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Critical intervention points for European adaptation to cascading climate change impacts

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A list of authors and their affiliations appears at the end of the paper

In an interconnected world, climate change impacts can cascade across sectors and regions, creating systemic risks. Here we analyse cascading climate change impacts on the EU, originating from outside the region, and identify critical intervention points for adaptation. Using network analysis, we integrate stakeholder-co-produced impact chains with quantitative data for 102 countries across foreign policy, human security, trade and finance. Our archetypal impact cascade model reveals critical intervention points related to water, livelihoods, agriculture, infrastructure and economy, and violent conflict. Livelihood instability, with violence exacerbating conditions in conflict-prone regions, tends to amplify risks of cascading impacts emerging from low-income countries. High-income countries can trigger cascading impacts through, for example, reduced crop exports. Our findings highlight the importance of policy coherence in addressing interconnected vulnerabilities rather than isolated risks. Thus, agricultural intensification without integrated water management may exacerbate scarcity, whereas safeguarding livelihoods alleviates cascading risks related to forced migration, violent conflict and instability.

Cascading climate change impacts are sequences of direct and indirect natural and social effects triggered by initial climate change-related events such as extreme weather[1]. Fostered by the interconnectedness of natural, human and socio-economic systems, they are characterized by chain reactions that propagate through geographical, sectoral and temporal boundaries. Cascading climate change impacts can induce unforeseen and sometimes far-reaching effects, potentially affecting political and social stability worldwide[2–6]. A notable example illustrating the complex interplay between climate change and socio-economic stability is the Arab Spring and its cascading impacts on the European Union (EU). Extreme weather caused crop failure at many locations globally in 2010 and 2011[7]. This shortfall in staple food production was further exacerbated by an export ban of grains by Russia, the high demand for biofuel crops and copycat investor behaviour in the financial commodity markets ('herding'), which drove up crop prices, ultimately leading to a food crisis[8,9]. Countries heavily reliant on crop imports, already grappling with poverty, inequality, weak governance and a history of conflicts, found themselves particularly vulnerable to higher food prices[7,10]. The additional societal pressure, in the context of historical state repression, contributed to the outbreak of conflicts and civil war in the Middle East and North Africa, which in the EU resulted in an increase in refugees and associated political fallout regarding immigration[11,12].

Despite the wide societal relevance of cascading climate change impacts, and with the exception of a few examples such as the Arab Spring, there is little knowledge on how to study these complex system dynamics in real-world settings. A myriad of dynamics can influence how impacts propagate[1,13], and these dynamics do not always follow a unidirectional hierarchical cascade[13] but can have feedback loops that amplify or dampen effects[13–15]. Research on cascading impacts in global socio-economic systems mostly looks at the co-occurrence of impacts across interconnected systems[6] or investigates individual systems within impact chains[16,17]. More detailed analyses exist at the local level as case studies[18,19] or sector-specific studies (for an overview see, for example, ref. 6). However, a notable gap concerns the integration of socio-economic data into quantitative models for analysing

e-mail: cornelia.auer@pik-potsdam.de

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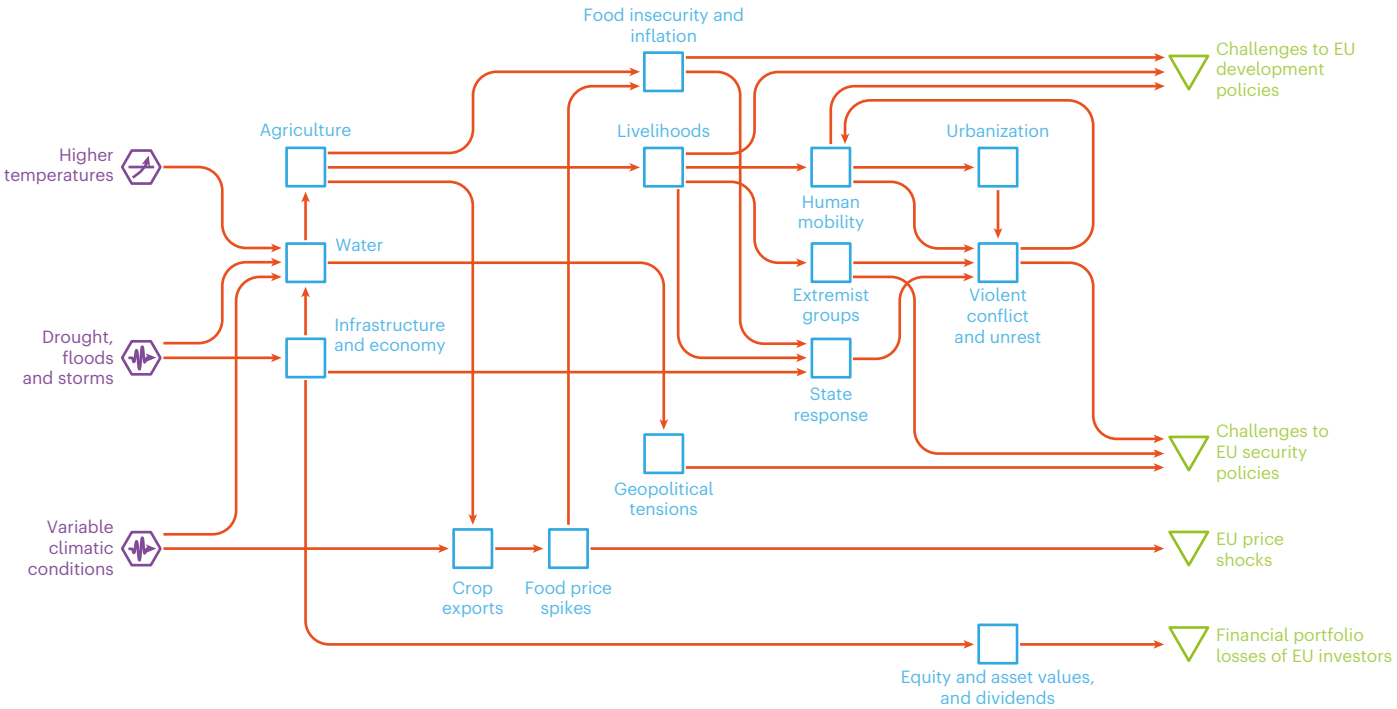

Fig. 1 | Archetypal network of cascading climate change impacts on the EU. The global network of cascading climate change impacts on the EU extracted from 14 impact cascade diagrams that were co-produced with stakeholders from the fields of foreign policy, human security, trade and finance. The figure distinguishes between climate triggers (purple icons), affected system components or process nodes (blue squares) and risks to the EU (green triangles). Propagation channels of impacts ('edges') are depicted as red lines.

impact transmission in heterogeneous systems. This integration is crucial for advancing our understanding and management of complex, interacting systems[17].

To address this gap, we analyse networks of cascading climate change impacts across diverse systems and processes, identifying nodes that serve as potential intervention points for adaptation. Among these, we prioritize nodes on the basis of their central position in the network and empirical data for their ability to limit or prevent cascading effects[15]. We call them 'critical intervention points for adapting to cascading climate change impacts' (in short 'critical intervention points'). In this Article, we focus on impacts originating outside, but potentially propagating into, the EU. To this end, we co-produced potential climate change impact cascades with stakeholders and experts in the fields of foreign policy, trade, human security and finance within and outside the EU, through a structured 4-year process involving ten workshops, supported by desk-based research and simulations. Collaboratively, we developed 14 input impact cascade diagrams, following a conceptual framework[1], representing cascading impacts as networks of nodes (components of affected systems or processes) linked by edges (impact propagation channels). Each diagram depicts climate triggers outside the EU leading to cross-sectoral and cross-border impacts that may require EU adaptation responses. Utilizing frequent sub-graph analysis[20,21], we derived a single archetypal impact cascade network from the 14 input diagrams, capturing common node–edge patterns. We customize this network for 102 non-EU countries by applying country-specific edge weights based on indicators of country-level climate-related risks, vulnerability as well as natural resource, labour and economic dependencies. The analysis excluded non-EU countries lacking sufficient data and all EU countries because the EU is the focus of the analysis. This gave 102 country-specific instances of the archetype such that, by applying an inverse PageRank[22] analysis, distinct critical intervention points could be identified per country. The analysis ranks nodes (for example, water, food and conflict) by accounting for both the network structure (that is, shared topology) and country-specific edge weights that modify node importance. Finally, we aggregated countries via consensus clustering[23,24] to identify regions with similar critical intervention points, highlighting shared vulnerabilities and adaptation needs as well as focal points for policy coherence. Extended Data Fig. 1 provides an overview of the methodological steps involved in this study.

Results

Applying frequent sub-graph mining on the 14 impact cascade diagrams (Methods, Extended Data Fig. 2 and Supplementary Table 2) enabled us to distil a single archetypal impact cascade network (Fig. 1 and Extended Data Fig. 3), capturing repetitive patterns and dynamics that emerge for the climate triggers 'higher temperatures', 'variable climatic conditions' and 'droughts, floods and storms'. Moreover, the analysis reveals several nodes that can be either system components or processes that frequently propagate cascading impacts. For human security and development, these include 'water', 'agriculture', 'infrastructure and economy', 'state response', 'livelihoods', 'violent conflict and unrest', 'geopolitical tensions', 'extremist groups', 'human mobility' and 'urbanization'. For supply chains and businesses, the nodes 'crop exports' and 'food price spikes' were identified. In the financial sector, 'equity and asset values, and dividends' emerges as a central node. Our stakeholder engagement reveals that these particular impacts occurring outside the EU could potentially cascade into the continent. Of particular concern to stakeholders are 'challenges to EU development policies' and 'challenges to EU security policies', 'EU price shocks' and 'financial portfolio losses of EU investors'. For a full description of all nodes, see Supplementary Note 2.

Country-level critical intervention points

Building on the archetypal impact cascade network, we designed a data-driven, country-level analysis to identify critical intervention points for adapting to cascading climate change impacts from the perspective of the EU. We excluded all 27 EU countries because they

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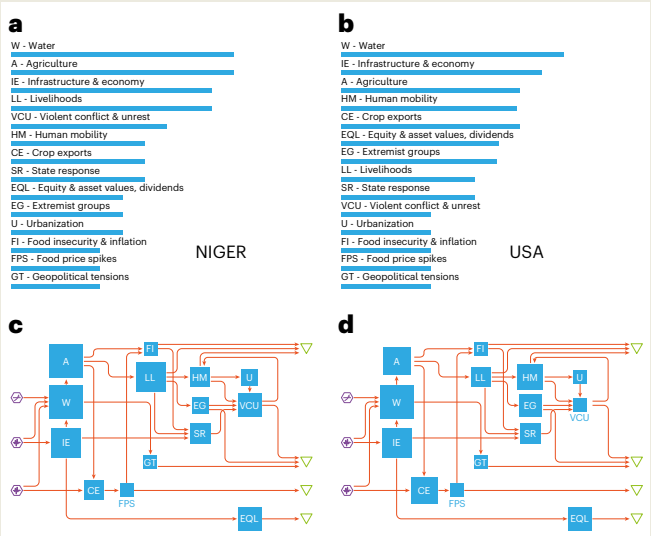
BOX 1

Analysis for Niger and USA as two example countries

We illustrate our findings with the results for Niger and the USA (Fig. 2), where differing edge weights yield distinct intervention priorities. Water has the highest PageRank in both countries and is the main critical intervention point. Secondary priorities diverge: in Niger, agriculture is also a critical intervention point, ranking as high as water owing to its systemic linkages with livelihoods, conflict and migration, all of them also highly ranked. In the USA, infrastructure and economic resilience are highly relevant, with agriculture retaining importance owing to its disruption risks by crop exports. The high rank of equity and asset values underscores the interconnectedness of the EU and US economy and finance.

These two examples also demonstrate how node importance arises from different contexts. For instance, the high rank of water in the USA reflects its role in buffering the EU against cascading climate impacts, although the edge weights for the USA do not emphasize water-related risks. The network analysis reveals an indirect link between water availability and 'crop exports': The USA not only is a large agricultural producer, where water is required, but also exports crops and hence has high weights on 'crop exports'. Issues with water availability can therefore trigger declining exports and spikes in food prices, which is detected by our recursive PageRank analysis. Countries in the Sahel, such as Niger also show the highest ranking of intervention points related to 'water'. 'Agriculture' also remains a key node, but in these regions, 'water' is also tightly connected to 'geopolitical tensions', which is not the case in the USA. Niger's high weights on 'geopolitical tensions' point towards potential cascading impacts starting from a food–water–conflict nexus.

While the cases of the USA and Niger are provided as examples, analysts can reconstruct similar intricate impact pathways for each of the 102 countries covered in our analysis by looking at the input weights (Supplementary Table 4) and the inverse PageRank values (Supplementary Data 1). Even if a node in a particular country is not currently under stress, a high inverse PageRank value and low input weights indicate a central position in potentially triggering cascading effects. Therefore, this node could be prioritized for monitoring and adaptation planning. Conversely, if both the PageRank value and input weights are high, cascading impacts are likely to emerge, reinforcing the acute need for adaptation measures in the country. We have brought together the standardized input weights and the inverse PageRank values for each of the 102 countries in Supplementary Data 2 and marked those pairs where input weights at the network edges suggest low risk but where PageRank detects a risk.



Application of the archetypal network for Niger and USA as two example countries. a,**b**, Rankings of the importance of nodes from top to bottom for Niger (**a**) and the USA (**b**) based on their inverse PageRank values. **c**,**d**, The archetypal impact cascade network instances for Niger (**c**) and the USA (**d**) with nodes scaled in proportion to the inverse PageRank result values for each country. A high ranking defines nodes as critical intervention points that act as potential hubs for cascading impacts on the EU.

are the focus of the analysis and also excluded non-EU countries that lacked sufficient data. We assumed that the archetypal impact cascade network represents generic connections to the EU for each of the 102 countries, as defined by our stakeholder process. Data-driven weights were assigned to the 39 edges connecting the 25 nodes for each country, reflecting the potential for negative impact propagation. Higher weights indicate greater risk of transmission; for example, increased weights between livelihoods and human mobility suggest a higher likelihood of displacement due to livelihood losses, based on indicators of development and deprivation. This approach maintained a consistent network structure while accounting for country-specific vulnerabilities through individual edge weighting. These weights came from publicly available indicators (for example, from the World Bank and the Joint Research Centre), always using the most recent available data, and from simulation models (for all data sources, see Supplementary Note 1). After constructing the archetypal impact cascade network instances for the 102 countries, we used an inverse PageRank analysis to identify critical intervention points, that is, nodes that rank highly for the respective countries, act as potential hubs for cascading impacts on the EU and could be priority points of intervention (see for two specific country examples Box 1).

Analysis for 102 countries

We further analysed the ranking of nodes for all 102 countries (see also Box 1 for Niger and USA as two specific examples). For most countries (34/102), the highest ranked critical intervention points relate to 'water' followed by 'livelihoods' (32/102), 'agriculture' (25/102), 'infrastructure and economy' (7/102) and 'violent conflict and unrest' (1/102) (Fig. 2). Also among the second and third highest ranked critical intervention points, 'agriculture', 'water', 'infrastructure and economy' and 'livelihoods' dominate. Additionally, critical intervention points related to 'human mobility' (1/102; 5/102 second and third), 'crop exports' (1/102 in both second and third) and 'state response' (1/102 in both second and third) emerge among the second and third highest ranked critical intervention points.

Further, almost half of the analysed countries feature 'livelihoods' among the top three highest ranked critical intervention points. This node is connected to 'human mobility', 'state response' and 'extremist groups' in the underlying archetypal impact cascades network, indicating that all these aspects are affected by livelihood challenges. The node is more relevant for low and lower middle-income countries (46 of 52 countries, as classified by the World Bank[25]) as compared with upper middle and high-income countries (33 of 50 countries). As an

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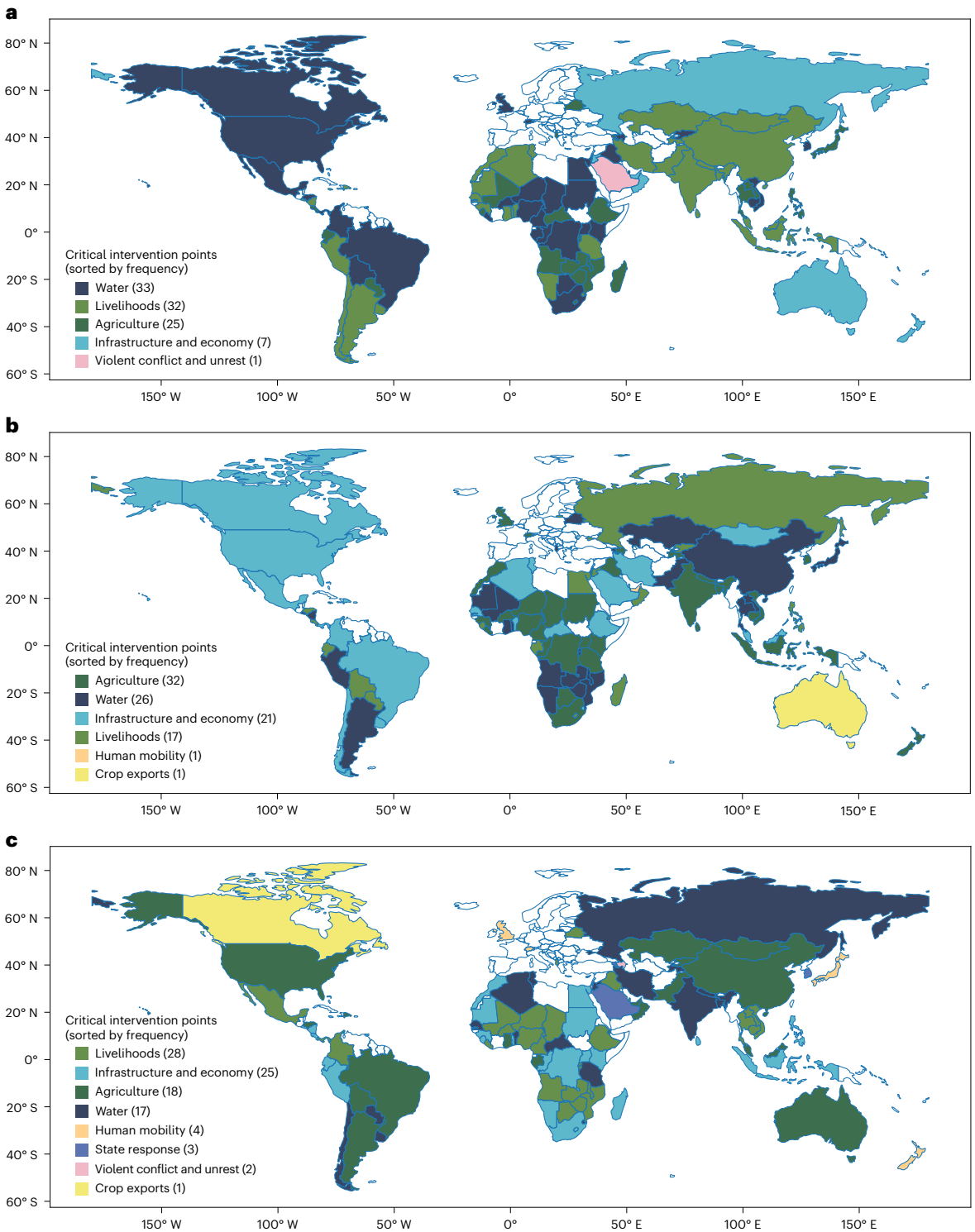

Fig. 2 | Country-level critical intervention points for addressing cascading climate impacts on the EU. a–**c**, The most influential (**a**), second most influential (**b**) and third most influential (**c**) nodes of the archetypal impact cascade network based on our PageRank analysis, for all 102 non-EU countries for which data are available. Legends sort the critical intervention points by frequency. Maps created with GeoPandas in Mercator projection with base map from Natural Earth (https://www.naturalearthdata.com).

example, our results highlight that, in countries such as Tunisia, India and Pakistan, livelihood issues potentially activate extremist groups, leading to further impacts. A similar, albeit weaker trend applies to 'agriculture', with 43 low and lower middle-income countries versus 35 high and upper middle-income countries being susceptible to climate impacts on agriculture triggering livelihood losses. Among those are 17 high-income countries that are large exporters of agricultural products (Supplementary Table 4) and hence susceptible to triggering cascading effects on 'food price spikes' via international trade. Conversely, the node 'infrastructure and economy' appears more frequently among high- (30) than lower-income (24) countries, as this node is linked not only to 'state response' and 'water' but also to 'equity and asset values,

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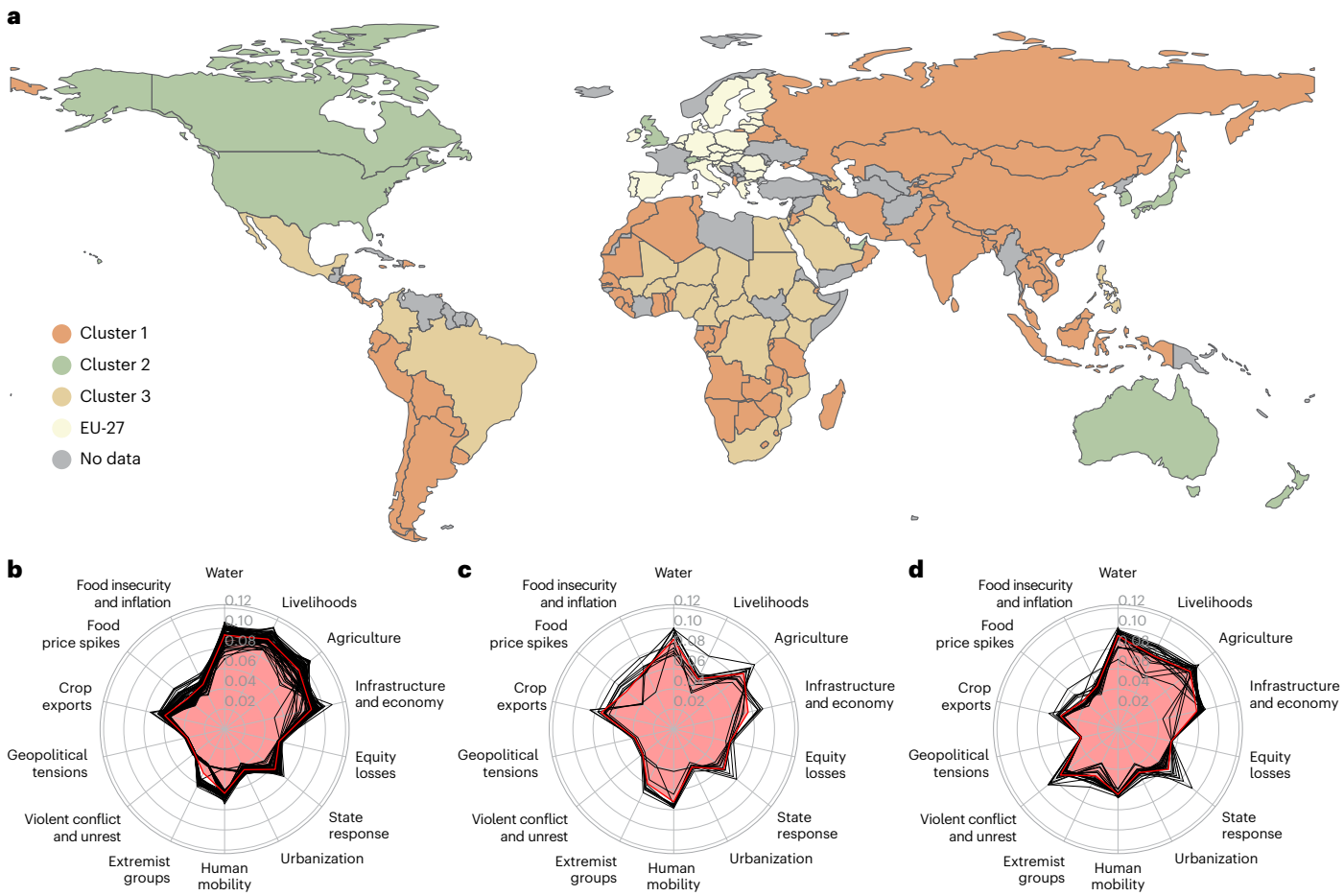

Fig. 3 | Clusters of critical intervention points across countries. a, A world map showing groups of countries clustered by similarly important critical intervention points for adapting to cascading impacts on the EU based on *k*-means. The basis of the clustering of the countries is the importance values of the nodes computed with the inverse PageRank methodology. **b**–**d**, Spider plots for cluster 1 (**b**), cluster 2 (**c**) and cluster 3 (**d**) with the nodes as axes. The black lines represent PageRank values of individual countries in the cluster for each node. The red line connects country-mean values for each cluster. EU countries are excluded because they are the focus of the analysis. Map created with GeoPandas in Mercator projection with base map from Natural Earth (https://www.naturalearthdata.com).

and dividends', which is more relevant in high-income countries. Of the high-income countries, Saudi Arabia is the only country for which 'violent conflict and unrest' ranks highest. In other conflict-prone countries such as Iraq, Sudan and Ethiopia, basic issues such as 'food price spikes', 'livelihoods' and 'infrastructure and economy' rank higher.

Clusters of critical intervention points across countries

Some countries exhibit close similarity in numeric inverse PageRank values (Supplementary Data 1), making reliance on numerical rankings alone suboptimal. Thus, we applied a *k*-means clustering approach[23] (Methods) to the inverse PageRank values of each country, grouping countries by the overall structure of their rankings while preserving the underlying rank information and emphasizing common adaptation needs.

This analysis reveals a clear division into three clusters (Fig. 3 and Extended Data Table 1): Clusters 1 and 3 encompass a mix of low- to high-income countries primarily from Africa, Asia and Latin America with either low (cluster 1) or high levels of 'violent conflict and unrest' (cluster 3). Cluster 2 is exclusively composed of high-income countries. Note that rankings of nodes are relative within each country, meaning that interventions in a high-income country with a high-ranking agriculture node may still be less substantial than those in a low-income country owing to the overall lower vulnerability of high-income countries.

To assess the uncertainty of our approach, we determined the optimal number of clusters analytically and validated cluster stability through consensus clustering (Methods). These sensitivity analyses showed that three is the optimal and most stable number of clusters for our dataset (Extended Data Fig. 4).

The system nodes 'water', 'agriculture', 'infrastructure and economy' are critical intervention points throughout most countries in all three clusters (Fig. 3). Notably, the node 'livelihoods' distinctly separates the clusters: higher income nations (cluster 2) exhibit a lower risk of livelihood and income loss among their populace, whereas this risk is more pronounced in lower- and middle-income countries (clusters 1 and 3). Moreover, the significance of the node 'violent conflict and unrest' is discernibly elevated in cluster 3, which encompasses conflict-prone nations in the Middle East, North Africa, the Sahel region and Latin American countries such as Brazil and Mexico. Cluster 2 exhibits a higher median for 'crop exports', attributable to the presence of strong exporting nations such as the USA and Australia, alongside import-dependent countries such as Norway and the UK. Finally, the high importance of a functioning 'state response' across all clusters underscores the role of governance and institutions, regardless of income level.

Discussion

We identify critical intervention points that could be targeted to enhance EU adaptation to cascading climate change impacts originating outside of the EU. Using stakeholder engagement and quantitative

network methods, our approach facilitates the identification of common and influential cascading impact transmission patterns affecting the EU. This information can guide adaptation planning by highlighting nodes that should be assessed for their potential to trigger cascading impacts. By capturing indirect transmission pathways, our method uncovers influential nodes missed in simpler analyses, as seen in the case of 'water'. More specifically, our analysis shows that 'water' and 'agriculture' emerge as central critical intervention points to adapt to cascading climate change impacts. Both are intrinsic to more than one distinct impact transmission system with the potential to affect the EU: they directly affect 'livelihoods'[25] with cascading impacts such as 'violent conflict and unrest' or 'human mobility' in lower-income countries[26–28], but they also affect the exports of agricultural commodities from higher-income countries and food price inflation[29–31]. Therefore, EU adaptation policies may need to be designed differently depending on the cluster in which countries with 'water'- or 'agriculture'-related critical intervention points belong. For lower-income countries (Fig. 3b,d) to ensure food security and stable livelihoods, the EU could support sustainable agriculture that does not compromise water management and provide support mechanisms for emergencies[25,32]. Here, Team Europe initiatives[33,34], which transfer funds directly to partner regions, offer a positive approach. The EU could further explore trade, regulatory and demand-side measures for sustainable water use in exporting countries[35]. In contrast, for higher-income countries, EU policies could address cascading impacts from 'water' and 'agriculture' via 'crop exports' by promoting supply diversification.

'Livelihoods' emerged as a critical intervention point for low and lower middle-income countries. While this is a key challenge against the backdrop of recent international development assistance cuts, EU countries could continue to prioritize livelihood support programmes, which are central to sustaining and diversifying incomes. Further, access to resources is essential for individual and regional stability[36]. The EU legislation on corporate due diligence and corporate accountability[37] can help in securing local land rights and decent incomes outside the EU. Stabilization of fair incomes helps to avoid important factors such as forced mobility[38], political grievances[39,40] or the growth of extremist groups[41–43]. Further, the EU should comprehensively plan its supply chain adaptation strategies: Abandoning existing trade relations[44,45] may inadvertently jeopardize local sustainable livelihoods, potentially inflicting a double blow on concerned regions: first from climate impacts, then from lost income sources[46].

The node 'infrastructure and economy' has central relevance in our analysis, in the context of bothEU investments in high-income countries and international support to low-income countries. The latter, as well as being crucial for economic recovery in the aftermath of climate disasters, is also invaluable proactively, in the form of climate finance and official development assistance for adaptation (for example, aid with high insurance premiums). The debt burdens in the global south[40] leave little fiscal space for an adequate 'state response' to address climate shocks. Emergency borrowing for climate crises diverts resources from critical adaptation needs, including maintaining essential public services, securing insurance mechanisms and preserving access to emergency financial resources[47–50]. This can create a vicious cycle where climate vulnerability worsens debt stress, which in turn reduces adaptive capacity.

The management of 'violent conflict and unrest' is critical to adapting to cascading climate impacts, especially in the context of a heightened risk of forced displacement. However, interventions in these high risk areas are challenging and often beyond the capacity of the EU alone[40].

'Food price spikes', 'crop export' dynamics and concerns around 'food insecurity and inflation' are particularly relevant for countries heavily involved in the trade of agricultural commodities. Market and policy responses such as embargoes can amplify climate change risks, leading to global food price spikes[5,50], jeopardizing essential needs. Examples of 'shock absorbers' include stockpiles, monitoring of price developments and special mandates to act if thresholds are exceeded. As a last resort, price caps can buy time to implement countermeasures[47].

Finally, 'human mobility' is a concern for EU development policies. For individuals, migration can be a successful climate adaptation strategy, but its effectiveness depends on affordability and economic diversification[48,49,51]. In summary, any adaptation effort of the EU to address these critical systems requires close cooperation with the affected countries, respecting local expertise and sovereignty[52–54].

Despite strong roots in existing qualitative (for example, stakeholder engagement) and quantitative (for example, network modelling) methods, we acknowledge limitations to our analysis, which introduce uncertainty in the results. While our sensitivity analysis showed that uncertainty is low for our choice of clusters, inherent uncertainties remain associated with the data selected for weighting the edges for each country and the PageRank parameterization. Also, the stakeholder engagement, while extensive, originates from one EU-funded project, inherently skewing focus. Our archetypal impact cascade network, derived from 14 impact cascade diagrams, cannot provide an exhaustive assessment of all possible impact cascades in all countries and sectors. Future studies could foster the representative power of the archetypal connections by integrating a wider range of input cascades across varying social and political conditions or include more granular impact cascades for specific regions of interest[55]. For both, we suggest representing the network in a multilayer graph[56,57] to keep complexity manageable.

Further, we rely on historical data and hence may miss unprecedented or unknowable impact chains. Likewise, our analysis assumes static, linear relationships between nodes, which might not be adequate for complex links that are contested, for example, for 'violent conflict and unrest'[58] or 'human mobility'[59]. However, given the flexibility of our archetypal impact cascade network, future work could replace static edge weights with nonlinear functions[58], integrate 'storylines'[15] and facilitate the analysis of specific interventions[60,61]. For specific events, integrating storylines can further enhance the practical relevance and credibility, while providing a robust quantitative basis for analysis.

Finally, the methodology could be expanded to identify positive 'resilience cascades', using environmental challenges as potential 'windows of opportunity' for systemic transitions[62–65]. Here, our analysis could identify the most promising system nodes to support such transitions with coherent policies. It is essential, however, that the approach complements, rather than distracts from, practical adaptation efforts, with all insights cross-checked by local experts and regarded as supportive rather than definitive.

Despite limitations, we find value in analysing the complexity of interrelated cascading impacts from traditionally siloed disciplines. Our results provide a foundation to generate cascading risk profiles for individual countries and groups, enabling the design of targeted adaptation measures and policies. Recommendations[66] arising from this research may offer an initial blueprint for more coherent adaptation strategies in an interconnected world. Effective adaptation requires strategies addressing interconnected vulnerabilities, not isolated risks.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-025-02455-2.

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Cornelia Auer[1] ✉, Christopher P. O. Reyer[1], Weronika Adamczak[2], Chris Aylett[3], Magnus Benzie[4], Jan Philipp Berndt[5], David N. Bresch[6,7], Francesco Bosello[8,9,10], Giacomo Bressan[11], Timothy R. Carter[12], Simon Croft[13], Elisa Delpiazzo[8,9,10], Sophie Desmidt[14], Adrien Detges[15], Anja Duranovic[16], Stefan Fronzek[12], Katy Harris[17], Mikael Hildén[12], Lukasz Jarzabek[2], Ramon Key[8,9,10], Richard King[3], Paula Kivimaa[12], Richard J. T. Klein[17], Hanne Knaepen[14], Glada Lahn[3], Piotr Magnuszewski[2], Mikael Mikaelsson[17], Irene Monasterolo[16,18], Claire Mosoni[12,19], Ilona M. Otto[20], Ramiro Parrado[8,9,10], Samuli Pitzen[12], Benjamin Pohl[15], Oriol Puig[21], Hetty Saes-Heibel[1], Emilie Stokeld[13], Sara Talebian[17], Fabien Tondel[22], Ruth Townend[3], Chris West[13], Eckart Woertz[23,24] & Nico Wunderling[1,25]

[1]Potsdam Institute for Climate Impact Research, Member of the Leibniz Association, Potsdam, Germany. [2]Centre for Systems Solutions, Wroclaw, Poland. [3]Chatham House, the Royal Institute of International Affairs, London, UK. [4]Stockholm Environment Institute, Oxford Eco Centre, Oxford, UK. [5]Lund University, Lund, Sweden. [6]Institute for Environmental Decisions, ETH Zurich, Zurich, Switzerland. [7]Federal Office of Meteorology and Climatology MeteoSwiss, Zurich, Switzerland. [8]Ca' Foscari University of Venice, Venice, Italy. [9]CMCC Foundation–Euro-Mediterranean Center on Climate Change, Venice, Italy. [10]RFF-CMCC European Institute on Economics and the Environment, Venice, Italy. [11]Vienna University of Economics and Business (WU Wien), Vienna, Austria. [12]Finnish Environment Institute (Syke), Helsinki, Finland. [13]Stockholm Environment Institute York, University of York, York, UK. [14]European Centre for Development Policy Management, Brussels, Belgium. [15]adelphi Research, Berlin, Germany. [16]School of Economics, Utrecht University, Utrecht, the Netherlands. [17]Stockholm Environment Institute, Stockholm, Sweden. [18]Center for Economic Policy Research, London, UK. [19]University of Helsinki, Helsinki, Finland. [20]Wegener Center for Climate and Global Change, University of Graz, Graz, Austria. [21]Pompeu Fabra University, Barcelona, Spain. [22]Meta Practica, Maastricht, Netherlands. [23]German Institute for Global and Area Studies, Hamburg, Germany. [24]Barcelona Centre for International Affairs, Barcelona, Spain. [25]Center for Critical Computational Studies, Goethe University Frankfurt, Frankfurt am Main, Germany. ✉e-mail: cornelia.auer@pik-potsdam.de

Methods

Our methodology used an extensive new set of empirically derived and model-based research analyses of 14 regional impact cascades. A network analysis was used to identify common and recurrent patterns of impact cascades affecting the EU that might merit policy intervention. Indicators that characterize aspects of these impact cascades at country level worldwide were identified from empirical data. Synthesis was achieved by applying statistical methods of normalization across the combined datasets. Extended Data Fig. 1 provides an overview of the data sources and methods applied.

Stakeholder engagement and co-production of impact cascade diagrams

The 14 impact cascade diagrams underlying our analysis were developed through a comprehensive stakeholder engagement and co-production of knowledge process organized over a 4-year period from 2019 to 2023 as part of the project 'Cascading climate risks: towards adaptive and resilient European societies—CASCADES'. The stakeholders provided the majority of input on potential impact cascades that could reach Europe. Some impact cascades have been extended by expert elicitation, desk-based studies or model results from within the CASCADES consortium as documented in Supplementary Table 2.

Stakeholders were selected through an initial stakeholder mapping exercise[67] to provide a wide range of expertise on foreign policy, human security, development, trade and international value and supply chains, as well as finance. These are examples of topics that, in their appropriate context, may have a central role in the propagation of climate change impacts[1]. The selection of regions and case studies used as examples for the stakeholder exercises was based on an initial screening of how the EU is connected to the rest of the world[68] and further refined according to available data and stakeholder interests. For topics concerning foreign policy, human security and development, the key focus areas were the Euphrates–Tigris Basin, central Sahel, North Africa and Middle East (two different case studies) regions because of their special relevance to the EU. Two additional case studies also focussed on South Asia and Central Asia (impact cascade diagrams 1–7 in Supplementary Table 2). The impact cascade diagrams exhibit patterns of how climate-related impacts propagate through interconnected system components and processes. Key nodes include system components such as water, agriculture, economy, infrastructure, livelihoods and food security. Further nodes in the impact cascade diagrams include processes such as state response, crop exports, human mobility, urbanization, violent conflict, extremist groups and geopolitical tensions, which can either mediate or escalate outcomes. Ultimately, these impacts can spill over into the EU, manifesting as challenges for development and security policies or as price shocks.

Trade and international value and supply chains were analysed by examining 'choke points' in global transport routes, such as the Suez Canal, Panama Canal, and Turkish Straits, affected by climate extremes such as storms and droughts. Additionally, impacts including crop failure and national transport disruptions caused by heatwaves, wildfires and river flooding (impact cascade diagrams 8–11 in Supplementary Table 2) were evaluated. These events consistently showed patterns of reduced exports and rising commodity prices, which can severely impact food security. The effects of cascading impacts on the financial system were analysed through case studies such as tropical storms in Mexico, heavy rainfall in Tunisia and sea level rise in North America (impact cascade diagrams 12–14 in Supplementary Table 2). Cascading impacts affect first the economy via capital destruction and productivity loss, negatively affecting firms' production and profits. These, in turn, translate into financial losses (for example, asset values), with knock-on effects on the repricing of investors' portfolios, and into higher investor risk in the EU.

Following case study selection, stakeholders were invited to join engagement activities that focussed both on specific topics fitting their personal profile, such as 'security', as well as on combinations of linked topics such as (food) trade, development and finance. A range of engagement methods were employed, including interviews, focus groups and policy simulations (Supplementary Table 1 and Extended Data Fig. 2). Additional stakeholders were continually brought in as they were identified by their initial peer groups (snowball sampling) and on the basis of new relationships emerging in the project context[68,69]. The selection of stakeholders, topics and regions was hence built on a systematic and comprehensive assessment of possible stakeholders, topics and regions and then refined to cover a diverse range of issues.

Altogether, ten workshops were held during the 4-year stakeholder engagement process, where potential cascading impacts were mapped in a consistent way. Supplementary Table 1 and Extended Data Fig. 2 highlight the composition of stakeholders, topics and exact dates of the workshops. The initial input impact cascade diagrams were systematically collected from the CASCADES scientific partners. To ensure cohesive integration of the interdisciplinary information, they were organized following the methodology of the conceptual framework from ref. 1. The framework depicts the transmission of climate change impacts diagrammatically as a network of nodes, symbolizing impacted systems, and connectors (in graph theory also called 'edges') that represent the channels along which impacts propagate. The interpretation of what constitutes a node or an edge, the direction of causal propagation, the sectors and jurisdictions involved and the ultimate destination of the potential impacts transmitted (described as the recipient risk) were for the stakeholders and analysts to define. Each impact cascade diagram illustrates how climate change impacts can propagate into the EU. These diagrams formed the basis for creating an archetypal impact cascade network, using a common framework and terminology for consistent analysis across diverse sectors, regions and stakeholders.

Deriving an archetypal impact cascade network from impact cascade diagrams

We created an archetypal impact cascade network from the 14 different impact cascade diagrams by applying a frequent sub-graph analysis to identify repetitive patterns across the impact cascades. The resulting archetypal impact cascade network was corroborated by participating researchers and supplemented with additional information, as required (for example, whether two similar impact cascades could be fully combined or if edges needed to be added).

Archetype analysis is a methodology that can help to identify and understand recurring patterns within complex systems[55,70–72]. It entails analysing a set of representative cases to extract common underlying structures, dynamics or behaviours. Here, it enables the identification of systemic vulnerabilities, and potential critical intervention points, which can contribute to more informed decision-making. Multiple approaches exist to identify archetypes[55]. We used a process-centred approach that employed frequency analysis of recurring interaction patterns, which is typically employed for small sample sizes[55]. Frequent sub-graph analysis[20,21] has been used in a range of application areas in medicine and social sciences. It focusess on the identification of recurring patterns within a set of graphs.

Note that, throughout the main text, we use the term 'network' for better accessibility. However, here in Methods, we will use the term 'graph', which is the standard terminology in mathematical and analytical contexts, particularly in graph analysis methods. We harmonized the 14 impact cascade diagrams as input graphs (G_i) to make them comparable and machine-readable, where $G_i = (V_i, E_i), i \in \{1 : n\}$, where V_i are vertices or network nodes and E_i are edges or transmission channels of impacts between the nodes. The nodes V_i of all G_i were processed such that similar node identifiers in different graphs were consolidated into one term; for example, a node with identifier 'armed groups' in

one graph and a node with identifier 'extremist groups' in another graph both received the harmonized identifier 'extremist groups'. This standardization enhanced the comparability of graphs and is documented in Supplementary Table 3. We acknowledge that this harmonization necessarily induces a simplification of the relationships, but it helps to ensure comparability between the different graphs. Further, because the 14 input graphs describe primarily impact cascades that revolve around specific events, we reclassified and clustered identifiers into corresponding systems (for example, 'reduced water availability' and 'decline in soil moisture' were reclassified under the identifier 'water') or processes.

Using the machine-readable graphs, we applied maximal frequent sub-graph mining[73,74] over all the G_i using the recursive pattern growth approach gSpan. We set the minimum support threshold at $\theta = 3$, meaning that all sub-graphs must occur at least three times, which is a trade-off between detail and the overall size of the graph: for example, a possible sub-graph that consists of the connected system components 'human mobility' → 'violent conflict and unrest' → 'state response' would have been added if it had occurred a minimum of three times in the 14 input cascades. Finally, from all the candidate sub-graphs, we extracted the maximal frequent sub-graphs $G_k = (V_k, E_k), k\,in\{1:m\}$ by isomorphic sub-graph matching. Hereby, a sub-graph is maximal if none of its super-graphs is frequent with respect to a support θ. In graph theory, two graphs G_i and G_j are isomorphic if there exists a bijection $f: V(G_i) -> V(G_j)$ between the vertex sets such that any two vertices u and v of G_i are adjacent in G_i if and only if $f(u)$ and $f(v)$ are adjacent in G_j.

With the isomorphic sub-graph matching, we extracted the largest common structures (sub-graphs) in the set of input graphs that fulfil the requirement $\theta = 3$. Finally, we obtained the archetypal impact cascade network G by merging the maximal frequent sub-graphs along their common nodes and edges: $G = \{v, e|v \in \{V_k\}, \text{and } e \in \{E_k\}\}$. For a technical depiction of the outcome, see Extended Data Fig. 3. Edge frequency values were used only to check the minimum support threshold in the frequent sub-graph analysis. Because they partly reflect the stakeholder/expert group composition and could bias results, we discarded them when building the archetypal impact cascade network. Node importance was instead based on real-world indicator weights and graph centrality (see 'Analysis of the archetypal impact cascade network with inverse PageRank for 102 countries').

After extracting the initial archetypal impact cascade network, the CASCADES research team reviewed it for validation and refinement (Supplementary Table 5), adding three missing edges (Supplementary Table 6).

Analysis of the archetypal impact cascade network with inverse PageRank for 102 countries

To analyse the archetypal impact cascade network and identify critical intervention points, we used recursive feedback centrality via the PageRank[22] methodology, which has been adapted for use in fields ranging from biology (GeneRank[75]) to finance (DebtRank[76]). PageRank, originally developed to assess the relative importance of web pages, evaluates not only the relevance of directly connected nodes but also the indirect propagation of importance throughout an entire network. This algorithm quantifies recursive feedback centrality, making it particularly suitable for analysing cascading impacts, where indirect connections through intermediary nodes are crucial. In our analysis, we modify the traditional application of PageRank by inverting all edges of the graph, resulting in a method that we refer to as inverse PageRank. While applying standard PageRank identifies nodes where impacts accumulate, our inverse approach identifies nodes that act as hubs and trigger cascading impacts by being connected directly or indirectly to many other nodes. We call these nodes critical intervention points and retrieve them as top nodes in a ranked list by using our methodology. For instance, a drought may disrupt the node 'water', leading to adverse effects on 'agriculture', which subsequently threatens the 'livelihoods' of small-scale farmers and drives 'human mobility', potentially towards the EU. To effectively measure the importance of 'human mobility', we need an approach that considers the entire chain of impacts, not just direct consequences such as 'livelihood' loss. By applying PageRank to the inverted graph, we can derive a ranking of importance values that reflect the underlying causes of 'human mobility', such as the impact on water and agricultural dependency. This recursive feedback centrality measure provides a more comprehensive understanding than local node importance metrics, such as in-degree or out-degree, which only account for direct impacts.

The archetypal impact cascade network provides a graph $G = (V, E)$ with nodes $v \in V$ and cascading channels between systems as edges $e \in E$. To identify critical intervention points, we reversed G to obtain the graph $G' = (V, E')$, with E' being the inverted edges $e'_{ij} = e_{ji} \in E$. Analysing the inverted graph G' ranks nodes by their cascading influence, i.e. how many other nodes they directly or indirectly affect. Nodes that frequently appear at the start of impact chains emerge as critical intervention points, indicating where adaptation measures could be most effective.

The PageRank of one vertex v_i was defined as $PR_i = (1-d)/n + d\sum_{j=1}^{n} PR_j/c_j$, with d being the damping factor and c_j the number of outgoing edges from vertex v_j. The inverse PageRank analysis returns a vector of ranked weights $\mathbf{pr}(G') = (w_{n_0}, \ldots, w_{n_n}), with\ n = |V'|$, which technically denotes the entries of the dominant right eigenvector of G's adjacency matrix. In the remainder, we call $\mathbf{pr}(G')$ the importance vector of G'. Note that we rescaled the weight so that each column adds up to 1.

Next, we conducted a data-driven inverse PageRank analysis at the country level. We applied the archetypal impact cascade network to all countries of the world (102 in total; country definitions from the United Nations), except countries from the EU because those are the focus of the analysis and those where we could not assign a full set of data-driven weights.

For each country graph, we assigned data-driven weights ranging between 0 and 10 to the archetype edges, where 10 denotes the worst and 0 the best conditions. These weights were derived from existing indicators available for each country such as the INFORM Risk index dataset, the Notre Dame Global Adaptation Initiative (ND-GAIN) index dataset, the Chatham House Resource Trade Earth dataset and from the Intertemporal Computable Equilibrium System (ICES) model. A description of the datasets and the mapping of edges and indicators is provided in Supplementary Note 1 and Supplementary Table 4. The weights signified the importance of connections; that is, edges with higher values suggest a potential increased likelihood of one node negatively influencing the other. Thus, for an edge between water and agriculture, we assigned the indicator 'freshwater withdrawal rate' (ND-GAIN dataset) to express the importance of the 'water' node on the 'agriculture' node. Assigning weights to edges rather than nodes allowed for flexibility in choosing indicators that best represent the specific relationship between two nodes. Different indicators can be used for edges starting from the same node but ending at different nodes. For instance, the edge starting from 'infrastructure and economy' to 'livelihoods' is represented by the indicator 'physical infrastructure' (INFORM risk index), which denotes the resilience of the infrastructure to climatic extremes. The edge that points from 'infrastructure and economy' to 'equity and asset values, and dividends' is assigned equity loss classes from the modelling results presented in ref. 77 that describe potential equity losses for individual investors across countries. Note, however, that multiple edges starting from an identical node can also share the same indicator if appropriate.

In total, we took 14 indicators from INFORM risk, 6 from ND-GAIN, 1 from ICES, 1 from Chatham House Resource Trade Earth, 1 from ILOSTAT (statistics of the International Labour Organization), 1 from the International Monetary Fund IMF) Coordinated Direct Investment Survey

and 1 from the European Central Bank Statistical Data Warehouse (Supplementary Note 1).

To highlight nodes whose systemic importance is not apparent from local edge weights alone, we systematically identified cases where a node's inverse PageRank value was among the five highest ranked nodes and at least five times greater than its mean outgoing edge weight. Such nodes are only revealed by our approach, which leverages the recursive feedback centrality captured by PageRank (Supplementary Data 2).

Clustering of countries with *k*-means on critical intervention points

The PageRank importance vectors for the individual countries enabled us to identify critical intervention points, that is, priority points for adaptation. However, as the resulting 102 importance vectors are hard to digest, we used a clustering that reduces the granularity of the information and still conveys the major insights. Geographic regions of similarity were clustered by the importance vectors $\mathbf{pr}(G_i) = (w_{i_0}, \ldots, w_{i_n})$, with $n = |V_i|$ as distinct data points that we received from the data-driven analysis of the 102 country-based graphs $G_i = (V, E_i), 1 \le i \le 102$. Note that all 102 graphs are structurally equal, but the edge weights differ.

The clustering on the importance vectors was based on the *k*-means clustering[23] combined with a consensus clustering strategy to minimize numeric noise[24]. *k*-Means assigns the *n* data point ensembles $\mathbf{pr}(G_i)$ to *k* clusters such that the variance within clusters is minimized while the variance between clusters is maximized. Thus, the total sum of the squared distances between the data points and the clusters' centroids $\{\mu_1, \mu_2, \ldots, \mu_k\}$ is minimized. The total sum of the squared distances was defined as $J = \sum_{i=\{1:n\}} \sum_{j\{1:k\}} \|w_i - \mu_{ij}\|^2$ where *k* is the number of clusters.

Sensitivity analysis for the optimal number of clusters

To identify the optimal number of clusters, we applied the elbow method and the silhouette score (Extended Data Fig. 4). We combined the elbow method[23] with an automated knee point detection[78] algorithm. The elbow method runs the algorithm with a range of numbers of clusters (for example, 2–20) and plots the percentage of variance explained by the clusters. The knee point detection algorithm then identifies the optimal number of clusters as the point with maximal curvature, which corresponds to the pivot of the elbow curve. In our case, this led to an optimal number of three clusters. The silhouette score[79] is a measure of how similar an object is to its own cluster (cohesion) compared with other clusters (separation). The silhouette score ranges from −1 to 1, where, the higher the value of all objects, the stronger the cohesion in the clustering configuration. The silhouette score indicated a peak at 3 clusters and lower peaks for 7, 11, 12 and 14 clusters. On the basis of the convergence of the results from these two distinct methods, the optimal number of clusters was determined to be three.

Sensitivity analysis for consensus clustering

After having determined the optimal number of clusters, a further uncertainty assessment was required for the clustering since *k*-means clustering can produce different output owing to numeric variations. Therefore, we conducted a sensitivity test based on a consensus clustering[24]. We ran 200 iterations of *k*-means with random restart for the three clusters. In each run, the pairwise cluster association was recorded for each country pair (i, j) in a co-association matrix m (also known as a consensus matrix), which represents the pairwise clustering stability, by incrementing $m(i, j)$ per run, where countries i and j are part of the same cluster. On the basis of the co-association matrix, we performed a hierarchical dendroid clustering using the Ward linkage method. This sensitivity analysis defined the final composition of the clusters, that is, the assignment of countries to the respective clusters (Supplementary Data 1). The final clustering delivered country groups containing countries (classified by income levels based on the World Bank[80]) most frequently clustered according to similar values of importance for potential critical intervention points (Extended Data Table 1).

Ethics statement

This research was deemed to comply with all relevant ethical regulations. The CASCADES project's internal Ethical Board developed and implemented the guidelines for the study procedures under the scrutiny of an external ethical advisor at Chatham House. We have obtained informed consent from all participants in accordance with the Regulation (EU) 2016/679.

Data availability

The 14 impact cascade diagrams co-produced with the stakeholders are provided in Supplementary Table 2. The data sources for weighting the edges of the archetypal impact cascade network for every country are described in Supplementary Table 4 and Supplementary Note 1. These data are also available as an input data set for the code repository via Zenodo at https://doi.org/10.5281/zenodo.15706192 (ref. 81). The output data produced both by the inverse PageRank and by the clustering are provided in Supplementary Data 1 and 2.

Code availability

The code used to generate the main results of this study is available via Zenodo at https://doi.org/10.5281/zenodo.15706192 (ref. 81).

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Author contributions

Conceptualization: C. Auer and C.P.O.R. with support from A. Detges, C.W., N.W. and I.M.O. Stakeholder engagement/interviews: H.S.-H., W.A., C. Aylett, D.N.B., M.B., F.B., G.B., T.R.C., S.C., E.D., S.D., A. Detges, A. Duranovic., S.F., K.H., M.H., L.J., R. Key, R. King., P.K., R.J.T.K., H.K., G.L., P.M., I.M., M.M., C.M., I.M.O., R.P., S.P., B.P., O.P., C.P.O.R., E.S., S.T., F.T., R.T., C.W. and E.W. Data collection from available sources: C. Auer with help from J.P.B. ICES data: F.B., R.P., E.D. and R. Key. Analysis: C. Auer with support from C.P.O.R. and N.W. Writing: C. Auer and C.P.O.R. with contributions from all authors. Figures: C. Auer, C.P.O.R. and P.M. Internal review and editing: T.R.C., C.W., C. Aylett, R. King., M.H., I.M.O., S.F., N.W., I.M., A. Duranovic, H.K., B.P., F.B., F.T. and R.T.

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Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Cornelia Auer.

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Extended Data Table 1 | Clusters of regions with similar critical intervention points

Cluster characteristics	Countries
Cluster 1: Countries in this cluster represent countries across all World Bank income groups. Their greatest commonality is the importance of the critical intervention points 'Water', 'Livelihoods', and 'Agriculture'.	**Low-income countries**: Burundi, Congo, Dem. Rep., Madagascar, Malawi, Mozambique, Nepal, Rwanda, Senegal, Sierra Leone, Tansania, Togo, Uganda
	Lower-middle-income countries: Angola, Bangladesh, Benin, Bolivia, Cambodia, Djibouti, Honduras, India, Indonesia, Kenya, Kyrgyzstan, Lao PDR, Lesotho, Liberia, Mauritania, Morocco, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Philippines, Sudan, Swaziland, Tajikistan, Tunisia, Ukraine, Usbekistan, Vietnam, Zambia, Zimbabwe
	Upper-middle-income countries: Albania, Algeria, Argentina, Belarus, Botswana, China, Costa Rica, Dominican Rep., Ecuador, Gabon, Ghana, Iran, Jamaica, Jordan, Kazakhstan, Mauritius, Mongolia, Namibia, Panama, Peru, Paraguay, Russia, Sri Lanka, Thailand, Turkmenistan
	High-income countries: Chile, Oman, Qatar, Uruguay
Cluster 2: The most pronounced feature of Cluster 2 is that in these countries the node 'Livelihoods' is not a pronounced critical intervention point. Indeed, the countries are all high-income countries. They share the importance of 'Water', and 'Agriculture' with all other clusters.	**High-income countries**: United Arab Emirates, Australia, Bahrain, Canada, Switzerland, United Kingdom, Japan, Republic of Korea, Norway, New Zealand, Singapore, United States of America
Cluster 3: This cluster has the distinct feature of 'Violent conflict & unrest' to emerge as a critical intervention point. The cluster shows a wide diversity among income levels of the countries. As in Cluster 1 'Water', 'Livelihoods', and 'Agriculture' emerge as highly important, though to a varied extent between countries. Some countries exhibit high values with respect to the node 'State response'.	**Low-income countries**: Burkina Faso, Central African Republic, Democratic Republic of the Congo, Ethiopia, Mali, Mozambique, Niger, Uganda, Chad
	Lower-middle-income countries: Armenia, Azerbaijan, Cameroon, Kenya, Nigeria, Philippines, Sudan
	Upper-middle-income countries: Brazil, Colombia, Egypt, Iraq, South Africa
	High-income countries: Israel, Mexico, Saudi Arabia

Individual countries are assigned to income groups as defined by the World Bank (see Methods).

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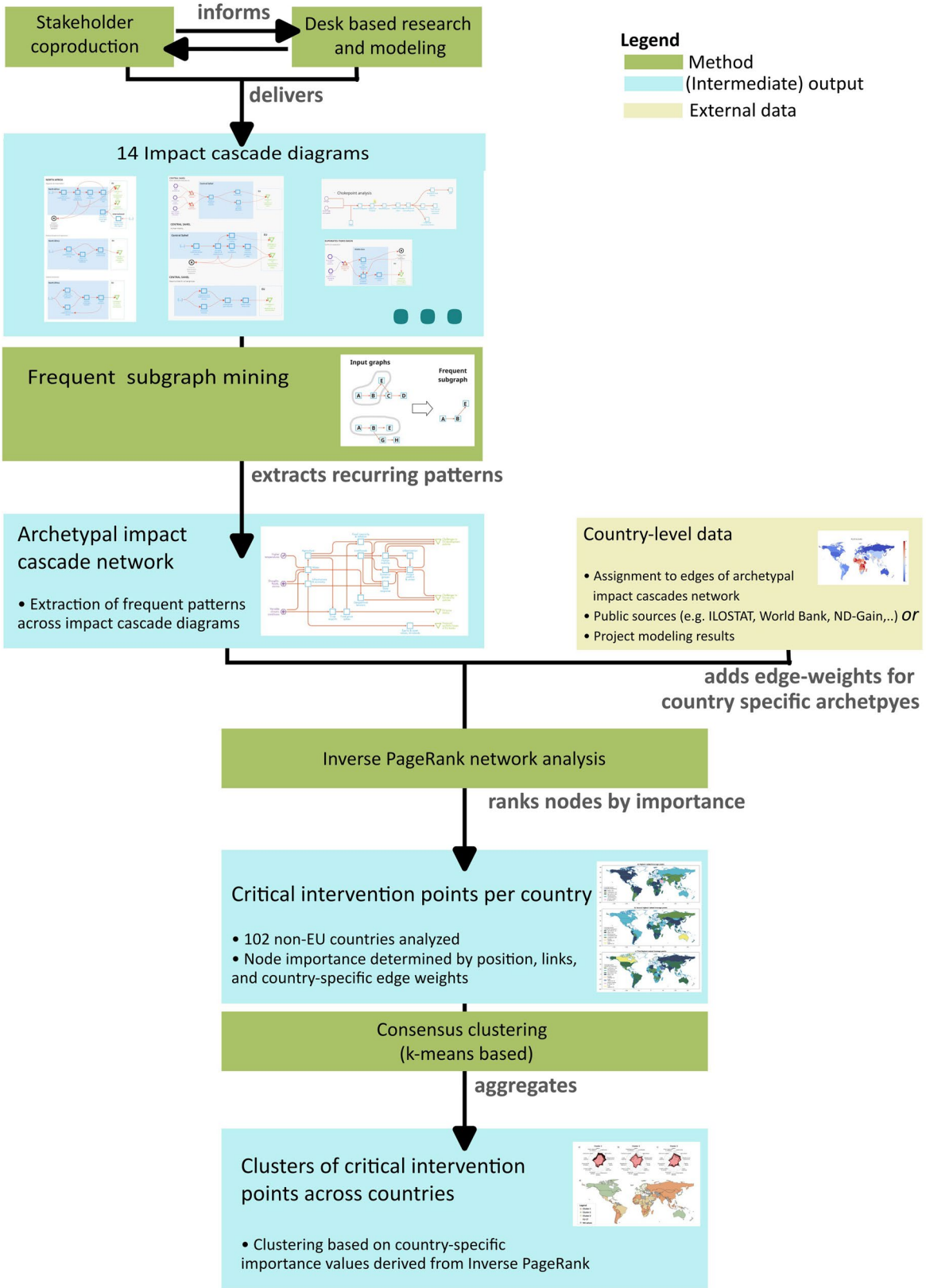

Extended Data Fig. 1 | See next page for caption.

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Extended Data Fig. 1 | Overview of the approach used to extract critical intervention points for adapting to cascading climate change impacts on Europe. A process of co-production with stakeholders and desk-based research with modelling resulted in 14 hypothetical impact cascade diagrams for different regions and sectors (all depicted in Supplementary Table2). The statistical analysis comprised three main steps. First, frequent subgraph mining was used to synthesize the 14 impact cascade diagrams into one archetypal impact cascade network (see main text Fig. 1). Second, country-level data on impacts and vulnerabilities across 102 countries were mapped onto elements of the archetypal impact cascade, and the Inverse PageRank network analysis method was applied to rank the most important critical intervention points per country (the three highest ranked per country are depicted in main text Fig. 2). Third, consensus clustering was used to group the most important critical intervention points into regional patterns to obtain a more comprehensive overview of the results of the PageRank analysis (see main text Fig. 3). Maps created with GeoPandas in Mercator projection with base map from Natural Earth (https://www.naturalearthdata.com).

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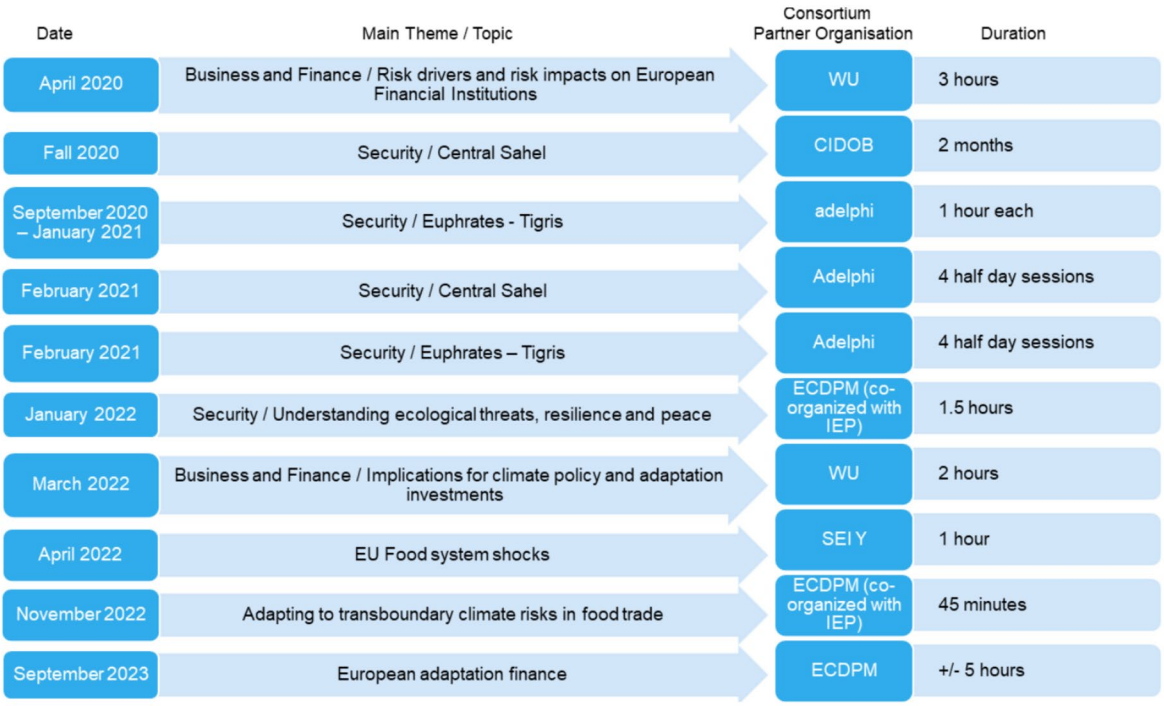

Extended Data Fig. 2 | Overview of 10 stakeholder events over the course of the 4 year long stakeholder engagement process within the CASCADES project that supported the development of the 14 impact cascade diagrams. WU = Vienna University of Economics and Business; CIDOB = Barcelona Centre for International Affairs; ECDPM = European Centre for Development Policy Management; IEP = Institute for Economics & Peace; SEI Y = Stockholm Environment Institute York. More details about the stakeholder composition can be found in Supplementary Table 1.

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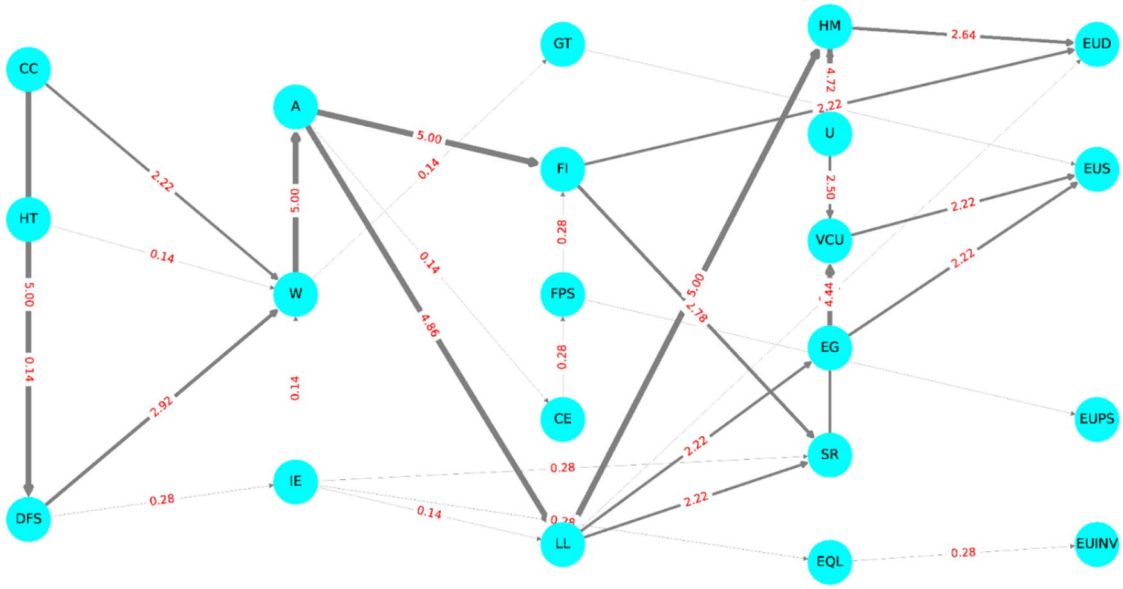

Extended Data Fig. 3 | Computer generated depiction of the archetypal impact cascade network. This network is the result of the frequent subgraph analysis and the subsequent subgraph merging of the impact cascade diagrams collected through stakeholder co-production, expert elicitation, desk based research and modeling results. The relative frequency of connections between nodes is illustrated by the thickness of the connecting edges and the red values above the edge. CC = Variable climatic conditions, HT = Higher temperatures, DFS = Droughts, floods, storms, W = Water, A = Agriculture, FI = Food insecurity & inflation, IE = Infrastructure & economy, LL = Livelihoods, HM = Human mobility, U = Urbanization, VCU = Violent conflict & unrest, SR = State response, EG = Extremist groups, GT = Geopolitical tensions, CE = Crop exports, FPS = Food price spikes, EQL = Equity & asset values, dividends, EUD = Challenges to EU development policies, EUS = Challenges to EU security policies, EUPS = EU price shocks, EUINV = Financial portfolio losses of EU investors.

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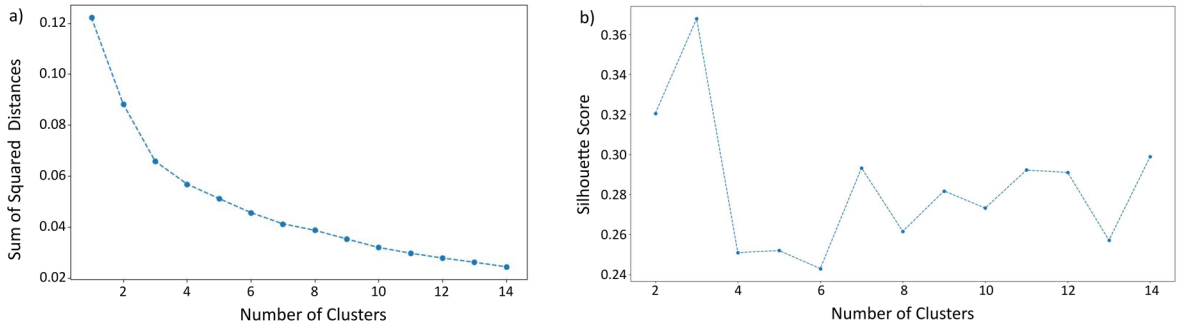

Extended Data Fig. 4 | Identification of optimal number of clusters. (**a**) The elbow method analyzes the sum of squared distances in dependence of the number of k-Means based clusters of 102 countries with respect to their PageRank importance vectors. The result yields an optimal number of three. (**b**) The silhouette score for intra cluster cohesion and extra cluster separation confirms the number of three clusters.