

Chapter 5

Connecting Hazard and Impact: A Partnership between Physical and Human Science



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Abstract The bridge from a hazard to its impact is at the heart of current efforts to improve the effectiveness of warnings by incorporating impact information into the warning process. At the same time, it presents some of the most difficult and demanding challenges in contrasting methodology and language. Here we explore the needs of the impact scientist first, remembering that the relevant impacts are those needed to be communicated to the decision maker. We identify the challenge of obtaining historical information on relevant impacts, especially where data are confidential, and then of matching suitable hazard data to them. We then consider the constraints on the hazard forecaster, who may have access to large volumes of model predictions, but cannot easily relate these to the times and locations of those being impacted, and has limited knowledge of model accuracy in hazardous situations. Bridging these two requires an open and pragmatic approach from both sides. Relationships need to be built up over time and through joint working, so that the different ways of thinking can be absorbed. This chapter includes examples of partnership working in the Australian tsunami warning system, on health impact tools

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for dispersion of toxic materials in the UK and on the health impacts of heatwaves in Australia. We conclude with a summary of the characteristics that contribute to effective impact models as components of warning systems, together with some pitfalls to avoid.

Keywords Economist · Epidemiologist · Engineer · Hazard · Impact · Exposure · Vulnerability · Ethics · Training data · Evaluation

5.1 Introduction

There is a growing recognition that users and decision makers make better informed decisions when warnings incorporate information about potential socio-economic impacts. In this chapter we show that:

- The impact of a hazard depends on the vulnerability of individuals and communities that are exposed to it.
- Weather-related impacts may be human (e.g. death or injury), financial (e.g. property damage or business loss) or service related (e.g. loss of power or transport links).
- Direct impacts can create a cascade of multiple indirect impacts.
- Impact predictions may be produced using process models or statistical models and should be probabilistic.
- Observations of impacts are fundamental for understanding, for monitoring and for verification but are often only accessible through partners.
- When linking impact and hazard models, care must be taken that variables represent the same things in each model, that space and timescales match and that biases are removed.
- Impact forecasters and hazard forecasters often have a very different understanding of the end user's problem. These differences must be shared and reconciled.

5.1.1 *Impact and Risk*

Impacts of natural hazards can be described in terms of their spatial extent, duration and severity, either focussed on an individual asset (e.g. road transport network) or aggregated to describe impacts across a region. They can be classified as direct or indirect, and tangible or intangible. Direct losses represent the damage, loss of life or economic loss that results directly from the event and tend to map closely to the spatial footprint of the hazard. Indirect losses include reductions in output or revenue, disruptions to markets and distribution networks and impacts to personal

well-being and community cohesion. These impacts frequently have broader geographical reach and may have long-term destabilising effects. Tangible impacts are those which can be quantified and are typically well recorded, while intangible impacts are not easily measurable (e.g. place attachment to ancestral land and changes to mental health). Most impact models focus on the tangible and direct losses associated with a hazard, but it is recognised that for effective and sustained recovery, there needs to be a better understanding of indirect and intangible impacts.

Modern risk analysis builds on research conducted under the ‘behavioural paradigm’ and the ‘development paradigm’ (Smith & Petley 2009), which together reorientated the focus away from predominantly engineering solutions aimed at containing the hazard, to a better understanding of the social and behavioural drivers of impact variability. Some of the first computer-based risk models were developed within the insurance and reinsurance sector (catastrophe models), where risk simulations are used to quantify the impacts of potential future hazards based on the exposure and vulnerability of the assets in an insurer’s portfolio (Grossi & Kunreuther 2005). Such models typically focus on the physical vulnerability of exposed elements, omitting other aspects of vulnerability (e.g. economic, social and attitudinal) that are more challenging to quantify.

Although risk is widely recognised to be a function of hazard, vulnerability and exposure, the ways in which they are expressed can vary significantly across disciplines. For the insurance sector, understanding the financial implications of future hazardous events is critical so that they can deploy capital, and price insurance coverage appropriately. As a result, catastrophe models focus on quantifying the physical damage (number and type of assets damaged or destroyed) and translating that into monetary loss. By contrast, the National Meteorological and Hydrological Services (NMHS) are increasingly adopting impact-based warnings to inform the public and emergency managers of potentially impactful weather in the near future. Impact-based warnings communicate the level of risk, supported by general statements of potential impacts, using predefined impact category descriptors, and the spatial and temporal likelihood of the hazardous event.

For impact and risk models to be effective in early warning, decisions on how to develop these models should be led by the user’s needs and determined by the availability of appropriate data. In cases where a general, broad assessment of future potential risk is effective, it may be possible to use general information (e.g. a previous high-impact weather event and its impacts) as an indicator of what the future risk from a similar high-impact weather event might be. However, where a user needs to prioritise emergency decisions, more detail on the vulnerable people and assets within the hazard footprint is essential, as is understanding the potential catastrophic situation that may emerge from unprecedented compound or cascading socio-natural events. Addressing these different styles of risk forecast requires different underpinning data and different approaches to aggregation of the data within the model.

5.2 Impact Forecasting

Approaches to estimating the impact of weather-related hazards vary widely according to the user application and the type of hazard. Nevertheless, there are some common factors that it is worth considering first. Historically, experience and precedent were the main sources of information on severe impacts. The weather forecaster or emergency manager who had experienced a previous event would know what to expect when similar conditions recurred. A warning service would often be instituted based on a review of a particular event, with hazard warning thresholds set based on impact evidence from that event. A recurring practice has been the use of climatological thresholds to describe the variability in severe weather and therefore the anticipated impact a weather event may have. This assumes that areas exposed to regular severe weather will have built resilience to these events, compared to areas whose definition of severe weather is a lower magnitude weather event. However, with the development of more sophisticated methods, formal statistical techniques for identifying the relationship between hazard and impact need to be used. An area of increasing concern is the identification and prediction of indirect and cascading impacts – where one impact leads to other, potentially more serious, impacts. An important part of any hazard-impact assessment is therefore to identify the variety of pathways by which a hazard may have an impact. This is especially evident for urban populations, where remote hazards may interrupt critical infrastructure supplying large numbers of people, but is also relevant for rural populations dependent on neighbouring cities for markets.

5.2.1 *Impact Data: Sources and Ethics*

For all risk and impact models, the first step is to identify the hazard to impact pathway. This involves understanding what makes an event hazardous and impactful and describing this with available data. The strength of any hazard-impact relationship is dependent on the data used for analysis. A key issue for impact modellers is the availability of impact observations that can be examined in the context of environmental hazards. Impact data (e.g. mortality data, road traffic accident data, insurance claims and financial loss) are collected in many countries, but the drive to collect data is often not for the purpose of risk modelling. In the UK, police who attend traffic accidents are required to record the accident, vehicles involved and causality information in a standard national format. The form includes a section on incidental weather, and therefore one might anticipate that such information would easily support the identification of relationships between different weather conditions and the potential for road traffic accidents. However, the data may be misleading, as the identified incidental weather may not have caused the observed impact. The decision to record incidental weather is also biased by recorder perception. For example, an officer may register that rainfall played a role in the accident because

the road surface is wet rather than because of rainfall at the time of the accident. Attributing impacts to a natural hazard type can be very challenging, especially when underlying vulnerabilities (i.e. driver tiredness, ability and responsiveness) are equally likely to have played a role in the observed impact. It should be recognised and, where possible captured, that impact records have their own biases due to the purpose and method of collection, and this needs to be accounted for when relationships are identified.

The quality of historical impact data determines the level of granularity that can be reached when understanding the drivers of observed impacts. Mortality data are collected in most countries, but the level of detail as to the cause and circumstances of death is very variable. The WHO promulgates a standard approach to classifying diseases and related health problems, but frequently the environmental hazards which can trigger these health outcomes are not recorded. Similarly, in developed countries direct economic impacts are most easily obtained from insurance or reinsurance data. However, insurance payouts may not equate to the cost of the damage, either because property was underinsured or because the replacement was of better quality than the original (betterment). Data are often aggregated prior to being made available to the impact modeller, so local variability due to variations in vulnerability and exposure is lost. For all risk and impact assessment, a distinction needs to be made between a ‘micro-level’ impact recording and a ‘macro-level’ impact recording. In the first case, the impact is assessed at the individual level and then may be aggregated to community or larger scale. In the second case, the national impact is assessed directly. Impact data obtained from social media or citizen science can be considered ‘micro-level’ data. One example of this type of data is illustrated through the University of Tasmania’s ‘AirRater’ (<https://airrater.org/>) smartphone app which both disseminates information on current atmospheric conditions (temperature, smoke, pollution and pollen) and collects clinical symptom reports from registered users (Robbins et al. 2017, Campbell et al. 2020). This allows epidemiological analyses of impacts associated with different atmospheric conditions, and, because the app is targeted towards vulnerable populations, the detailed driving forces of impact variability can be captured. Such data, where available in its raw form, can provide a wealth of detail. However, it should also be used with caution. People’s individual perceptions of the magnitude of an impact or the cause of the impact can be biased by their values, beliefs and social demography. Similarly, even the act of asking an individual to self-assess or monitor their activities, behaviour or health can result in a biased picture of reality and result in behaviour modification by the individual before any analysis has taken place. This is where different styles of surveying can help. Survey data are able to capture the incidence of a wider set of symptoms, either as a one-off sample of a representative population (a cross-sectional sample) or through repeated surveying of a cohort, to look at how events affect the same people through time (a longitudinal sample). Such approaches can draw out different types of biases and allow researchers to better understand the relationship between hazard and impact.

‘Macro-level’ impact data can remove individual perception bias and typically enable an improved view of the overall impact of an event. This is because both

positive and negative impacts of an event are captured particularly, for example, where macro-level financial impacts are recorded. The aggregation of data removes small-scale forcings and provides a more holistic interpretation of impacts, which is useful for large-scale comparative studies and for analysing trends in impact behaviour over time and across broad spatial scales. Impact data sources (based on micro- or macro-level reporting) and collection practices influence the way that such data need to be processed prior to analysis. This includes considering what quality control measures may be needed (e.g. there is evidence that the volume of data from social media can be used to self-verify its ability to distinguish events from non-events; see Cavalière et al. 2020), the latency of the available data for analysis and the value of drawing together multiple sources to obtain a better representation of observed impacts. Recording bias, impact data quality and impact attribution are typically managed by impacted sector data custodians, although, as highlighted earlier, not always with risk and impact modelling in mind. To utilise the available datasets robustly and effectively therefore requires sustained collaborative effort.

Almost all impact data are affected by accessibility issues. For example, sources of health impacts include ambulance taskings, hospital admission and general practitioner consultation data, none of which is available for general use due to patient confidentiality requirements. In some countries, anonymised or aggregated data are relatively simple to access, while in others an accredited research licence is required. Similarly, impacts on engineering structures such as utility and road infrastructure can, in principle, be obtained from failure logs, accident and maintenance records, but formal records or reports of engineering failures are rarely available publicly.

Accessibility goes hand in hand with confidentiality. All impact studies must be undertaken within a legal and ethical framework that ensures confidentiality of any data that could be associated with an individual, a business or a specific location. These frameworks have implications on the types of analysis that can be completed and the potential detail of assessment that can be achieved. This is well demonstrated in the health-hazard analysis space. Statistical analysis of health outcomes is constrained by ethical standards which protect the identities of individuals who have experienced a health event. Name, age, sex, current morbidities, family residence, incident location and the nature of the health event are collected and securely stored. How data are collected can mask the contribution of a hazard to a health event, particularly as it is rare for medical systems or practitioners to encode for the presence of a hazard. The strict protocols protecting personal data typically include thresholds for spatial domains (location of event), minimum numbers of people assigned to an impact classification (typically no less than 10) and/or data being grouped by span of time. As most weather-related hazards are on a daily timescale, this will usually result in release of human health impact data across broader domains in order to reach the threshold of ten affected individuals. Human health impacts are classified by either death or type of morbidity. Daily morbidity records are an order of magnitude larger than death records, allowing statistical analysis to be conducted at higher spatial resolution than excess deaths, which are studied across broad regions down to the scale of a large city. The higher case numbers of

people living with medical conditions enable ethical standards and statistical significance to be achieved at higher resolution, potentially at suburb scale.

Health-related studies might be assumed to be a special case for ethical consideration. However, even where impact data are openly available (e.g. from social and news media), they should be subject to ethical considerations. Impact data provide insights into vulnerabilities and sensitivities of people, systems and places which can be emphasised when processing, aggregation and visualisation techniques are applied. This can mean that data are no longer neutral or impartial and this can have significant political and ethical connotations. Impact data can highlight ‘underperformance’ or lack of adherence to globally or nationally recognised guidelines (e.g. humanitarian and UN guidelines or industry standards) or highlight positive and negative adoption of policies or working practices (e.g. within the energy industry where it could be possible to identify variability in the ways companies maintain their assets based on the occurrence of impacts on their networks). Beyond performance aspects, impact data can highlight particularly vulnerable groups or assets when aggregated or visualised in certain ways, and therefore handling of such data needs to be carefully managed to prevent negative targeting of such groups, which can further enhance their vulnerability. This is particularly relevant where natural hazard impacts intersect with fragile and conflict-affected situations.

5.2.2 Impact Relationships: Identifying Pathways from Hazards to People, Service and Financial Impacts

A critical requirement for impact modelling is the identification of the right set of predictors. It may seem obvious that the predictor for building damage from a storm is wind speed and that is reflected in the existence of impact-related wind scales: e.g. the Beaufort scale and the Fujita scale. However, wind direction is critical for many structures, such as walls and roofs, while antecedent or coincident rainfall affects some building materials. Much building damage and transport disruption are caused by falling trees, which are more likely when they are in leaf (if deciduous varieties) and when the ground is wet. For less obvious connections such as health impacts, establishing which environmental predictors a disease is sensitive to, if any, may be a challenge in itself (Fleming et al. 2014). With multiple predictors, care must be taken when sourcing data. For instance, if wind is recorded from the nearby airport, but particulate concentration (PM₁₀, say) is recorded from a city centre monitoring location, the inconsistency may bias any relationship that is found.

In the case of flooding, the hazard comes from critical combinations of precipitation intensity and duration, catchment morphology and land use as well as soil moisture. Those parameters will not only influence the hydrological responses (slow flood versus flash flood) but will also strongly influence the type and severity of impacts. Slow river floods are rarely associated with fatalities but often with large economic losses related to their greater extension and duration. By contrast, flash

floods, even if localised, can be much more deadly as they often surprise people during their daily activities (Jonckman 2005; Ruin et al. 2008, 2009, 2014; Diakakis et al. 2020). Studies looking at the circumstances and profiles of flash flood victims allow researchers to make connections between the victims' ages and genders, the type of place and time of their accidents and the flood dynamic (Ruin et al. 2008; Terti et al. 2017). Such detailed analysis of the combination of impactful social and physical circumstances is necessary to comprehend the diversity of predictors that need to be examined and tested for impact prediction (Terti et al. 2015).

Advanced approaches to identifying statistical relationships, using machine learning, can find very sophisticated and indirect relationships that have the potential to greatly strengthen impact-prediction capabilities. However, when less direct impact associations are identified in data, they should be challenged as to cause and effect before being used in a predictive sense. Identifying and removing potential confounding relationships is a key part of this process and requires careful experimental design – either to remove them through sampling or to include their effects as part of the statistical model. Trends should also be removed from data prior to modelling. A linear trend, such as one might find arising from the general improvement in healthcare, is relatively easy to identify and remove, but data jumps may also be present due to changes in the law (e.g. building codes, maximum lorry/truck sizes) or in industry (e.g. new materials) that could easily be misrepresented as linear trends – or ignored altogether. The significance of any relationship should always be scrutinised, and even when a high level of significance is present, the full probability distribution should always be used, rather than just the mean relationship, to ensure that spurious precision does not mislead.

Where statistical relationships are difficult to determine based on available observations, other methods can be adopted. In principle direct impacts on assets such as buildings, dams and road and rail infrastructure can be modelled using detailed, process-based approaches. For example, the probability of a lorry/truck overturning due to strong winds may be assessed based on wind speed and the direction of the wind relative to the vehicle, the height and weight characteristics of the vehicle, its velocity and the underlying road characteristics. A mechanical model can be used to describe the process of vehicle overturning under different hazardous conditions, and this can be used to identify the relationship between hazard and impact, and develop impact-orientated thresholds which can be utilised in forward modelling (Hemingway & Robbins 2020). Likewise, engineered structures such as bridges, dams and overhead power lines are usually designed to withstand relevant hazards such as strong winds or high-water levels up to a specific threshold, beyond which the structure can be expected to be damaged or to fail. Engineers often represent the failure of a structure by a fragility curve that relates the probability of failure to the imposed load. Fragility curves are generally considered confidential and in some cases are national secrets. Engineers can also undertake experiments under controlled conditions to obtain direct evidence of how hazards interact with infrastructure and result in impact. Rolls-Royce undertook testing of its aircraft engine performance in the presence of volcanic ash to produce volcanic ash flight envelopes (Davison & Rutke 2014), for example, while several other studies have used

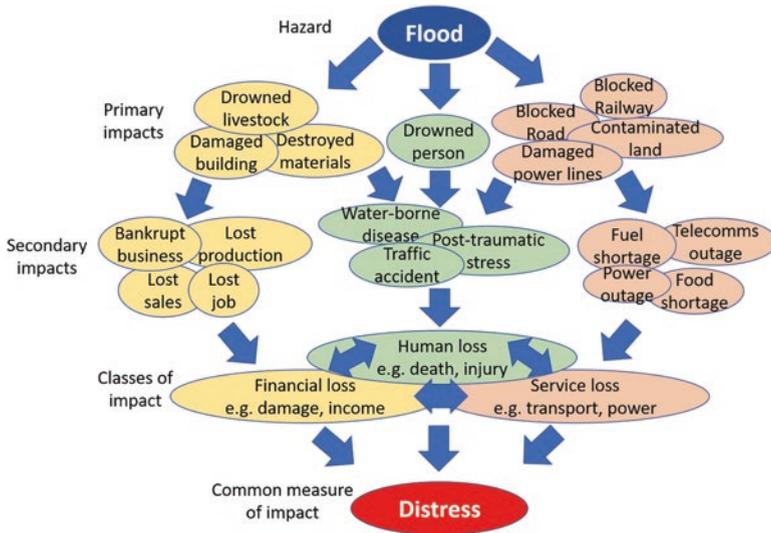


Fig. 5.1 Potential impacts from a flood, classified into financial, human and service losses. (© Crown Copyright 2021, Met Office)

shaking table tests to obtain primary data on the performance of different building types under different seismic scenarios (Fiorino et al. 2019; Xie et al. 2019). Obtaining primary data in this way ensures that the collected information is directly relevant to the researcher (and ultimately the user’s) needs and answers the key relationship questions that the researcher would like to model. This reduces the need to filter through secondary data sources which have their own biases. Primary data collection is, however, only as good as the designed experiment, test or survey, and therefore, it is important that care is taken in setting up these activities. It should also be noted that not all impact modellers have the capacity to undertake their own primary data collection and so secondary data sources may be the only viable option for identifying the hazard to impact pathway.

When considering the impacts of weather-related hazards, it is possible to divide them into three main classes: impacts on people, recorded as deaths, injuries and displacement; impacts on property and business, recorded as a financial loss; and impacts on infrastructure, recorded as loss of service (Fig. 5.1). These are not independent: damage to the home can lead to mental health impacts, while personal injuries incur treatment costs and can reduce productivity, and service loss has potential health and cost implications. In all cases, the associated distress is an underlying impact.

Examples of Methods: Impacts on People Studies of the impact of natural hazards on people are part of the science of epidemiology (see, e.g. US Department of Health & Human Services 2012), which is concerned with the frequency and pattern of health events in a population and their causes. Epidemiology relies on the

systematic collection, analysis and interpretation of data from valid comparison groups to assess whether what was observed differs from what might be expected. Analysis draws heavily on statistical methods (e.g. Armitage et al. 2002) to identify patterns in time or space, in relation to personal characteristics such as age or gender, or behaviours such as sport or occupation, or to exposure to environmental conditions such as severe weather or pollution.

The use of an epidemiological analysis in impact forecasting must start from the end user and the decisions they need to take. For a government or public service, an aggregate impact may be needed. For instance, in the context of health impacts, such as heat stroke, if the number of people needing treatment exceeds the available hospital beds or specialist equipment, action will be needed to transfer patients or redistribute vital resources. On the other hand, for a public warning, the expected impacts on the individual may be needed. Therefore, night-time temperatures may be a good indicator for hospitalisation of the elderly and chronically ill, but daytime temperatures may be a better indicator for impacts on sportspeople and outdoor workers. This distinction between the aggregate and the individual also appears in the sphere of financial impacts, covered below.

Analytic studies in epidemiology aim to identify and quantify the relationship between an exposure and a health outcome. The hallmark of such studies is the presence of at least two groups, one of which serves as a comparison group. To do this, assumptions must be made about exposure to the hazard in the area covered by the health record unless individual addresses are available. Even in the latter case, assumptions may have to be made about whether the person was at home and whether they were indoors or outdoors. This is especially difficult when assessing slow-acting impacts, e.g. from heat, cold or pollution. Unless there are reasons to study a particular sector of the population, perhaps with specific vulnerabilities, care must be taken that both the exposed and the unexposed populations selected for study are representative of the total population.

In observational case-control studies, subjects are enrolled according to whether they have the disease or not, then are questioned or tested to determine their prior exposure. Differences in exposure prevalence between the case and control groups allow investigators to conclude whether the exposure is associated with the disease. In observational cohort studies (e.g. as reviewed by Raaschou-Nielsen et al. 2013, for air pollution impacts), sample populations are identified and then studied to see how their health responds either to a prescribed exposure or to exposures that occur naturally. In the case of natural hazards, it is typical to select populations after an event has occurred, choosing exposed and non-exposed groups that have the same composition in terms of demography, for example. This is less reliable, since the groups may not be matched in some unknown characteristic of importance, and a large population is required in order to ensure sufficient members are exposed. An alternative methodology for transient impacts is the case-crossover analysis, which uses cases as their own controls (Lombardi 2010). For specific events, a cross-section approach is used, where two groups of people are selected, one exposed and one not exposed, from the same population and for the same time, with careful

selection within each to match the overall population characteristics. These are better suited to descriptive epidemiology than for establishing causation.

There are occasions where it may not be possible to clearly delineate exposed and non-exposed groups. For some types of heat event, excess deaths (better described as excess ‘all-cause’ deaths) are regarded as a reliable indicator of impact. Excess death is calculated against deaths expected for time of year, controlled for the presence of hazards and long-term mortality trend. By linking excess mortality with time-series analysis, it is possible to assess the relationship between known hazardous periods and hazard types, and impact variability (Armstrong et al. 2019). However, some studies will exclude deaths that can be attributed to an external cause, where the hazard is not thought to be a contributor. This can pose an interesting problem for heatwaves, as a population may progressively fatigue and potentially experience more ‘external cause’ impacts. In other instances, analysis may focus on only the exposed group to understand the variability of risk within the group. This is particularly relevant where hazard exposure varies significantly within a broad-scale footprint, as is the case with multi-hazard events (e.g. tropical cyclones and volcanic eruptions). Interestingly, in Brown et al. (2017), a key challenge was identified relating the recorded deaths associated with different volcanic eruption events with medical (e.g. laryngeal and pulmonary oedema; asphyxiation and blast trauma) and hazard (e.g. pyroclastic density currents) causes, so that spatial and temporal distributions could be assessed and risks to different populations determined.

A relatively new area of study is in mental health impacts following disasters. Munro et al. (2017) used a cross-sectional survey of those displaced by floods and identified significant increases in depression, and post-traumatic stress disorder (PTSD), while Garske et al. (2021) used social media data to track negative emotions during and after superstorm Sandy. The extent of mental ill health can depend not just on the hazard or whether people were warned but also on the challenges associated with recovery (Mulchandani et al. 2019, Schwartz et al. 2017), which can be directly linked to livelihood and poverty status. New technology is also permitting new approaches to overcome some of the challenges of connecting exposure and response to environmental stresses. For instance, ‘wearables’ can track a person’s exposures and physiological response while undertaking sport or other activities and has the potential to dramatically improve clinical research. As a field reliant on expertise from across science, engineering, analytics, healthcare, business and government, it embodies the collaborative ethos essential for building effective hazard-impact pathways.

In all the studies discussed above, care needs to be taken to allow for confounding variables affecting the impact. In some cases, these may have larger magnitude than the hazard. For instance, the day of the week and public holidays are dominant influences on most health statistics. These can be incorporated in the analysis using auxiliary variables. It is also important to include all potentially relevant environmental variables, not just those hypothesised to be dominant. Thus, temperature, humidity, wind and radiation may act together in cases of heat or cold health impacts. Where causal connections can be established, it may be possible to identify

specific groups of people who are vulnerable, and to target warnings at these groups, enabling specific protective responses (e.g. thunderstorm asthma; Dabrera et al. 2013).

Examples of Methods: Impacts on Services Services such as power, water, transport and telecommunications rely on extensive networks of infrastructure that are vulnerable to damage by hazards, either at the nodes of the network (e.g. water treatment plants, power switching stations) or by cutting the connectors (e.g. roads, pipes, cables). Some networks have built in connection redundancy, enabling rerouting to take place if one connector is broken. However, if a key node is taken out of service, it may affect tens of thousands of people, as seen in England in 2007 when a water treatment plant was flooded resulting in the loss of piped water to 420,000 people, several orders of magnitude more than those whose houses were flooded (Pitt 2008).

Reliable data on service impacts are difficult to access, often being commercially sensitive. This results in most work to determine relationships between hazard and service impacts being led by service providers, within their own organisations. Examples of publicly published documents that explore the root causes of such failures are rare, and this has resulted in two very different approaches being used. For public use, the aggregate impact can be analysed statistically, relating media and emergency services reports of impact to the hazard and some aggregate measures of exposure and vulnerability, such as population. The ability to conduct this type of analysis is dependent on the type and consistency of monitoring undertaken by the service provider. This, in turn, can be related to whether regulatory bodies enforce standards of delivery that require monitoring and reporting of service provision (e.g. the number of customer minutes lost, in the case of the energy sector, or fines related to excess sewage leaks, in the case of water companies). For the infrastructure owner, a much more detailed forensic analysis can be undertaken that relates the loss of service to system characteristics such as redundancy and design, operational characteristics (e.g. maintenance schedules) and management characteristics (e.g. availability of technicians on call). This analysis is likely to be mainly process-based, incorporating engineering models of structural failure and computer models of network failure. Ideally, there should be a connection between the statistical aggregated approach and the process-based forensic approach, and this may be possible where infrastructure is in full public ownership.

Impacts to services frequently encompass two impact components within close temporal proximity: the first being immediate (e.g. a broken node, vehicle accident, loss of track due to earthworks failure) and the second being elongated (e.g. loss of service for a period of time; congestion and extended travel times; closures and diversion increasing pressure on the broader network). This means that impact assessments for services need to consider both the drivers that lead to the initial impact and the controls that exacerbate or reduce the secondary/tertiary impacts, to enable a complete 'event' impact assessment. Complex system modelling can provide insights into this impact cascade and support identification of vulnerable or highly exposed hot spots across the network. This can be particularly relevant when

trying to understand damage to ecosystem services such as destruction of mangroves, leading to loss of storm protection, or destruction of habitat leading to a reduction in pollinators for crops. However, it is important to consider how this information might be incorporated in forward modelling, for example, should the model focus on forecasting the likelihood of the initial impact (short-chain impact) or look to forecast the total impact of an event (long-chain impact). Similarly, when looking at total impact, it is important to be able to ascertain the range of different impact severities that can be observed so that forward modelling can effectively delineate different scales of impact. We will come back to this in Sect. 5.2.3.

As highlighted previously, service providers may only monitor one of these two impact components or use proxies that partially capture these components, and therefore understanding the full scope of impacts associated with a hazardous event can be very challenging. In addition, as with impacts on people, confounding variables must also be considered. For example, immediate and elongated impacts on road networks can have a number of causes beyond adverse weather, including drivers' abilities, responsiveness, health and behavioural traits (e.g. an audacious individual versus a careful or timid individual); the network's resilience and capacity to absorb shocks; and proximity (in time and space) to available adjacent services that can support recovery. Careful statistical analysis using the same approaches as for epidemiology is needed to identify the part played by the weather. Call et al. (2018) used a cross-sectional approach to identify the contribution of hazardous weather to multi-vehicle traffic accidents on US highways and identified visibility obstruction (due to snow, intense rain or fog) as the primary cause on high-speed roads.

Methods for Financial Impacts Financial impacts of weather-related hazards can be both direct and indirect. It is also often convenient to incorporate financial valuations of intangible impacts representing the human and service losses. Thus, a full analysis of the costs arising from a severe weather event can be very complex even where impact chains are short. Figure 5.2 summarises the main headings under which impacts should be identified. In the top half of the diagram, we have the direct impacts for which financial data should exist, albeit they may be difficult to access. The lower part of the diagram deals with the intangible impacts, whose magnitude first needs to be obtained from data sources such as those discussed under human and service impacts, which then need to be monetised. The tangible and intangible often overlap, and care needs to be taken to avoid double counting. For instance, the direct cost of a traffic accident will include recovery and repair of the vehicle, attendance of the emergency services, recovery of the occupants, any required treatment for injuries and any loss of earnings to the occupants. Indirect impacts will include the effects of shock, discomfort from injuries and the opportunity costs of time lost due to road disruption. The cost of having medical and emergency services available to attend the accident may be part of the direct costs but may also be part of what society pays to reduce the impact of traffic accidents. It must also be noted that 'value' is perception orientated, varying depending on reporting level (e.g. individual, organisation, community or nation). The value reported is therefore closely related to the reporter type and purpose.

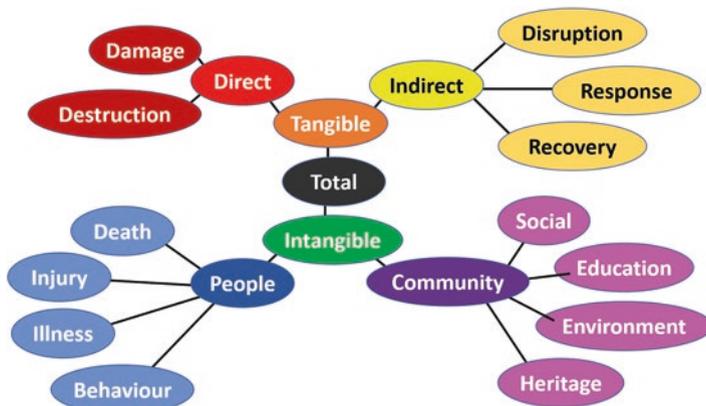


Fig. 5.2 Sources of economic costs of natural hazards. (Adapted from Deloitte, 2016)

The study of financial impacts is part of the science of economics. Financial costs to the individual or business are studied in Microeconomics (see, e.g. Kolmar 2017), while aggregate impacts on national finances are studied in Macroeconomics. Here we are mostly concerned with microeconomic methods, but it should be borne in mind that a disaster produces economic winners as well as losers and that the total cost of a disaster to the nation will be less than the sum of the losses borne by individuals and businesses.

Studies of the cost of weather impacts usually focus on the benefit of an intervention, such as a warning, rather than on the impact itself (e.g. Perrels et al. 2013). However, the methods used are often the same. These methods are summarised in WMO (2015). They may be divided into methods based on historical costs and methods based on people's perception of value. Like epidemiology, economic analysis relies on the application of standard statistical methods (see, e.g. Grant 2018, Cleff 2019).

Data on the financial impacts of severe weather are not systematically collected. Reporting for the Sendai framework (UNDRR 2015) includes regional and sectorial breakdowns of costs, but these are not yet widely available. The main disaster databases, such as EM DAT (EM DAT 2021) and DesInventar (UNISDR 2015), start from insured costs, adding estimates of uninsured and indirect costs when reported, e.g. in the media. Unfortunately, as shown by Panwar and Sen (2019), there is considerable uncertainty in these figures. Apart from insurance payouts, sources of economic data include reported production figures, tax returns, company reports and stock market valuations. Lazo et al. (2011) used state- and sector-level gross domestic product (GDP) data to relate changes in macroeconomic activity to weather anomalies. In doing so, they accounted for external changes in technology and for changes in the level of economic inputs (i.e. capital, labour and energy). An indirect method of assessing loss of business was investigated by Eyre et al. (2020) using the reduced level of social media posts on Facebook to indicate the period of business closure. Direct costs of responding to an emergency can also be obtained from

government spending on health and emergency services, on emergency grants to local administrations and on increased social support funding. Panwar and Sen (2020) found a clear signal of increased Indian government spending, increased debt and decreased tax revenue in the 2 years following major flooding events.

Having obtained economic data, analysis of the impact due to the hazard is usually achieved using time-series analysis, relating a change in the impact data to the time of a hazardous event, usually with an allowance for the economic impact to be delayed and to occur over a period. However, cross-sectional analysis may also be used, comparing the changes over the period of the hazard between areas affected and areas not affected. As with the application of these techniques in epidemiology, care must be taken to make the data consistent and to exclude confounding factors. For instance, if monthly earnings are used, it is necessary to adjust for the number of working days. Where impacts in different locations are being compared or aggregated, the composition of the affected populations in terms of demography, gender and economic status needs to be allowed for.

Intangible losses such as deaths and injuries can be given a value, based on loss of potential earnings. Legal liability is usually based on the ‘pecuniary’ costs associated with the loss – loss of potential income, in the case of death, or costs of treatment and loss of income associated with injury. However, intangible losses are more usually estimated using contingent valuation methods, such as willingness to pay, as described below. Similarly, service losses can be given a value based either on the cost of recovery or on the price that would have been paid for the missed services. However, for critical services such as water and power, where the price is often highly regulated, it is again more normal to value them using contingent valuation methods. This approach is also normally used for valuing ecosystem services such as clean air and water.

Contingent valuations may be estimated using a variety of survey techniques. The most commonly used is willingness to pay (WTP). For instance, it is widely used to place a notional average value on a life (VSL, the Value of a Standard Life) or injury, for economic applications. Its use requires expert input, or the results may not be credible. The US Department of Transportation (DOT; Moran and Monje 2016) established a VSL of \$9.6 million in 2015 based on WTP. They also monetised the value of injuries as fractions of VSL. Cho and Kurdzo (2019) used their data to estimate the economic value of the US radar network in reduced injuries and deaths from tornadoes. This approach requires that the estimate given when people are surveyed is consistent with their actual behaviour, at least in an average sense across the surveyed sample. An alternative approach seeks to estimate more directly how people value intangible losses by their behaviour and the costs they voluntarily bear. For instance, people will pay a premium for a more expensive car with extra safety features; or a worker may look for a premium for working in a job that is vulnerable to the weather. Again, expert design is needed to disentangle different influences as, for instance in the case of waterfront properties that are both more vulnerable and more desirable.

The value of weather-related losses may also be estimated from the costs that society bears to reduce or prevent losses, for example, the cost of aviation safety

features such as the airport wind-shear radar systems (Hallowell & Cho 2010) or the cost of winter road maintenance (Venäläinen & Kangas 2003). However, there is a danger of creating a circular argument if WTP was used to justify the installation in the first place. The cost of ambulance and emergency medical services may similarly be associated with a perceived valuation of the deaths that they prevent and the injuries that they treat.

It is sometimes possible to transfer valuations from one context to another, for instance between regions of a country. There are many studies investigating the value placed on particular medical treatments. Where those treatments are associated with recovering from a weather-related injury or disease, the valuation may be transferred. More generally, where similar impacts have different causes, the loss estimates should be similar. However, caution should be taken when transferring studies between countries, as valuations may be strongly influenced by country-specific economic and cultural factors.

All these approaches have the weakness that they depend strongly on the wealth of society. This may not matter too much for studies internal to one country, but when making international comparisons, it is not satisfactory. One way of circumventing this is to relate all financial costs to the household income of the individual, the turnover of the business or the GDP of the country.

5.2.3 Forward Modelling of Impacts

Having identified a cause and effect association that is relevant to the end user's decisions, it must be turned into a predictive tool to be of use. Approaches to impact modelling range from simple overlaying of hydrometeorological information with vulnerability and exposure datasets to produce qualitative statements about potential impacts (e.g. Robbins & Titley 2018), via statistically linking hazard magnitude (e.g. weather parameters or flood depths) to observed impacts, to formally quantifying the risk and impacts of events as a function of hazard likelihood, vulnerability and exposure. The decision on which approach is appropriate to implement depends on the strength and completeness of the hazard-impact relationship, the needs of the user, the data available for forward modelling and the required resolution and timeliness of model output. Often, statistical analysis can determine at what magnitude of hazard impacts may start to occur. This is particularly the case where the collected impact data used in the analysis were binary (impact or no impact). Where impact data are continuous in nature, it may be possible for the statistical analysis to identify break points or step changes where a change in hazard magnitude results in a different severity of observed impact (e.g. health impacts associating with increasing or decreasing temperature). This can allow thresholds to be established which can be used by hazard modellers to produce more informative impact-orientated forecasts. For some users, it may be enough that they know where and when to expect impacts (of any type). Others may need to understand the spatial and severity variability of potential impacts over time and have these described in terms

of the different types of impacts that may occur (e.g. Aldridge et al. 2020). For yet others, a specific quantification of impact (e.g. the number of homes that could be flooded) may be required for them to prioritise and make appropriate decisions. To obtain this detail, impact modellers can employ a range of techniques, but the main underpinning requirements include (1) a reliable description of the hazard and (2) a way to describe the ‘consequences’ of the interacting environmental hazard. The former will be discussed in Sect. 5.3, while the latter will be outlined below.

Where thresholds cannot be determined to address future potential risk, or where thresholds only address part of the risk assessment, additional information in the form of vulnerability of individuals, properties or infrastructure can be combined with their exposure to determine likely consequences (impacts) of the hazardous event. Vulnerability and exposure are often discussed as though they are well-defined characteristics. Exposure as defined by the UNDRR (2017) is arguably the easier to describe as it represents a measure (number) of people or tangible assets that are in a hazard-prone area. For physical exposure, this is often considered a fixed problem that can be solved by obtaining appropriate spatial data (e.g. satellite, Lidar, mapping surveys, traffic count point data), either by physically surveying an area or by purchasing commercial datasets. While such an approach is an important building block, it is by no means sufficient for its accurate representation in impact modelling. Firstly, it must be kept up to date. The optimum update frequency of exposure data is challenging to determine and varies depending on the type of data being used and the decisions that need to be taken. For building stock, road networks and agricultural elements (e.g. crop types), the datasets may need to be updated at least annually. For livelihood data, updates may only be needed on five-yearly timescales; however, large-scale shocks to the area where the data were obtained (e.g. conflict or mass migration) might radically change the data and mean that immediate update would be needed for the exposure to still be representative. Secondly, it is necessary to know how the population exposure varies with time. This is most easily illustrated by considering the exposure of children to a tornado. At night they are at home, so their exposure is the same as the other members of their household. During school hours they will be at school perhaps many miles from home in a building of different construction with different shelter possibilities. Before and after school, they may travel by car or bus on a public highway to reach a third location, perhaps playing sport. At weekends or during the summer break, they may visit relatives or undertake other recreational activities, possibly leaving the area altogether to be replaced by visitors who are unfamiliar with local hazards. Each different location has different exposures and vulnerabilities.

In the absence of real-time exposure data, impact modellers can use existing trends, if identifiable from historical data, to model the dynamic behaviour of people and assets so that this temporal variability can be captured. By way of example, the vehicle over-turning (VOT) model (Hemingway and Robbins 2020) forecasts the risk of disruption due to vehicles overturning in strong winds. Exposed elements are the vehicles on the road, counted through manual and automated count points, across the transport network. These data are used to map the average temporal variability of traffic flows by vehicle and road type on an hourly basis. Using this

information, a time-varying, average definition of exposure on the road network is used within a risk calculation. However, this is based on historical average usage of the network and does not account for changes in exposure due to road closures associated with road maintenance activities, or short-term shocks to the system that may dramatically reduce traffic flow. It is therefore important that the assumptions and caveats used in the model are clearly documented and transparent for downstream users, so that risk forecasts can be interpreted effectively. Another way to model drivers' dynamic exposure, especially when also interested in the socio-demographic characteristics of those exposed, is to use recent advances in mobility models following an activity-based approach. This framework, used to micro-simulate individual travel-activity patterns, considers travel behaviour as derived from the demand of activity participation and aims to predict the sequence of activities undertaken by individuals (McNally 1995). Activity-based models are of increasing interest for dynamic exposure assessment, as seen in air pollution exposure studies (Beckx et al. 2008, Beckx et al. 2009). Flood exposure studies can also benefit from the rich information provided by this kind of mobility modelling. Indeed, combining individual travel-activity simulations with road flood forecasts enables a thorough assessment of motorists' exposure and its evolution in time and space, relative to the flood hazard (Shabou et al. 2017, 2020).

Vulnerability is harder to define. Ways of defining, measuring and assessing vulnerability vary considerably across research disciplines (Wisner 2016). One reason for this is that vulnerability is often the result of numerous interrelated factors. Several studies use composite metrics or indices which pull together proxy indicators to provide an operational representation of a characteristic or quality of a system (Birkmann 2006, Fuchs et al. 2018), and describe the individual aspects of an asset that increase or reduce vulnerability to a particular hazard. The choice of number, type, weighting and integration method of the indicators is dependent on available data and also the complexity of the risk being modelled. These decisions have large implications on the resulting risk and impact assessment and ultimately on the downstream utility of the information for decision-making. As with exposure, vulnerability is temporally and spatially varying, and identifying ways to express this for forward modelling is important. Terti et al. (2019) used a supervised machine learning technique to link historic impact observations of flash flood human losses with social exposure and vulnerability proxy data in order to predict the outbreak of impact (e.g. fatalities, injuries) within a flash flood or fast-evolving weather event. This type of approach relies on a large set of reliable and precise impact data which, when available, allows the critical interplay of flood water and human mobility to be accounted for at hourly time steps. Alternatively, rapid vulnerability assessment in the wake of humanitarian crises (WFP 2018) can support a better understanding of changing vulnerabilities, as can the use of earth observation data and, potentially, social media. Updates to the vulnerability and exposure then need to be pulled into the impact model so that it has the best representation of current conditions and enables a more accurate impact assessment. Approaches to do this effectively are still being developed for short-term, routinely run impact models, but such updates

are critical in instances where modellers are interested in capturing multi-hazards and long-chain impacts, and in fragile and conflict-affected regions.

Most physical science impact models focus on describing physical vulnerability (i.e. the potential for physical impact). This is because most of these models look to identify direct and tangible impacts. However, in cases where the cascade of impacts is important (e.g. social protection), other forms of vulnerability (economic, social, cultural/environmental, psychological) become important (see, e.g. Cutter et al. 2003, Babicky & Seebauer 2021). For instance, in large cities, especially those growing rapidly in developing countries, migrants and poor people often create informal settlements in open areas that have not been developed because of high exposure to hazards such as flooding, landslides or land contamination. Without money they are likely to be poorly nourished, increasing their vulnerability to disease from flood water. Without power and communication, they will likely not receive any warning of an imminent flood, and in any case, they may not understand the language of the warning. Without transport, they may not be able to respond to the warning even if they receive it. These issues are not restricted to developing countries as highlighted by Wolshon (2006) who identifies the lack of transport of over 100,000 poorer people in New Orleans as the major failing of the evacuation when Hurricane Katrina hit in 2005.

As illustrated in the context of exposure data, where the hazard-impact relationship is based purely on historical evidence, the predictive model needs to be constrained to behave sensibly when outside the range of historical data, and to incorporate any anticipated extension of historical trends (both in terms of possible hazard magnitudes and impacts). The probability distribution from the historical analysis needs to be combined with uncertainty information from the hazard prediction and the results scrutinised in terms of the ability of the model to distinguish between occasions when action should and should not be taken, to see if they provide useful information for decision-making. As with any model, developing an impact model involves making choices and assumptions about the relevant pathways to impacts, the relevant aspects of vulnerability, the appropriate scale or level of detail or the value of some threshold or parameter. The impact model itself therefore adds to the overall uncertainty in the impact predictions, over and above the uncertainty in the hazard. Generally speaking, modelling uncertainty can be attributed to two main causes: (1) parameter uncertainty, arising from the impossibility to find exact parameter values due to lack of data, imperfect process understanding and the need to use approximations, and (2) structural uncertainty, related to how processes are being represented, aspects that were omitted or computational limitations on, for example, resolution. Note there is also a residual element of unpredictability arising from inadequacies of the models, limitations to the validity and completeness of our knowledge or simply inherent unpredictability in the process being modelled. Techniques exist to explore, understand and quantify model uncertainty, for example, through global or one-at-a-time sensitivity analysis of the key parameter values, or by exploring alternative model structures. Impact forecasts should always be accompanied by estimates of their uncertainty so that the warning can be based on a realistic risk assessment.

5.3 Capabilities of the Hazard Forecast

Chapter 6 will describe hazard prediction more broadly, but here we are concerned with understanding the ability of forecasts to capture those aspects of the hazard that are most relevant to its impact. The level of detail available in an operational warning system will depend on whether the hazard forecast is produced as part of a general portfolio of information or if it is a bespoke service. Accuracy depends on the quality of the underlying meteorological and environmental models and their ability to assimilate observations. Reliability requires a probabilistic approach, but also depends on effective feedback of verification to forecast improvement.

Prediction of impact requires relevant information about the hazard. In general, the restrictions on hazard data access are less than those on socio-economic data. However, while the analysis may show a strong relationship between hazard and impact, the specific predictors required may be much more difficult to access than standard weather variables. A simple example is lightning, which kills many people worldwide, but which is not generally predicted by weather models and for which forecasts tend to be very general. This is not helped by the fact that a lightning bolt can travel 10 km or more between cloud and ground.

Hazard forecast capabilities vary significantly among different hazards. The most damaging impacts are flood- and wind-related. For major river floods, the meteorological input may be predictable for a week or more ahead, and the travel time for the flood can add to this. However, details of the flood depth may be critical for impact and are dependent on highly uncertain knowledge of the river, including vegetation and sediment, and the state of repair of levées. While storm surges are often predictable days in advance, their inshore growth is extremely sensitive to the shape of the bathymetry, and thus to the track of storm winds. Flash floods are sensitive to errors in both location and intensity of the causal rainstorms, while urban surface water flooding occurs on space scales too small for proper resolution in current models. Wind hazard predictions have corresponding limitations due to the influence of topography and the built environment. Damage is often caused by gusts of a few seconds duration that are not directly predicted by models. The limitations of winter hazard forecasts are particularly associated with their sensitivity to the proximity of the freezing point, both at the surface, for frost, ice and the accumulation of snow, and above the surface, for freezing rain and ice storms. Hazards associated with severe convection, such as tornadoes and large hail, are inherently unpredictable given their small spatial and temporal scales, and the rapid development of the parent storms. Wildfire growth and movement is sensitively dependent on the interaction of the local wind and topography. While temperature is generally a well-predicted variable, its detailed distribution around and within buildings is not currently predictable. The same is true for pollution, exacerbated by a lack of real-time knowledge of emissions.

This brief summary of the limitations of hazard forecasts emphasises the dangers of a mechanistic approach to taking hazard data and turning it into a deterministic impact prediction tool for use in a warning. However, for each of these hazards,

there is a degree of predictability present that enables a probabilistic approach to provide usable impact information. Since the hazard is only predictable in a probabilistic sense and the impact is related to the hazard statistically, proper assessment of risk requires the appropriate combining of these sources of uncertainty. Whereas impact probabilities are based on statistics of historical association, time-dependent hazard probabilities should be obtained from ensemble prediction systems, when these are available. Careful analysis is required to ensure that the resulting risk assessment includes all relevant sources of uncertainty while avoiding double counting.

Lead times for accurate hazard predictions are important for warnings and vary widely according to the hazard. Prediction of the location of a tornado is only possible a few minutes ahead, whereas a major river flood may be predictable a week or more in advance. For very fast response, provision of impact forecasts fully automatically from the hazard inputs can be very attractive. However, care must be taken with quality control of the hazard inputs. This should start with ensuring that spurious hazard values are not used – for instance due to spurious echoes from radar data in a precipitation nowcast. Empirically based impact models have a limited range of application, due to constraints with the training data, so outputs should not be used automatically for hazard values beyond or even near those limits. As discussed above, outputs should be probabilistic. Where a fully automated system is in use, outputs with large uncertainty or that exceed historical norms should automatically be flagged for inspection before issue.

For impact prediction, hazard forecasts need to be evaluated in user-relevant terms. This places demands on the availability of hazard observations, which will be addressed in more detail in Chap. 6. The examples above hint at some of the challenges in selecting an appropriate variable and range of values to include in any evaluation. Where the hazard is very local, the model may not be representative of the same area as the observation, requiring downscaling of the forecast or upscaling of the observation before a meaningful comparison can be made.

5.4 Bridging the Gap Between Impact Forecaster and Hazard Forecaster

A traditional epidemiologic, economic or engineering study is often undertaken as a one-off project by an academic or consultant using a conveniently accessible impact dataset. They obtain hazard and exposure data from the easiest (or cheapest) available source, then perform the detailed statistical analysis, draw conclusions, publish the results and move on to the next, potentially unrelated, study. Subsequent application to warnings may be undertaken, independently, by a public or private hazard forecasting organisation, which selects the most accessible published impact relationship for translation into a predictive tool. In this process, the initial epidemiology suffers from a lack of understanding of the possibilities and limitations of

hazard science, while the warning application misrepresents the impact data and the limitations of the statistical analysis.

Development of effective operational impact warning services requires sustainable multidisciplinary partnerships to overcome these challenges. Each collaborator in the partnership builds awareness of data issues in partner disciplines leading to new best practices within and between collaborating partners.

Experience has shown that co-design of hazard/impact studies benefits from governance structures, such as:

- Steering groups – responsible for ethics, sanctioned analysis techniques that will deliver statistical confidence and outputs suitable for operational use.
- Working groups – responsible for negotiating adjustment and supply of data and execution of analysis.
- Stakeholder reference groups – responsible for feedback on how analysis results can be deployed in operational impact warning environments.

Co-design between the groups ensures meteorological hazard data are structured to match exposure and vulnerability data structures, enabling statistical analysis to be executed within the ethical and procedural constraints of the impact sector (e.g. health or engineering sector) to produce outputs at the highest statistically significant resolution possible to address user requirements.

5.4.1 Matching Data Needs

As we have seen, impact data are generally not openly available except in highly aggregated forms. This is true for engineering impacts, health impacts, infrastructure service impacts and business impacts. While data confidentiality is the primary barrier, there are also technical barriers arising from standards and formats, especially when the measured or observed quantity is highly specialist. Health practitioners use standardised disease, illness and cause of death (impact) codes to categorise illness and disease, while codes of practice support quality control and enshrine ethical practices for sustainment of life and privacy. These approaches mean that the release of health data to external researchers can be slow, degrading the value of subsequent impact studies (as described in Sect. 5.2.2).

Hazard data are available from a bewildering variety of sources with different characteristics. High-quality in situ observations are sparse in space, while remotely sensed observations only indirectly capture the variable of interest. Models provide ideal datasets, but even reanalyses have inaccuracies and biases that may distort the analysis. Hazard models often generate gridded data which are more easily adapted to match less flexible health and social data constraints. Hazard modelling centres often only archive a small subset of output data. Since impact models require to be fitted to long time series, that can be a key determinant in what data are best to use – with corresponding constraints on the resulting prediction system. Early identification of archive issues should be on the agenda for new partnerships, so that required

data can be retained. Care must be taken when impacts are dominated by small scales that corrections are made for altitude, shelter, proximity to water, etc. where necessary. The differences between these various data sources can significantly affect subsequent statistical analysis and must be consistent with the anticipated operational usage.

While national-scale impact modelling may be carried out by generalist statistical modellers and used for advice to governments or international organisations, detailed modelling for warnings at individual or community level requires the involvement of the data owner. Except where the impact is very direct, they may be sceptical of any link with the hazard, or of any value in identifying such a link. In such cases, establishing a mutually beneficial relationship is necessary before attempting any modelling.

Building successful impact models requires matching of hazard data and impact data: their temporal and spatial specificity and the variables and regimes of relevance. Models are often built using thresholds, usually in the hazard, but often driven by the significant thresholds in the impacts. It is essential to determine the abilities of models to predict these thresholds before making use of the results. Threshold exceedance should always be predicted probabilistically, both for hazards and for impacts. At the same time, some hazard prediction errors may be unimportant for the impact, and it may be possible to use a simpler, faster forecasting tool to produce the required information.

Impact modelling partnerships can produce results more suited to implementation of operational hazard-impact warning systems when partners co-design the hazard exposure/impact analysis research. Human health impact data custodians retain ethical management of experiment design and how the results are released. Social data custodians can equally address their data management requirements during the co-design phase. The ability to include social support, income, housing and census among similar data types is a very powerful determinant for health and economic outcomes. Similarly, physical spatial data allow the use of building stock age, quality, density and percentage of green areas for natural cooling as exposure controls for impact studies.

5.4.2 Evaluation

Model evaluation should be carried out in terms relevant to the end user and on independent data from those used in the historical analysis. For rare hazards, this may pose a challenge of achieving significance, especially if there are confidentiality constraints on use of the data, as in the health sphere. The development of effective partnerships can enable and enhance the robustness of evaluation techniques, while the sharing of such information can also enhance the partnership by providing a harmonisation of scientific understanding and focus direction. Impact model evaluation requires the verification of multiple components (e.g. hazard forecasts, exposure, vulnerability, thresholds, impact and risk forecasts, warnings), and the decision

on appropriate metrics is therefore critical to obtain a complete picture of model performance. This is particularly important when statistical models are being used, as changes in verification metrics may indicate the need for recalibration, either of the hazard inputs or of the impact model itself. Both input and output verifications are important, and both make heavy demands on data. Input verification needs to be relevant to the thresholds of significance for the impact model. So, for instance, where a hazard severity index is the input, it may be that only performance in the upper 5% is relevant. Co-designing the appropriate ranges, metrics and methods for verification is an important part of the partnership. Verification of the impact outputs involves access to routine impact data, possibly requiring regular post-event surveys (e.g. as used by Taylor et al. 2019) or routine extraction and processing of social media (Spruce et al. 2021) and other data sources (e.g. as used by Robbins & Titley 2018). The data acquisition methods should be standardised so that successive verification gives consistent results. This is by no means a straightforward process for impact data, particularly where data sources may be available intermittently, in non-direct formats and where classification of impacts (based on severity or type) depends on the aggregation of multiple sources. Careful consideration is needed in how data are classified and how this classification is processed for the purposes of evaluation. The nature of impact databases (often skewed towards larger-magnitude events), the style of classification or standardisation of the impact data and the time it takes to produce consistent and reproducible data may influence when evaluation and verification can take place, and partnerships need to be aware of this as it has implications for project longevity. It is important therefore that verification approaches are co-designed with end users, so that outputs are relevant to their needs and inform best use of the model, and with hazard modellers, so that sensitivities of the model can be assessed and guide improvements to the hazard prediction.

5.5 Examples of Partnership

Box 5.1 Joint Australian Tsunami Warning Centre (JATWC)

John Nairn

The Australian Tsunami Warning Service (<http://www.bom.gov.au/tsunami/about/jatwc.shtml>) has been sustainably developed and delivered through the Joint Australian Tsunami Warning Centre (JATWC). Plate tectonic and seismic monitoring skills within Geoscience Australia have been virtually coupled with the Bureau of Meteorology's ocean monitoring, modelling and continuous, non-stop message creation and dissemination systems. Curiously, JATWC's greatest success has been the overwhelming number of 'no threat' warning messages issued to the Australian community, countering the

(continued)

proliferation of warnings issued by numerous international warning centres. This service has very successfully curtailed inappropriate community reactions to no-threat seismic events and built community confidence for very rare tsunami warnings.

The bridge between hazard and impact is built upon the foundations of the data paradigms that underpin each discipline. The hazard gap is not very large between two geophysical disciplines in the example of the JATWC, although it is very clear that the best way to build the service was deemed to be through a joint facility where trust is codified, operationally tested and refined.

Coastal inundation from a tsunami is a public health threat. Flooding can result in drownings, and risks from exposed electricity hazards and infection sources including raw sewage and contaminated food and water supplies. Infrequent and widely distributed events generate a wide range of data sources which usually require social science practitioners to locate and document the nature and scale of inundation impacts. The JATWC hazard partners require these data to verify warnings issued. The opportunity to evaluate the service is naturally limited by the infrequency of coastal inundation attributable to tsunamis. It is extremely hard to build trust where health communities are so infrequently exposed to warnings, although it might be argued that confidence may be growing through the issuance of ‘no-threat warnings’.

Box 5.2 JAM Partnership

Sarah Millington

JAM (Joint Agency Modelling) is a tool for UK national emergency response to an atmospheric radiological release anywhere in the world (Millington et al. 2019), initially developed in response to the radiological atmospheric release from the Fukushima Daiichi Nuclear Power Plant in 2011. A partnership among the Office for Nuclear Regulation (ONR), Met Office, Public Health England, Environment Agency, Food Standards Agency, Scottish Environment Protection Agency, Northern Ireland Environment Agency, Food Standards Scotland and Natural Resources Wales provides an operational modelling system and delivery of agreed guidance using expertise and scientific software supported by training and routine tests. It is funded by UK government to provide input to the Scientific Advisory Group for Emergencies (SAGE) on the impacts of a radiological release from a nuclear facility. SAGE is a group of experts chaired by the Government Chief Scientific Advisor to deliver coordinated scientific advice to aid central government on forming the strategic emergency response.

(continued)

The process begins with notification of an incident at a nuclear facility to the JAM partners. The next step requires a source term – information about what has and what might be released, how much, when and where. This is provided by the nuclear facility operator or, if unavailable, by ONR using an agreed fixed format pro forma. The source information is fed into the modelling system, with NWP data and receptor parameters (e.g. assumed age for the dose calculations: infant, 10-year-old or adult). Several JAM partners have contributed to the modelling, but, for efficiency, all modelling is carried out at the Met Office.

At the heart is the Numerical Atmospheric-dispersion Modelling Environment (NAME), a Lagrangian particle-trajectory model used to model the atmospheric transport and dispersion of gases and particulates (Jones et al. 2007). Emissions are simulated as computational particles, advected by the NWP three-dimensional wind field with turbulent dispersion simulated using random-walk methods. The particles evolve with time, e.g. to simulate radioactive decay, dry and wet deposition. Time-integrated activity concentrations in air and in material deposited on the ground are estimated to provide health impact assessments.

A dose model provided by Public Health England calculates effective doses that are used to show potential areas where authorities should take action, such as sheltering indoors. The Food Standards Agency provides deposited values of radionuclides that would result in exceeding European standards for cow's milk and leafy green vegetables; these are compared with the estimated deposited values to indicate areas where restrictions should be considered. The Environment Agency applies a similar approach to indicate the geographical area of potential impact on surface water abstraction for drinking water.

Partners scrutinise model outputs and form a consensus brief for SAGE by teleconference, incorporating health impacts, food impacts, surface water impacts and uncertainties in the modelling. SAGE and government agencies use the brief with other scientific information to form guidance for those leading the national emergency response, typically led by a senior government minister. Updates to source terms and NWP data or questions from SAGE would initiate further cycles of the JAM process for as long as required (Fig. 5.3).



Fig. 5.3 Display of potential areas for protective health actions: (a) evacuation area, (b) sheltering area (c) distribution area for stable iodine in a fictional case based on the Chernobyl release using km-scale regional NWP data. (© Crown Copyright 2021, Met Office)

Box 5.3 Australian Heat-Health Partnership

John Nairn

Extreme heat is best understood as the accumulation of heat from persistent high temperatures. Unfortunately, media demands for simple headlines have focused on maximum temperature as the single determinant of heatwave severity. The minimum temperature is more important. As a result, heat-impacted sectors of the community have little credible experience of the impact of extreme heat. This is further confounded by the inconsistent inclusion of humidity, which is applied inconsistently and has been unnecessary for the development of response interventions as has been shown in Australia's heatwave service.

The Bureau of Meteorology's national heatwave service is based upon a location-based percentile treatment of 3-day average maximum and minimum temperatures (excess heat factor, EHF; Nairn and Fawcett 2014). This heatwave severity classification index determines the presence of low-intensity, severe or extreme heatwaves for each 3-day period. Several epidemiological studies have determined that rising EHF is a generally good determinant of escalating heatwave impacts across Australia. It would be highly misleading to suggest this arose from execution of a well-planned health and meteorological collaboration. Development of the EHF provided new insight into the physical nature of heatwaves and how they have changed within the climate record, past and projected (Nairn & Fawcett 2013). Public Health researchers found EHF attractive and invited collaboration with the author, leading to publication of a sequence of Public Health research articles demonstrating the efficacy of EHF. International support for an Australian heatwave service model was investigated with the support of a Churchill Trust Fellowship, which then led to the launch of the Bureau's pilot heatwave service in January 2014. This service was launched with the assistance of a heatwave stakeholder reference group, recruiting health and emergency service agency participation from across the nation. Pre- and post-season meetings shared performance data and gathered suggestions for how the service could improve.

Epidemiological studies have shown that EHF is an effective predictor of heatwave impact (Scalley et al. 2015, Jegosarthy et al. 2017, Williams et al. 2018). It has also been shown to be effective across climate (Perkins et al. 2012, Nairn & Fawcett 2017), multi-day (Nairn et al. 2018), multi-week forecasts (Hudson & Marshall 2016) and CMIP projection timescales (Wang et al. 2018). Deeper collaboration is required with health institutions to develop rapid verification of heatwave impact if the community is to build confidence in extreme heat warnings. Australia is still growing effective multi-agency partnerships, with significant progress undertaken through the recent (2020) completion of the Reducing Illness and Lives Lost from Heatwaves (RILLH)

(continued)

project. The Bureau of Meteorology led this collaboration of the Australian Bureau of Statistics (ABS), Department of Health (DOH) and Geoscience Australia (GA) to develop individual, suburban, city and regional heatwave vulnerabilities across Australia at regional, city and neighbourhood scales. Further work is required to understand how the results can inform behavioural recommendations for impact-based warnings that are sensitive to location.

5.6 Summary

- Data are fundamental to all impact forecasting. High-quality data are typically only available through partnership with data owners. Mapping data are required for exposure, socio-economic data for vulnerability and health, economic and service data for the impacts themselves. Data need to be accurate and consistent, requiring that they are collected, processed and updated to defined standards.
- Relevant impacts differ between end users. Whereas the public are interested in impacts on individuals, government, businesses and humanitarian organisations may be more interested in aggregate impacts. The methods and the data need to be selected according to the application.
- Hazards produce both tangible and intangible impacts, cascading from direct impacts to several levels of indirect impacts. They may be categorised into human, financial and service impacts, each of which can be translated to a financial value. When comparing financial impacts, it can be helpful to normalise according to household income, business turnover or country GDP.
- Impacts can be forecast by modelling failure processes or by fitting statistical models to historical data. Selecting the appropriate model requires an understanding of the information required by the end user as well as consideration of the available data.
- Hazard forecasts need to be carefully processed for use in impact models with any biases removed. They should also be probabilistic – with unbiased probabilities. For many applications they may need to be site-specific.
- To avoid the pitfalls in impact forecasting, it is essential that the provider of the hazard information and the impact model developer work closely together. Their understanding of the end user's problem will be very different, so prior to model development, it is essential that these differences are shared openly and the approach to be adopted is mutually agreed.
- Once a model is in use, it is important that the information user (e.g. the warner or emergency manager) has access to the expertise behind the model in order to query performance in critical situations. Ideally the relationship should be long term so that updates can be incorporated to use recent data or improved modelling.

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