functions for flood and wind towards higher intensities in the Sofala province.
- **SAM3 -** Combination of SAM1 and SAM2, at a financial trade-off of implementing both measures only on half of the infrastructures in the Sofala province. Components receiving this measure were randomly sampled.

Network adaptation measures (NAMs)

- **NAM1** - Increasing primary healthcare facility density by 50% across the Sofala region. Six geo-located points were randomly sampled within the Sofala province to mimic newly constructed facilities.
- **NAM2** - Ramping up of generator capacities for all types of healthcare facilities within the Sofala province. This was implemented by removing the power dependence heuristic in the region.

To evaluate the effect of SAMs, structural impact calculations were performed with adjusted impact functions, and resulting failure cascades and service disruptions were re-computed on the interdependent infrastructure network as explained above. To evaluate the effect of NAMs, new interdependent infrastructure networks were computed, as these measures changed the topology of the initial graph, by introducing new network nodes (additional healthcare facilities) and by modifying dependency links. Direct impacts and cascades were simulated accordingly. All adaptation measure packages were evaluated under all three hazard scenarios (TC wind only, flood only and compound wind-and-flooding).

3. RESULTS

3.1. Structural Damages and Service Disruptions

Figure 2 shows simulation results for numbers of people experiencing basic service disruptions under non-adapted ("initial") conditions, per hazard scenario. It is evident that wind-induced disruptions are the dominant cause for most types of experienced service disruptions (apart from access to mobility), and that service disruptions tend to spread well beyond areas which are directly (physically) affected by hazard impacts, cf. dashed lines for reference.

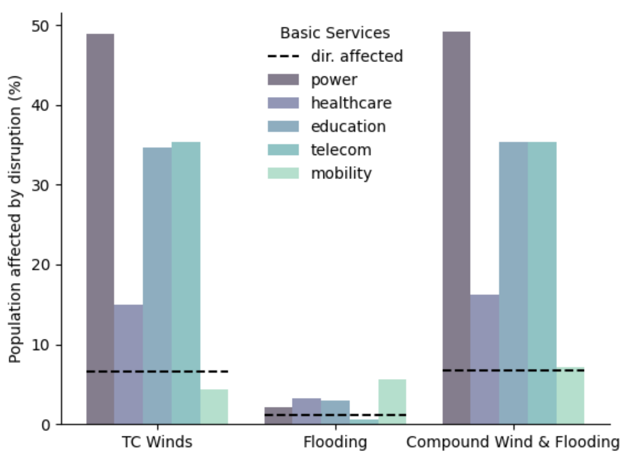

Figure 2 - Share of Mozambique's population affected by service disruptions, depending on the sub-hazards considered. Share of directly affected population marked in dashed lines for reference. Wind-induced disruptions dominate in magnitude over flood-induced disruptions, yet are not fully additive under a compound-event scenario.

Further, certain services are comparatively more prone to be disrupted by flooding than by winds, and vice-versa (cf. mobility and power, which are most and least affected depending on the sub-hazard). Lastly, the compound impact scenario reveals that sub-hazard impacts at the service level are not simply additive, but show escalating as well as redundant effects.

Figure 3 explores these dynamics for healthcare disruptions in more detail: For each population cluster, the failure-causing hazard scenario is marked. While some clusters experience disruptions due to either wind or flooding (orange and blue, resp.), others experience disruptions in both scenarios (pink, 'TC & FL'). Interestingly, some clusters *only* suffer from service disruptions in the compound hazard scenario (yellow, 'TCFL'), i.e. the interdependent system only fails to deliver services under joint impacts of both sub-hazards.

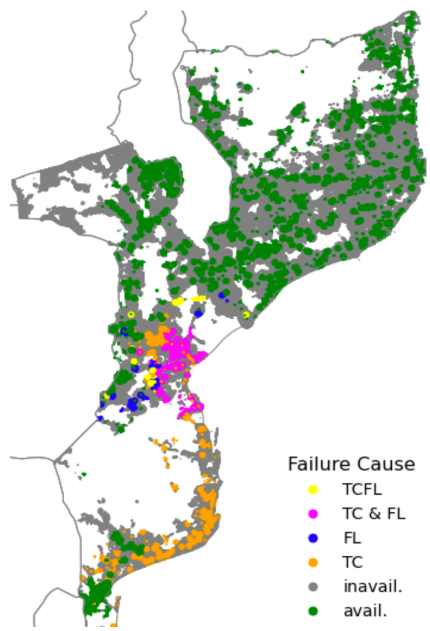

Figure 3 - Population clusters experiencing healthcare access disruptions, according to responsible (sub-)hazard scenario which causes the failure. TC & FL *refers to each sub-hazard independently causing access disruptions, whereas* TCFL *refers to the scenario in which only joint occurrence is significant enough to cause disruptions.* avail. *refers to undisrupted population clusters,* inavail. *to clusters which never had access to the service.*

3.2. Evaluating Adaptation Measure Packages

Figure 4 shows the effectiveness in reducing the number of people experiencing healthcare access disruptions according to measure and hazard scenario. Large differences are evident depending on which (sub-)hazard is considered: While package SAM2 (flood-proofing of roads and hardening of power infrastructure), for instance, works well in reducing flood-induced healthcare disruptions by reducing road access disruptions, it is the least effective one to mitigate wind-induced disruptions. Addition of more healthcare facilities (NAM1) proved futile without any further structural or systemic resilience-enhancing measures, as half of these facilities were directly damaged, while access ways were blocked to the remaining ones. Removing minor healthcare facilities' dependence on the main power grid (NAM2), in contrast, consistently showed positive effects. Yet, all measures decrease in effectiveness when considering the 'real' compound wind & flooding event as opposed to single sub-hazard scenarios.

Figure 5 demonstrates that some measures may feature substantial co-benefits in reducing other basic service disruptions (cf. SAM2 and SAM3, which have positive impacts on electricity and mobility). Lastly, the difference in aversion extents between figure 5 a) (structural damages) and 5 b) (service disruptions) highlight that, while adaptation measures may substantially reduce *physical* damages, this may not translate linearly into resilience at the *service provision* level. The opposite holds for network-based adaptation measures (NAMs), which have the potential to avert service disruptions, but do not reduce any physical damages.

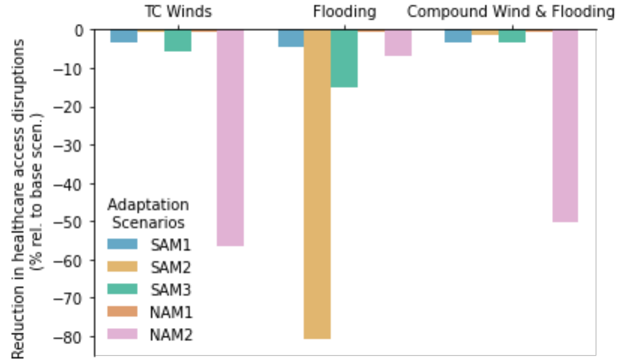

Figure 4 - Reduction of healthcare access disruptions through implementation of structural adaptation measures (SAM1-3) and network adaptation measures (NAM 1 & 2), compared to a no-adaptation scenario, under different (sub-)hazard scenarios.

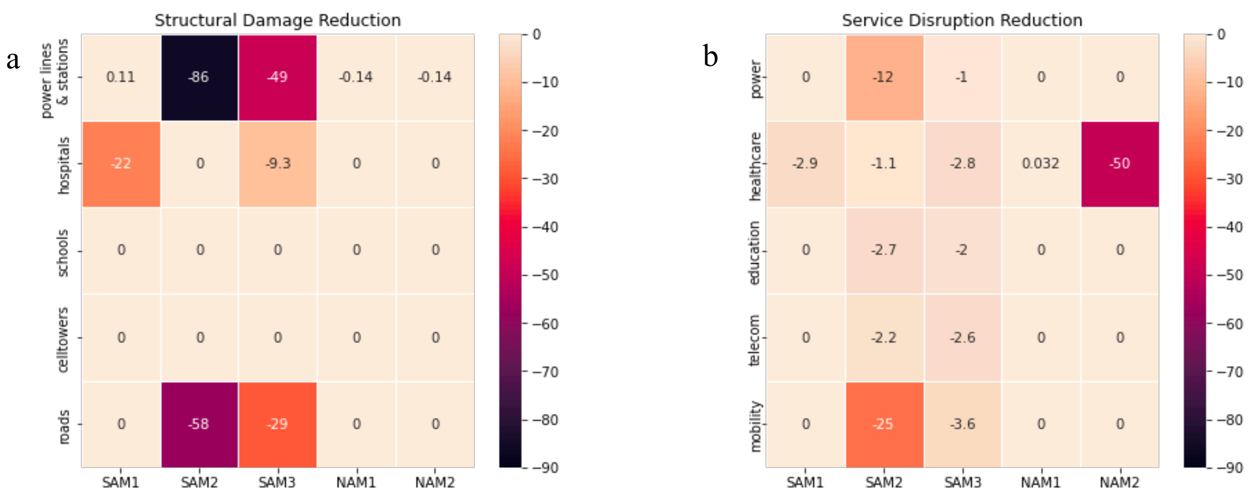

Figure 5 - a) Co-benefits of the implementation of structural adaptation measure packages (SAM1-3), under the compound wind and flooding scenario: reduction of structural damages (%) to critical infrastructure components across Mozambique, compared to the no-adaptation scenario. b) - Co-benefits of the implementation of structural adaptation measure packages (SAM1-3), under the compound wind and flooding scenario: reduction of other basic service disruptions across Mozambique's population (%) compared to the no-adaptation scenario. SAM2 has most co-benefits, yet is not the most effective one in mitigating healthcare disruptions (cf. Fig. 4).

4. DISCUSSION

This study provides us with some key insights in the modelling of systematic impacts of extreme events, based on the example of TC Idai in Mozambique. First, we find that most direct and indirect damages can be attributed to wind. However, some geographic areas are only affected by infrastructure failure when considering flood, and others only when considering the compounding effect of flood and wind. This demonstrates the importance of considering sub-hazards. Second, we find that system interdependences may lead to a different impact footprint of the event, with people losing access to healthcare infrastructure even in areas where no direct damage is observed. Third, we find that adaptation measures fare differently in mitigating direct and systemic (service-level) impacts. To protect the access to healthcare services, reducing facilities' dependence on the power system through generators seems to bring more benefits than flood and wind-proofing healthcare facilities, though latter fares better in reducing structural damages.

While interesting and unexpected dynamics can already be observed in this modeling prototype, three essential steps are required to make this framework suitable for robust decision-making: (1) Verifying the model assumptions and heuristics, (2) assessing the impacts of more events that better span the possibility space of current and future climate regimes and (3) considering the length of the disruption in the modelling.

As the results of this study are highly dependent on the heuristics used in the modelling, the first step would be to verify those. For example, we assume that smaller healthcare facilities do not have generators, which results in large disruption due to power failures. Reviewing event reports would allow us to compare modeled and observed impacts, and reverse-engineer some of the heuristics. Yet, while damage reporting on various infrastructure sectors was exceptional in the particular case of TC Idai (cf. Mutasa 2022 p. 11; Zimba et al. 2020; Williamson et al. 2023), under- and non-reported impact dimensions, and impacts in remote locations, are difficult to verify. Consultations with stakeholders who have experienced the event, or the reconstruction phase would be crucial to verify and adapt some of the less observable modeling assumptions (Zischg et al. 2021).

The second step involves moving from analyzing one historical event to considering probabilistic event sets driven by different climatic conditions. Several methodologies allow for the creation of synthetic tracks for current or future climate. The TC module in CLIMADA creates a chosen number of tracks from historical tracks by applying a direct random-walk process to those and simulating future climates by modifying frequencies and intensities (Bresch & Aznar-Siguan, 2021). Alternatively, the fully statistical STORM model can also provide present and future tracks (Bloemendaal et al. 2020). However, as demonstrated in the results for TC Idai, this is not sufficient to assess infrastructure risk, as a significant portion of people losing access to healthcare can be explained by flooding. A globally applicable framework has recently been developed to simulate storm compounds surge and river flood caused by a specific storm, using a local high-resolution 2D hydrodynamic flood model (Eilander et al. 2022a).

Finally, the time duration of the (partial) disruptions should be considered, as people may for instance temporarily lose access to healthcare facilities due to flooding of roads, yet experience longer lasting restrictions from destroyed facilities.

5. CONCLUSION

In this study, we examined the impacts of a compound wind and flood event (TC Idai) on critical infrastructure components (roads, power grid, healthcare facilities and schools), system functionality, and service provision levels in Mozambique. We highlighted the importance of considering all relevant sub-hazards of a disaster, as well as system interdependencies, to capture the potential for cross-system failure cascades and differential vulnerability patterns. Focusing on improving resilience of the healthcare sector, we evaluated several structural and network-changing adaptation measure packages in their effectiveness to reduce physical infrastructure damages as well as the number of people who experience service disruptions.

Results indicate that some measures may have substantial co-benefits in terms of reducing other service disruptions, yet that often, structural damage aversions fall short of translating linearly into service disruption aversion. We discussed pitfalls of our stylized proof of concept, and laid out an agenda to use the presented open-source model for probabilistic and hence more comprehensive adaptation measure appraisals which are capable of integrating climate change signals to support the development of robust adaptation strategies.

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