Narrative-based Risk Communication: A *Lingua Franca* for Natural Hazard Messages?

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Abstract: Audiences routinely ignore government and expert messages about risk. However, Narrative Policy Framework research and other studies of narrative persuasiveness – specifically the influence of narrative characters like heroes, victims, and villains – have generated promising results. We offer narratives as a potential *lingua franca*, or bridge language, for communication about natural hazards between experts and the citizenry. We expected that people would respond differently to alternate types of character-driven narrative language and that such responses would also differ from reactions to scientific or expert language. We applied human coding and natural language processing to transcripts of semi-structured citizen interviews about flooding in order to identify hero and victim language. We then used the identified language to develop congruent, character-driven narratives. We tested affective response to eight different messages using dial response technology. Research participants were residents in three communities along the Yellowstone River in Montana that were also the sites of the original citizen interviews. In all, we find that use of heroes is a resoundingly effective narrative mechanism in terms of producing a positive affective response. Victims, on the other hand, are not effective in the way anticipated. Interestingly, comparisons between probability-based science messages and certainty-based science messages yield no difference.

Preparing for natural hazards is critical to minimizing the disastrous effects of extreme events like significant river flooding. Suboptimal preparedness amplifies the impact of such extreme events, resulting in devastation for communities and costly response efforts (Grothmann & Pratt, 2005). Consequently, risk communication efforts in hazard management are of paramount importance. These endeavors attempt to reduce hazard vulnerability and close the gap between scientific prediction of risk and the public's perception of the same risk (Dransch, Rotzoll, & Posner, 2010; Krewski, Turner, Lemyre, & Lee, 2012). Yet conventional risk communication is predominantly comprised of the latest scientific information that in isolation is often ineffectively assimilated (Jones & Crow, 2017) into people's hazard preparedness (Fischhoff, 2013). This is particularly problematic given periodically updated scientific hazard predictions in the face of volatile climate conditions. In sum, significant barriers to successful hazard preparedness persist (Goble & Bier, 2013), as conventional risk communication continues to default to the dissemination of science information like maps, data, and reports.

Simple diffusion of scientific information rarely affects hazard preparedness partly because scientists and citizens do not share a common language to describe risk. For example, scientists rely on the language of probability, uncertainty, frequency, and magnitude, whereas citizens use local language and descriptors and referents based on cultural values, cognitive biases, local knowledge, and experiences (Kahan, Jenkins-Smith, & Braman, 2011; Leiserowitz, 2006; McNeil et al., 2013; Slovic, 2010). Citizens communicate these aspects of their risk perceptions and decisions through stories that they recount to one another (Andreas et al., 2010; Lorente & Alonso, 2014). As people are already thinking about risk in narrative form, we ask whether a narrative-based risk communication framework can serve as a *lingua franca*, or a bridge language, for managers and scientists to use in more effective risk communication. In this study, we assess how individuals respond to conventional science-based risk messages (hereafter "science messages") and to narratives that incorporate the same science language.

We begin this study by discussing the aims of risk communication, responses in the literature to risk communication critiques, and the rise of using stories in risk communication. We then offer a brief review of the Narrative Policy Framework, which provides a rationale for testing different risk narrative structures. After presenting our hypotheses, we detail our methods and data, including the innovative use of natural language processing and dial response technology. The former is used to identify and integrate local language when constructing risk narratives, and the latter allows assessment of real-time affective responses to science messages and narratively structured messages. Finally, we present the results of our empirical analyses and discuss their implications.

Risk Communication

Conceptually, risk combines the likelihood (probability) of a negative event occurring and the severity of the event for people (McNeill et al., 2013; Paton, Smith, & Johnston, 2008). Risk communication[1] aims to reduce vulnerability to this risk through preparedness. Such preparedness is particularly difficult in the case of extreme events, as the probability of the risk occurring is low while the resultant consequences of such an event are high. If an event is perceived as having a low probability of occurrence, then it stands to reason that people and communities would abstain from putting time and resources into preparing. Even if an event is perceived as having a low occurrence *and* a high level of severity, preparation remains inadequate as the costs of preparation outweigh the benefits in people's calculations (e.g., Wachinger, Renn, Begg, & Kuhlicke, 2013). As such, communities at risk of extreme events like large floods are typically underprepared.

Achieving appropriate hazard preparedness has been the province of risk communication efforts that work to improve information flows and communication networks (Fischhoff & Scheufele, 2013;

[1] Risk communication is centered on preparedness in advance of a hazard event, whereas "crisis communication" focuses on mitigation of ongoing and post-event effects (Sellnow, Ulmer, Seeger, & Littlefield, 2017).

Paton, 2008); unfortunately, risk communication efforts continue to encounter significant barriers. For example, the uni-directional flow of hazard information from experts to the public is inadequate at increasing preparedness (Kane et al., 2014; Krewski, Turner, Lemyre, & Lee, 2012; Paton, Smith, & Johnston, 2000). People tend to dismiss this expert information as too complex and irrelevant to local experiences and knowledge. Consequently, a growing literature examines the ways risk communication scholars have responded to the inadequacies of conventional risk communication. We sort this body of literature into three broad responses: (1) consideration of the display of scientific information, (2) exploration of the social processes that shape risk perception, and (3) examination of individual processes that shape risk perception. We briefly describe each of these research trajectories below.

Data display. Recent science communication research generally has emphasized ways to present data analysis results more clearly (e.g., Clare, 2013). The use of maps to portray the spacio-temporal nature of natural hazards is becoming increasingly popular with technological advances. Dransch, Rotzoll, and Poser (2010) test what they call "map-mediated risk communication" to disseminate expert information and thereby increase awareness. Similarly, Cao, Boruff, and McNeill (2017) used improved technology to allow users to access maps at a more personal pixel level. While the use of such visuals as maps offers the public some important perspectives about the likelihood and severity of extreme events, the direction of information flow continues to be uni-directional from expert to public.

Social processes. Some scholars posit that the improvement of hazard preparedness requires researchers to understand the public's social processes of risk perception and decision making. Such social processes take multiple forms. For example, the quality of relationships among people, communities, and civic agencies influences preparedness (Paton et al., 2008). Further, the Social Amplification of Risk Framework (e.g., Pidgeon, Kasperson, & Slovic, 2003; Stanciugelu, 2013) examines how risk information is intensified through various dissemination venues (e.g., media, family, neighbors, the web), thereby affecting risk perception and decisions. Additionally, differences in attitude and judgment (e.g., trust) between scientists, authorities, and the public lead to misunderstandings and misinterpretations of information and role responsibility (Haynes, Barclay, and Pidgeon, 2008). While such studies have found some encouraging descriptive results of the social or interactive processes of risk perception and decision making, *how* hazard managers can influence trust, quality of relationships, venue, and public attitudes and judgments remains relatively unexplored.

Individual cognition. Researchers also study risk perception at the individual level (e.g., Slovic, 2010; for a review, see Wachinger et al., 2013). For example, Kahan and Braham (2003) apply a cultural theory of risk to understand how individuals' risk perceptions derive cognitively from social norms. Many studies find that trust of information source affects an individual's preparedness (e.g., Kellens, Zaalberg, & De Maeyer, 2012; Paton, 2007). Other researchers examine the role of cognitive biases (e.g., confirmation and disconfirmation bias) in the assessment of risk (e.g., Jaeger, Renn, & Rosa, 2001). Risk research often controls for direct and indirect experiences, often finding that these variables are a critical mediating factor in an individual's assessment of risk (e.g., Wachinger et al., 2013). Some research in economics examines the impact of incentives on individual decision-making (e.g., Hudson, Botzen, Feyen, & Aerts, 2016). While these studies all identify important individual factors (i.e., cultural orientation, trust of information source, cognitive biases, experience, and incentives), we find research centered on the role of affect and message imagery most compelling for the present purposes.

Slovic's and Lowenstein's work over a decade from 1991-2001 (e.g., Lowenstein 1996; Lowenstein et al., 2001; Peters and Slovic, 1996; Slovic et al., 1991, 1998) has resulted in a cluster of studies examining the role of affect or emotional responses in risk assessment. Essentially, a stimulus that evokes an affective response (e.g., positive or negative feelings) is more likely to influence individual assessments of risk and ensuing behavior than objective facts. In other words, decisions are not only products of rational thinking but are also based on what people feel. Feelings associated with risk thus influence an individual's cognitive judgments about the likelihood and severity of a hazard. These findings led to greater attention being paid to risk communication stimuli or messages themselves (e.g., Slovic, Peters, Finucane, & MacGregor, 2005). For example, scientists are realizing how messaging strategies such as frames can assist in helping the public to understand broader implications of scientific findings (e.g., McKaughan & Elliott, 2012). Some communication experts have argued that the problem with preparedness lies in agencies not doing enough to "help people visualize what a bad [hazard] might be like" (Sandeman, 2009, p. 322). In lieu of haphazardly casting about for frames and visualizations, one recent study utilized community members to produce a documentary film that effectively shaped local preparation decisions regarding earthquake-resistant construction. (Sanquini, Thapaliya, & Wood, 2016). What all of these studies share is a vague notion that it is important to use some kind of rhetorical communication device (e.g., frames) or imagery or story to evoke an affective response. Theoretically, this affective response will then change how audiences receive risk communication and will result in an adjustment of risk perceptions and decisions.

While narratives are largely understood as powerful in their ability to persuade people (e.g., Hinyard & Kreuter, 2007), few studies have focused on the effects of narratives in risk communication. In the health domain, narrative risk-based studies (de Wit, Das, & Vet, 2008; Janssen, Osch, de Vries, & Lechner, 2013) resoundingly find stronger effects using "personal accounts" as opposed to science messages. The narrative risk communication studies discussed above examine the differences between the impact of technical information and narratively presented information. These narrative constructions are problematic in that they are *ad hoc* constructions of story made up by scientists or researchers. In other words, these nascent studies have successfully identified that narratives influence risk perceptions and reported decisions, but what clearly is not understood are the *mechanisms* involved in narrative persuasion in the hazards domain.

Finally, the issue of how to communicate scientific messages has also received some consideration in the academic literature (e.g., Corbett & Durfee, 2004; Weiss, 2003) but has received more significant attention recently in the popular press (e.g., Lewis & Gallant, 2013; Ward, 2017). The crux of the issue is that lay audiences tend to translate "probability" statements as "scientists do not know" (Union of Concerned Scientsists, n.d.). Some researchers (e.g., Jones, 2018) are probing the idea that presenting extreme events as inevitable or certain at some point (rather than focusing on probabilistic predictions) can improve preparedness.

Narrative Policy Framework

Whereas previous narrative risk communication studies have not espoused a theoretical basis for narrative *construction* in their experiments, the Narrative Policy Framework (NPF; Shanahan, Jones, McBeth, & Radaelli, 2017) offers scaffolding for identifying and testing the effects of specific narrative mechanisms. In line with other communication scholarship (e.g., Green & Brock, 2000), the NPF proposes that narratives are powerful in decision making and in the policy process writ large. Much of the NPF's micro-level research has focused on the effects of specific narrative elements on individual perceptions and opinions. These elements (i.e., characters, plot, setting, and moral of the story) are located in what the NPF describes as narrative form or structure. The most vital element is that of the character (hero, villain, victim), as it is foundational to what constitutes a narrative (Shanahan et al., 2013). The employment of these elements and of narrative strategies provides the mechanisms by which perceptions and opinions change.

As discussed above, seminal work in risk communication studies points to the importance of individual affective responses to messaging. Researchers have found that risk communication in narrative form has a greater effect on risk perception and decision making than does communication via more conventional science messages. However, neither this literature nor NPF research has really examined the mechanisms at work to date, typically making assumptions about how characters lead to changes in attitudes and behaviors instead. NPF researchers know that narratives focusing on the hero are effective in shaping an individual's opinions (Jones, 2014), but the linkages from hero to affective response to opinion change are not entirely clear. How much hero language is necessary to induce an affective response? At what point is that affective response large enough to change attitudes or behaviors? Additionally, are positive affective responses the only ones that effect change? What about strong negative responses? Much of the content of narrative risk communication is based on presentation of harm, intended to activate fear to motivate people into action (de Boer, Botzen, & Terpstra, 2014). The NPF defines the victim character as one who is harmed or who fears being harmed. Unlike studies centered on the hero, the NPF has not deeply examined the persuasive effects of victims or victims-turned-heroes. The NPF offers the means of zeroing in on the mechanisms at work in narrative risk communication. An important step here is examining individual affective responses to different character language, which is what the present study aims to do.

Research Question and Hypotheses

In this study, we seek to address the following research question: Can narrative-based but scientifically informed risk communication serve as a *lingua franca* for relaying messages about hazards? In other words, do people respond differently to scientific risk information embedded in a specific narrative structure than they respond to scientific risk messages without such structure? In answering this broader question, we evaluate the following hypotheses:

H_1: The contour of the average second-to-second affective response to scientific risk messages is flatter than the contour of the average second-to-second affective response to risk narratives with character language.

H_2: Affective response to hero language is more positive than affective response to scientific risk language.

H_3: Affective response to hero language is more positive than affective response to victim language.

H_4: Affective response to victim language is more negative than affective response to scientific risk language.

H_5: A victim-to-hero narrative arc produces the largest swing in affective response.

H_6: Affective response to certainty language differs from affective response to probability language.

Next, we briefly present our case study, followed by a detailed discussion of methods, analysis, and results.

The Yellowstone River in Montana

The Yellowstone River – flowing 670 miles from its source in the mountains southeast of Yellowstone National Park to its confluence with the Missouri River in western North Dakota – is the lifeblood of eastern Montana (Ward, Anderson, Gilbertz, McEvoy, & Hall, 2017). Although the region is most often associated with aridity and a lack of water (Anderson, Ward, Gilbertz, McEvoy, & Hall, 2018), severe flooding sporadically threatens the well-being of various communities along the river (United States Army Corps of Engineers and Yellowstone River Conservation District Council [USACE & YRCDC], 2015). When flooding does occur, it usually affects the basin unevenly. While the upper basin's main flooding threat comes from snowmelt-driven runoff, the lower basin generally is more susceptible to flooding from individual storm events. Moreover, localized ice jam events threaten specific communities in unpredictable ways (USACE & YRCDC, 2015). The Yellowstone River does not have any large flood-control dams; however, the opening of Yellowtail Dam in 1967 has reduced flood magnitudes on the Yellowstone downstream from its confluence with the Bighorn River (USACE & YRCDC, 2015).

The present study involves discussion of flooding in three different Montana communities along the Yellowstone River – Livingston, Miles City, and Glendive. Located in Park County, Livingston has undergone significant economic transformation over the past several decades and now depends heavily on recreation and tourism for its economic base (Haggerty & Travis, 2006). Livingston is known for its proximity to Yellowstone National Park and its world-class trout fishing. Annual flooding in late May and early June threatens not only commercial and residential buildings but also threatens Livingston's recreation economy. Extreme flooding particularly threatens Livingston's spring creeks, which provide unique fish habitat and serve as a destination fishery. Consequently, significant levees and riprap protect both the upstream spring creek fisheries as well as residential and commercial real estate in town (USACE & YRCDC, 2015).

Miles City, located about 260 highway miles downstream from Livingston, has a slightly higher population with approximately 8,600 residents. Due to its unique location at the confluence of the Tongue River and Yellowstone River, Miles City has a significant risk of ice jam flooding (USACE, 2007). As a response to historic floods in both 1929 and 1944, a dike or levee system was constructed in the 1930s and 1950s and then improved in the 1970s (KLJ, 2015). Although the USACE has recommended construction of a new and improved levee since the late 1940s, a lack of local support has thwarted these efforts, and a majority of the city's residents live within the 100-year floodplain (KLJ, 2015).

Ice jams also pose the greatest flooding danger for Glendive. Located just 90 miles upstream from the Yellowstone's confluence with the Missouri River, Glendive is the economic hub of Dawson County with a population of about 5,300 people. Although the area historically has depended on agriculture and transportation, tourism and oil and gas extraction have emerged as important aspects of the local economy (GreatWest Engineering, 2016). Commercial and residential property on Glendive's west side pose the main flooding concern. Despite the USACE's construction of the West Glendive Levee in 1959, FEMA included much of the area within its 100-year floodplain. The city's decision to ignore FEMA's regulations and allow additional commercial building in the floodplain has not only increased the city's flood risk but has also hampered its economic development (USACE, 2014).

Data & Methods

We employ mixed methods research in a design that contains case study elements (i.e., three communities in Montana) and cross-sectional elements (i.e., across individuals, messages, and time). The mixed methods used in collecting data include quantitative methods like dial response and self-completion questionnaires as well as qualitative methods like semi-structured interviews. The broader goal of the project is to build scientifically informed narratives for communicating about hazards while using language derived from the target population. In order to do so, we first needed to gather the audience's language. Accordingly, the first subsection discusses the semi-structured interviews that provided the raw material for narrative construction. Further, we have narrowed our focus to the use of character language in narratives, so our primary interest is in the types of words that best align with different narrative characters. The second and third subsections explain the use of human coding and natural language processing (NLP) to identify such character language. A fourth subsection describes the procedures used to build eight different messages, including those that incorporated character language. We also needed to assess whether the messages influenced the audience as hypothesized. Therefore, a fifth subsection discusses the dial response and survey procedures employed in assessing message effects. A final subsection describes the statistical methods used to evaluate message responses.

Semi-Structured Interviews

The source material for the construction of narratives came from semi-structured interviews conducted with 45 individuals across three communities along the Yellowstone River in Montana. These three communities – Livingston, Miles City, and Glendive – were chosen because they had all experienced recent flooding events and because they contain levee infrastructure bordering the Yellowstone River and some part of their community.[2] The purposive sampling procedure aimed to achieve a sample with a range of individuals from across affected sectors in the communities. The resulting sample included residents living alongside the river, interested citizens, and business owners. The interviewees were roughly evenly distributed across the three communities. We conducted these interviews from February-June 2017.

Two sections of the interview protocol (see Appendix A) pertain to this study: (1) problem definition and information sources and (2) heroes and victims. The first section focused on problems, benefits, and risks associated with flooding on the Yellowstone River, as well as sources of information for learning about such flooding. The second section did not ask directly about hero and victim characters but rather asked about harm from flooding (to elicit victims) and preparation for and recovery from flooding events (thereby eliciting heroes). Based on previous experience, the researchers also knew that villains would emerge as characters as a natural consequence of these other questions.

The Human Ecology Learning and Problem Solving (HELPS) Lab at Montana State University transcribed 42 audio files from the interviews, as two individuals were interviewed simultaneously and another two individuals refused audio recording per the informed consent procedures. The aim was to allow interviews to unfold at a relatively leisurely pace so that interviewees would feel comfortable and would use their own descriptive language. The audio files ranged in length from 25 to 147 minutes, though the median interview length was about 58 minutes. The resulting transcripts ranged in length from about 3,500 words to over 32,000 words, with a median of 9,016 words. The researchers subsequently coded approximately 439,000 words across the 42 transcripts.

Coding of Transcripts

Coding for characters was an iterative process that began in a deductive manner. Previous NPF codebooks provided the foundation for the coding (see Shanahan, Jones, McBeth, & Lane, 2013). Existing NPF research also provided definitions for the character nodes. Heroes are fixers of problems, victims are entities being harmed, and villains are entities that cause problems or harm (see McBeth, Shanahan, Hathaway, Tigert, & Sampson, 2010). Given their prevalence in the interviews, we coded for villains as well. Four researchers began by independently coding the same transcript in NVivo11. Given the volume of data, the coding focused only on text related to flooding hazard. The main nodes, established deductively, were the hero, victim, and villain character categories. The specific identities of these characters, the subnodes, emerged inductively from the data (e.g., government floodplain administrator under the hero node or individual homeowner under the victim node). The researchers then convened to compare coding procedures and categories. Based on this comparison, they revised and consolidated the codebook. Three of these researchers then independently coded a second transcript in full. They met again to refine the node structure and coding scheme further. These iterative comparisons were important for ensuring reliability in coding. The researchers then coded the remaining 40 transcripts based on the refined coding scheme. They tracked potential inconsistencies across the three coders is an ongoing manner to ensure reliability.[3]

Natural Language Processing

Across all interviews, the coded text associated with characters—hero, victim, and villain—was subjected to Natural Language Processing (NLP) to identify and rank word choices. The rationale for using

[2] One of the 45 interviewees was a resident in a fourth Yellowstone River community. We retained this interview, as this property had also experienced recent flooding and the content of the interview did not deviate from interviews in the other communities.

[3] A fourth coder will recode approximately 20% of the interviews across the three original coders to calculate inter-coder reliability; however, as of this conference, this work is not yet complete.

computational techniques to locate which characters to include and exclude from building narrative-based risk messages are twofold. First, we wanted to ensure reliability in our choices. Second, the bodies (i.e., corpora) of character-related text, made up of coded passages or segments from the transcripts, were large and unwieldy. Specifically, the hero corpus contained about 35,400 words, while the victim corpus contained about 58,300 words. Therefore, the task of enhancing narrative messages so that they would be more effective with intended target audiences required the use of computational techniques to distinguish words that were more uniquely "hero" or "victim" words. Simple word frequency counts would be insufficient given overlapping language between the corpora, repeated use of "stop words" (i.e., common words without substantive content like definite and indefinite articles), and the inability of word frequencies to convey uniqueness to a particular corpus.

Assessment of the coded text using NLP techniques required carrying out certain preprocessing procedures. Natural language (i.e., human-generated language) presents a huge combinatorial problem for computers, which view each character, word, sentence, and segment of coded text as an individual feature in some way. Preprocessing focuses on reducing the number of features without altering the meaning of the text. In the preprocessing stage, natural language is transformed into measurable form and represented in a term-document matrix. After being converted to plain text, the three character language files (hero, victim, and villain) were read with readLines() from the base R package. NVivo11 had separated the coded segments of text by headers of metadata. This metadata was used as a regular expression to extract the language into new documents. Researchers used the tm package in R (Feinerer & Hornik, 2017) to create a corpus for each label out of these new documents. Each segment of coded text was a "document." Other steps in preprocessing included: conversion of all text to lowercase, encoding of text in UTF-8, scrubbing of unhelpful characters (like punctuation), removal of stop words using a default tm package list and a custom list, and breaking down of documents into unigram terms (i.e., one word per term). The final preprocessing step was representation of the corpora as term-document matrices in which rows represented the unique terms found in the corpus, columns represented the documents of the corpus, and cells stored the term count (i.e., the number of occurrences of a term in a document).

The goal of the subsequent text analysis stage was finding and presenting the information that would be most useful when constructing the narratives. This iterative stage required continuous feedback from domain experts. We explored four types of text analysis based on the term-document matrix representation. Topic modeling, which finds the topics shared by documents within a corpus, was the first type of text analysis. We used the Machine Learning for Language Toolkit (MALLET) package (McCallum, 2002; Mimno, 2015) and built a topic model via latent Dirichlet Analysis (Ponweiser, 2012) for each corpus. We displayed the top 100 words from each topic using word clouds. The resulting models were not very interpretable and did not further our understanding of the dataset.

The second type of text analysis was sentiment analysis, which scores the emotion or tone of natural language within a corpus. We generated a score with emotionally negative sentences scoring below zero and emotionally positive sentences scoring above zero. This method potentially aligned well with the later dial response testing procedures (see discussion below). The hope was to characterize the corpora against each other and use that characterization to impact word choice when writing from a particular corpus' point of view. For example, we hoped to answer questions like whether victim language is more negative than hero language in general. Each sentence in a given corpus received a polarity score (without first removing stop words and punctuation in this case). Using qdap's polarity function in R (Rinker, 2013), we scored each sentence based on degree of positivity or negativity.

The software includes a standard dictionary of positive and negative words in the English language. However, researchers enhanced the dictionary with a list of dozens of positive words and dozens of negative words from the flooding domain. The researchers based these words on a search of news media and social media related to the domain, particularly using hashtags to identify relevant streams of discussion. The function first scans each sentence for words that appear in the dictionary of flagged words. Positively flagged words have a base value of +1 and negatively flagged words have a base value of -1. The function then looks to create a context cluster around such words, including any words that might amplify or negate the sentimental effect the word has. Following formation of context clusters, the function calculates scores using the equation below. Each *x* is a flagged sentiment word, and *n* represents the word count of the sentence.

$$\delta = \frac{\sum(x0i, x{\uparrow}i + x+i \cdot (-1)\sum(xi\neg), x{\uparrow}i + x-i \cdot (-1)\sum(xi\neg))}{n} \quad \text{where } x{\uparrow}i = -\frac{1}{n-1}$$

Figure 1 shows an example plot of the polarity scores from the hero corpus (created using software from Wickham, 2009). In the upper graph, blue indicates negative polarity and red indicates positive polarity. Each bar represents a sentence from the corpus. The duration axis is just a means of spreading out the sentences. The bottom portion of Figure 1 shows sentences as dots with corresponding polarity scores. The vertical axis is simply jittering to aid visualization. The black dot, which is on the positive side of the figure, shows the mean polarity score of the corpus. While this analysis was useful in gauging the polarity of one corpus as compared to another, it did not identify words that were relatively unique to the different corpora. However, the sentiment analysis did serve as a fitness measure for working drafts of character-based narratives. For example, we expected hero narratives to be generally positive and expected victim narratives to be generally negative. Further, we expected the victim-to-hero narrative to start negative and become more positive as the narrative progressed.

[Figure 1 about here]

The third type of text analysis was classification, which is a machine learning task in which unlabeled examples are given labels by a model that is trained on a dataset of pre-labeled examples (i.e., the training set). The model looks at the features in the unlabeled example and compares them to what it knows about the training set. Considering the large number of features, we constructed a naïve Bayes classifier, again using the MALLET package for R (McCallum, 2002; Mimno, 2015). In the end, we used this method as a metric for assessing draft narratives. The classifier scored newly constructed draft narratives to indicate whether the narratives belonged to the correct corpora.

Ultimately, we settled on using word frequencies, the fourth type of text analysis, to inform the creation of the narratives. However, simple word frequencies would not be sufficient. Given the different sizes of the corpora, we needed to normalize by dividing the term counts by the number of total words in a given corpus. Also important was ensuring that one or a few interviewees would not skew the word frequency results by using certain terms repeatedly. Accounting for such a phenomenon required restructuring the text into hero, victim, and villain corpora in which each document represented all the coded language of that type from a particular interview. For example, document three in the hero corpus held all the hero-coded language from interview three. We were then able to calculate the document frequency (Dfc), which is the number of interviews in which a term appeared. The data reorganization also permitted calculation of the transformed relative frequency (TRF), which is the relative frequency of terms within the interview-based corpora. We took the square root of the number of times a particular term appeared in an interview within a given corpus, added up these square roots of raw frequencies across interviewees, and then divided this figure by the total number of words in the entire corpus (e.g., all words in the hero corpus). The Dfc measure checked against a small number of interviewees skewing the results, and TRF became the definitive word frequency ranking system.

Some terms appeared frequently in multiple corpora. Consequently, we subtracted the TRF for one corpus from the TRF for another. This procedure created scores in the range of about -20 to 20. This allowed for ranking of words by their relative importance to each corpus. Given the focus on hero and victim characters, we generated a measure for hero TRF – victim TRF (or HTRF-VTRF). Terms with positive values were hero terms, and terms with negative values were victim terms. We took the head and tail of the list (the top and bottom 4% of words) to create the hero and victim vocabularies.

Message Construction

With the hero and victim vocabularies in hand, we proceeded with message construction. As discussed earlier, we wanted to examine whether using "certainty" language rather than "probability" language would make a difference for audience reaction. In addition to constructing scientific probability and certainty messages, we also wanted to assess the effect of injecting narrative characters via victim, hero, and victim-to-hero language. Therefore, we constructed a total of eight messages. The base messages were scientific probability and certainty messages. When combining these base messages with the character language, we also ended up with a probability hero narrative, a probability victim narrative, a probability victim-to-hero narrative, a certainty hero narrative, a certainty victim narrative, and a certainty victim-to-hero narrative (see Appendix B).

<u>Scientific message construction</u>: In consultation with hydrologists on the research team, we crafted two scientific messages that lacked narrative characters and that avoided, to the extent possible, hero and victim language identified by natural language processing. One message focused on the frequency of flooding (probability), while the other focused on the fact that flooding will occur in the future (certainty).

Our scientific probability message was couched in terms used to describe flood frequency analysis (FFA) of historic river flow data. FFA is the most commonly employed method to assess flood risk in the U.S. In the parlance of FFA, a "100-year flood" is associated with a river discharge rate (e.g., cubic meters of water moving downstream per second) that is exceeded approximately once in a 100-year period. Thus, terms like "50-year flood," "100-year flood," and "500-year flood" are commonly used by governmental science agencies (like the U.S. Geological Survey) and disaster response agencies (like the Federal Emergency Management Agency) to communicate the magnitude of floods. Yet using such terms can result in a subtle understatement of flood risk because the terms ignore the fact that probability of a flood increases with the time period considered. For instance, although river discharge associated with a 100-year flood has only a 1% chance of occurring in any given year, there is a 22.2% chance of such an event occurring each generation (25 years) and a 54% chance of such an event occurring in the average life time of a baby born in the U.S. (78 years). Another way to think about the 100-year flood is that 54% of rivers will experience a 100-year flood over the average lifespan of a person born in the U.S. We designed our scientific probability message to highlight this aspect of flood frequencies, using a 30-year period (the typical length of a home mortgage):

> "Flooding occurs when water flows over land that is usually dry. Flooding can result from rain, snowmelt, and high flows in waterways. Flooding can also result from waterways being blocked by debris or ice and from infrastructure failures. A flood large enough to qualify as a 100-year flood has a 1% chance of happening in any single year. Yet the chance of flooding also adds up over time. For example, a 100-year flood has a 26-percent chance of occurring in any 30 year period."

Our scientific certainty message was designed to mimic the language that scientists are starting to use in communicating earthquake risk. Our language is designed to help people understand that, like large earthquakes, large floods will happen in the future, even if we do not know exactly when. Our certainty language was based on the idea that Holocene river sediment deposits indicate where floods have happened over the last 10,000 years and are, therefore, an indication of areas where floods will happen again. Our certainty message, which begins with the same definitional language as the probability message, was:

> "Flooding occurs when water flows over land that is usually dry. Flooding can result from rain, snowmelt, and high flows in waterways. Flooding can also result from waterways being blocked

> by debris or ice and from infrastructure failures. The potential for flooding along waterways is greater than commonly understood. Towns are often situated on sand and gravel that was deposited along waterways during past large floods. Similar floods will occur in the future, flooding these towns."

Construction of narratives: Given the brevity of the scientific messages, we constructed narratives by simply adding narrative language to the scientific messages. This ensured that the scientific information included in each narrative was held constant across all tests, but this also had the unavoidable side effect of making the narrative messages longer. Construction of the narratives focused on using the respective vocabularies generated by NLP, although term overlap was not completely avoidable due to language common to the flood domain.

The process of constructing the messages was iterative, with a good deal of input and feedback from the larger multidisciplinary research team. As mentioned earlier, we used certain NLP techniques for diagnostic purposes. For instance, a "word use signature" histogram was calculated for each narrative message by plotting the frequency of HTRF - VTRF scores (zero indicating neutral between hero and victim) for the words in each narrative (e.g., Figures 2a and 2b). A word that appears more than once in a message also shows up more than once in the histogram. As anticipated, the probability hero narrative shows a bias to the right – or hero language – side of the scale, while the probability victim-to-hero narrative shows a distribution centered closer to zero. Table 1 also provides the median values for HTRF-VTRF for each message, which is essentially central tendency information related to the histograms. We also applied the naïve Bayes classifier developed from the interview analysis to each message to verify that a narrative scored highly as a member of its own particular corpus. For example, the probability hero narrative was almost certainly classified as a member of the hero corpus.

[Table 1 about here]

In final form, each narrative began with the first two sentences from the scientific messages. This language served as an introduction and provided a baseline for later measurement of audience response. We held the character language parallel across the probability and certainty versions of each message. For example, the victim language attached to the probability message is identical to the victim language attached to the certainty message. The hero narrative emphasizes the entities responsible for fixing flood-related problems, including the audience members. The victim language emphasizes negative outcomes for the audience members and their communities. The victim-to-hero messages creates an arc in which the negative outcomes can be overcome by the audience members and their communities.

[Figures 2a and 2b about here]

Field Testing of Risk Communication Messages

The three communities that were the sites of the semi-structured interviews also became the sites for field testing the eight risk communication messages. The goal, again, was to test the language with audiences similar to those that generated the vocabularies via the semi-structured interviews. The testing technology required the construction of videos with audio for all eight messages. The videos were recorded Microsoft PowerPoint presentations with white words on dark blue backgrounds and audio overlays. Each slide contained a single sentence from the message to prevent audience members from reading ahead. The narrator attempted to remain as calm and impassive as possible when reading the messages to ensure that audience members were keying in on the content alone.

To obtain a sample of participants to test these eight messages, the researchers ordered a random sample of 500 addresses from Survey Sampling International for each of the three study communities.

Postcards went out to these addresses inviting one adult from the household to participate and offering a $50 incentive in return. The research sessions were scheduled to take place in the respective communities on prearranged dates in October and November of 2017. Potential participants could sign up via the website of the HELPS Lab. A second postcard went out to non-respondents two weeks later and invited individuals to spread news about the sessions. Eventually, the researchers also advertised via local newspapers and social media accounts linked to city governments. The research team conducted four sessions in each community. The final sample included 90 research participants: 36 from Livingston, 22 from Miles City, and 32 from Glendive. The sample was nearly evenly split in terms of women and men but did skew somewhat older than the general populations of adults in these communities.

The test sessions, which lasted approximately one hour each, featured dial response technology, a survey, and a follow-up focus group.[4] The maximum number of potential participants in a session was 12, and the actual number ranged from 4 to 11. The dial response technology, the Perception Analyzer from Dialsmith, permits instantaneous and continuous measurement of audience response to either live or recorded messages. Participants hold dials with preloaded data ranges as specified in the software. For this study, response options ranged from 0-100. The middle (vertical) position of the dial indicated 50 and was the neutral score. Participants were instructed to respond throughout the message with regard to how positive or negative the message was making them feel. The facilitator asked participants to start at the neutral position of 50 and indicated that 0 was the most negative score and 100 was the most positive score. Each session included a brief practice with using the dial response technology. The researchers randomized the order of the eight risk communication messages across sessions to eliminate message order effects. The software read each participant dial once per second and fed this information into both a video overlay and a spreadsheet of data. The video overlay graphed the mean response from across the dials on a second-by-second basis and also laid this graph over the top of the video being presented. Following each message, the facilitator also asked the participants to provide an overall score (on the same 0-100 scale) for the way the message made them feel overall. We refer to this latter measure as the "summative score" for the messages.

Each participant filled out a questionnaire following the dial response portion of the session. The brief questionnaire included items that dealt with: highest education level completed, the level of concern for flooding in their community, gender, birth year, and political ideology. The response options for concern about flooding were "very concerned," "somewhat concerned," "not too concerned," "not at all concerned," and "unsure." The response options for political ideology were "strong conservative," "conservative," "slight conservative," "middle of the road," "slight liberal," "liberal," and "strong liberal." The questionnaire also asked for participants to indicate their session and dial numbers, which allowed for linking these questionnaire responses later to the second-to-second dial responses.

Statistical Analyses

The dial response sessions and the survey responses provided the data necessary for testing the six hypotheses stated earlier. The second-to-second data are useful for showing affective response to narrative arc and for testing affective response across different segments of a message (e.g., probability vs. hero language within the probability hero narrative). The summative scores are also useful for gauging differences in affective response to messages. Finally, the survey items supply data necessary for assessing person-level influences on affective response.

The following section presents the results of the statistical analyses designed to test each of the hypotheses. The section discusses the graphing of average affective response throughout the course of a message and comparison of this response against the narrative arc for each message. We generally use t-

[4] Due to space concerns, we do not discuss the focus groups here.

tests as the method used for gauging the meaningfulness of differences in affective response based on narrative character language. Additionally, transformation of the data matrix produces 720 observations (i.e., 90 participants with summative scores for 8 messages each). The individual person becomes the grouping variable in this structure, while an individual message evaluation (i.e., an individual person's overall affective response to a message) becomes the dependent variable. The potential range for this dependent variable is 0-100, though in practice relatively few values fall near these limits. The distribution of the variable is approximately normal (though slightly left-skewed) with a median value of 61. Consequently, we treat the dependent variable as non-censored and continuous. The messages in this formulation become independent variables that serve as separate treatments. Each message treatment takes the form of a binary indicator variable (0 = no treatment, 1 = treatment), excluding one such message as the comparison category. The coefficient for one of these message variables, then, represents the shift in intercept between the excluded message and the particular message treatment being observed.

Given the clustered nature of the data and the continuous dependent variable, we use mixed-effects multilevel linear regression to test these 720 individual message evaluations. The data structure permits testing the effects of different message language on individual affective response, as well as testing for the effects of person-level variables on this response. While one cannot include group indicator (i.e., dummy) variables *and* estimate coefficients for other group-level variables with classical regression, multilevel mixed-effects linear regression usefully allows for varying intercepts and/or varying slopes at the group level and for cross-level interactions (see Gelman & Hill, 2007). These characteristics make the approach ideal for the analysis here. Beyond the statistical significance of the coefficients themselves, Wald tests of linear hypotheses provide information about the equivalence or non-equivalence of coefficients.

Results

We present our results in the order of our hypotheses. The testing of certain hypotheses includes use of both the second-by-second dial response data *and* the summative scores.

H_1: The contour of the average second-to-second affective response to scientific risk messages is flatter than the contour of the average second-to-second affective response to risk narratives with character language.

To test the first hypothesis, we examine the mean affective response for the 90 participants across the duration of each message (see Figure 3). The horizontal scale has been transformed into a percentage of the message duration to allow for direct comparability. *Vertical* lines inside the figure indicate changes from one type of language – scientific, hero, or victim – to another in the message. The solid vertical lines indicate changes for narratives with probability language, while dashed vertical lines indicates changes for narratives with certainty language (thereby matching the graphed lines themselves for each type). Visually, looking across the four panels in Figure 3, the scientific messages do generally appear to produce flatter responses over their durations than do the narratives.

[Figure 3 about here]

However, more robust tests are needed. The "Between-messages comparisons" section of Table 2 shows the results of variance ratio testing to test the variance of the probability and certainty messages against the risk narratives. The probability message is flatter than its probability hero and probability victim-to-hero narrative counterparts. Similarly, the certainty message is flatter than its victim-to-hero narrative counterpart. Other results – notably comparisons between the science messages and victim narratives – are not statistically significant. On the whole, however, *hero language generally seems to produce significant deviation from the flatter responses to the science messages*.

[Table 2 about here]

H_2: Affective response to hero language is more positive than affective response to scientific risk language.

H_3: Affective response to hero language is more positive than affective response to victim language.

To test the second and third hypotheses, we return initially to Figure 3 and Table 2. The "Within-messages comparisons" portion of Table 2 compares the aggregate mean score across all seconds of one type of language in a given message against the aggregate mean score across all seconds of another type of language *within the same message*. The aggregate mean scores are the mean affective response across all 90 individuals for all associated seconds in the message. For example, the first entry here compares the aggregate mean affective score for the hero-language seconds in the probability hero narrative to the aggregate mean affective score for the science-language seconds in that same narrative. Within the four risk narratives containing heroes, the hero language evoked significantly more positive affective response than did the science language (either probability or certainty; H_2). Similarly, the affective response to hero language was significantly more positive than the affective response victim language in both instances (H_3).

Tables 3 and 4 are also pertinent here. Table 3 displays the results of the multilevel mixed-effects regressions that use summative evaluations of the messages. Diagnostics reveal that 39.11% of the variance is at the person (group) level, with the remainder at the message level. Diagnostics also reveal that use of the multilevel model is an improvement over the classical regression model. As the coefficients in Table 3 are difficult to interpret, Table 4 displays the results of Wald tests for the equivalence of coefficients. The regressions in Table 3 also specify random intercepts for individual persons (not reported), thereby accounting for other differences in how persons use the technology and respond to the messages beyond those explicitly modeled. The second specification adds a number of person-level independent variables, none of which is statistically significant beyond what is found in the first specification. However, controlling for these variables seems important.

[Table 3 about here]

As concerns the second hypothesis, two of the results in Table 4 deal with the gap between hero narratives and science messages. Narratives with hero language produced more positive summative scores in terms of affective response. This applies to both the probability hero narrative and the certainty hero narrative.

The six results in Table 4 relevant to the third hypothesis are also supportive of that hypothesis, as narratives with hero language produce more positive summative scores in terms of affective response than do narratives with victim language. Two of the rows in Table 4 test this difference directly, while the other four rows involve comparisons that are less direct. For an example of indirection comparisons, the second-to-last entry under "Probability message and associated narratives" examines the difference between evaluation of the probability victim-to-hero narrative and the probability hero narrative. The very next entry considers the difference between the probability victim-to-hero narrative and the probability victim narrative. Only the second comparison is statistically significant. This result suggests that the real difference is between the hero and victim language. The final two entries under "Certainty message and associated narratives" result in an equivalent conclusion.

[Table 4 about here]

Additional evidence relevant to the assessment of the second and third hypotheses also appears in Table 5. This table displays the results of paired sample t-tests between peaks and troughs in different types of language as shown in Figure 3. Four of the results in Table 5 assess differences between peak responses to hero language and trough responses to science language (H_2). In all four cases, affective response to the hero language is more positive in a statistically significant way. Two of the results in Table 5 are relevant to the difference between peak hero response and peak victim response (H_3). We end up using victim language peaks (rather than troughs) as a consequence of the finding below that response to victim language is more positive than response to neutral language. In both of these cases, the hero language produces an affective response peak that is statistically more positive. In conclusion, the evidence overall supports the idea that *hero language induces a more positive affective response than does science langauge*. The evidence overall also supports a claim that *hero language induces a more positive affective response than does victim language*.

[Table 5 about here]

H_4: Affective response to victim language is more negative than affective response to scientific risk language.

In stark contrast to the results for the previous hypotheses, victim language does not induce a response that is statistically more negative than the affective response to the science language. The evidence in Tables 2-5 and Figure 3 runs uniformly contrary to this hypothesis. In Table 2 any differences are small, and response to victim language is always *more positive* – which runs contrary to the hypothesis. In one of the cases, the final row of Table 2, the victim language is actually more positive than the science language in a statistically significant way. Table 4 offers evidence from the summative affective evaluations of messages. Here again the directionality is opposite of the prediction, with evaluations of victim narratives being more *positive* than science messages in a statistically significant way. Similarly, Table 5 shows some statistically significant swings in response based on language type. Half of these swings are statistically significant, though they are always in the opposite direction of the prediction. Consequently, the evidence *does not support a claim that victim language induces a more negative affective response than does science language, but the opposite claim does find some support in the data*.

H_5: A victim-to-hero narrative arc produces the largest swing in affective response.

Visually, in Figure 3, the most dramatic swings in affective response appear to happen when switching from victim to hero language at the end of the victim-to-hero narratives. Tables 4 and 5 also supply pertinent evidence. The final four rows of Table 4 examine differences in differences. For example, the first of these rows checks whether the difference in summative affective response between the probability victim-to-hero narrative and the probability message is larger than the corresponding difference between the probability hero narrative and the probability message. The pattern of results suggests that the victim-to-hero arc is not definitively more influential, though it does produce a greater summative score in a statistically significant way than does a victim arc. Table 5, in its final four rows, similarly displays results from testing of differences in differences for swings in response. The only scenario in which the victim-to-hero swing is more dramatic in a statistically significant way is when comparing this swing against the shift between victim and science language within the certainty victim narrative. This result appears in the last row of data in Table 5. However, the tests here are purposefully difficult based on the use of peaks for victim language. With mixed evidence, we conclude only that *the victim-to-hero arc outperforms a victim arc in terms of inducing positive affective response*. The same does not appear to be true when comparing victim-to-hero arcs against hero arcs.

H_6: Affective response to certainty language differs from affective response to probability language.

Our data do not support the sixth hypothesis. Figure 3 does not visually show any large gaps between the mean second-to-second affective responses across probability and certainty messages.

Comparing numbers in Tables 2 and 5 shows little difference, as well. Table 4 supplies the most direct evidence. The first four tests directly compare probability and certainty language, and nothing here is statistically significant. Consequently, we conclude that *probability and certainty language in these messages do not produce different affective responses in the audience*.

Discussion

Can narrative-based science risk communication serve as a *lingua franca* for conventional science risk communication? To address this question, we sought locally based language, used NLP techniques to choose character language empirically, and embedded probability and certainty science statements in these risk narratives. We sought not only to discover the power of narrative-based risk communication as compared to conventional risk communication, we also sought to explore with greater precision the ways in which narrative characters induce different affective responses. In other words, we looked to test certain pieces of the underlying mechanisms.

Our results support the broader understanding that narratives matter in risk communication. Indeed, people do respond differently to scientific risk information *embedded* in a specific narrative structure than to non-narrative science risk messages on their own. Importantly, we investigated the effects of specific narrative mechanisms on affective responses of participants, a cognitive process that is assumed to take place but has not been measured in risk communication studies. Overall, heroes reign. Across the board, participants have significantly higher affective responses to messages with heroes as compared to those without characters and to those with victims.

We certainly encountered some surprises, too. First, we expected victims to evoke more negative affective responses. The statistical tests reveal differences in affective response between victim language and science language (either within or between messages) only in the direction opposing our prediction. We predicted negative responses based on the negative feelings associated with being a victim: anxiety, fear, etc. However, we believe that our audiences evaluated victim language in a relatively positive way because they *agreed* with the language. Furthermore, the victim-to-hero swing may have been muted as a result of splitting up the victim language in those narratives. Second, we did not expect that people would respond to probability and uncertainty messages in very similar ways. Given a general lack of understanding in the public of what probability messages mean to convey, we suspect audiences were viewing the messages as similar portrayals. Both approaches are merely science messages disconnected from the everyday lives of audience members. This finding certainly merits further research, however.

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Table 1. Messages with brief descriptions and validity check statistics

Message	Description	Median (HTRF – VTRF)
Probability	Standard probability hazard message	0.04
Certainty	Certainty hazard message	0.26
Probability hero	Probability message with hero arc	1.19
Certainty hero	Certainty message with hero arc	1.21
Probability victim	Probability message with victim arc	-0.53
Certainty victim	Certainty message with victim arc	-0.31
Probability victim-hero	Probability message with victim-to-hero arc	0.26
Certainty victim-hero	Certainty message with victim-to-hero arc	0.26

Notes. HTRF is the hero transformed relative frequency. VTRF is the victim transformed relative frequency. The median values are across all words in a particular message.

Table 2. Two-sample and paired sample t-tests

Between-messages comparisons	First Value	Second Value	Ratio or Difference	P-value
Probability second-to-second average SD				
Probability SD vs. probability hero SD (H_1)	2.689	3.461	0.777*	0.032
Probability SD vs. probability victim SD (H_1)	2.689	2.968	0.906	0.235
Probability SD vs. probability victim-to-hero SD (H_1)	2.689	3.593	0.748*	0.017
Certainty second-to-second SD				
Certainty SD vs. certainty hero SD (H_1)	2.763	3.270	0.845	0.118
Certainty SD vs. certainty victim SD (H_1)	2.763	3.200	0.863	0.150
Certainty SD vs. certainty victim-to-hero SD (H_1)	2.763	3.697	0.747*	0.020
Within-message comparisons				
Probability hero narrative				
Hero > science (H_2)	62.496	58.229	4.267***	0.001
Probability victim narrative				
Science > victim (H_4)	58.117	59.110	-0.993	0.856
Victim > science ($H_{4\ opposite}$)	59.110	58.117	0.993	0.144
Probability victim-to-hero narrative				
Hero > science (H_2)	61.711	57.489	4.222***	0.001
Hero > victim (H_3)	61.711	58.519	3.192***	0.001
Science > victim (H_4)	57.489	58.519	-1.030	0.903
Victim > science ($H_{4\ opposite}$)	58.519	57.489	1.030	0.097
Certainty hero narrative				
Hero > science (H_2)	62.044	58.229	3.815***	0.001
Certainty victim narrative				
Science > victim (H_4)	59.251	59.296	-0.045	0.520
Victim > science ($H_{4\ opposite}$)	59.296	59.251	0.045	0.480
Certainty victim-to-hero narrative				
Hero > science (H_2)	63.335	59.040	4.295***	0.001
Hero > victim (H_3)	63.335	60.550	2.785***	0.001
Science > victim (H_4)	59.040	60.550	-1.510	0.978
Victim > science ($H_{4\ opposite}$)	60.550	59.040	1.510*	0.022

Notes. The standard deviation tests at the top of the table are conducted as variance ratio tests. Given the nature of the first hypothesis, the test is whether the variance for the probability and certainty messages is appreciably smaller than the variance for the narratives (i.e., the ratio is statistically smaller than 1). The variance ratio tests are based on averages for the second-to-second data across all 90 participants. Ratios appear in the third data column. These tests are two-sample tests, as the data come from separate messages.

The remainder of the tests in the table are directional tests that compare mean scores for affective evaluation across all seconds of certain types of language in a message. For example, the first test compares the mean score across all seconds of hero language in the probability hero narrative against the mean score across all seconds of science language *in that same narrative*. Explicit tests of hypotheses are noted in parentheses. These tests include the initial science language for all messages. The sample size is 90 (the number of participants) for these tests.

*** $p \leq 0.001$ ** $p \leq 0.01$ * $p \leq 0.05$

Table 3. Multilevel Mixed-Effects Regression on Individual Summary Message Evaluations

	Specification #1: Messages & Towns		Specification #2: All Variables	
Individual-Message Variables	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Probability message	0.122	2.394	0.068	2.448
Probability hero narrative	13.167***	2.675	13.170***	2.729
Probability victim narrative	6.167*	2.463	6.352*	2.516
Probability victim-hero narrative	12.989***	2.520	13.091***	2.574
Certainty hero narrative	13.100***	2.559	13.045***	2.607
Certainty victim narrative	7.244**	2.723	7.068*	2.773
Certainty victim-hero narrative	15.022***	2.544	14.943***	2.586
Personal-Level Variables				
Town 1	5.964	4.224	6.683	4.180
Town 2	7.810*	3.273	11.040***	3.448
Educational level			1.644	1.634
Female			0.479	3.308
Age			0.036	0.094
Political ideology			0.490	0.753
Concern about flooding			3.321	2.251
Constant	47.565***	2.379	26.836**	10.319

Notes. The number of observations for each specification is 720 (i.e., 90 persons multiplied by 8 messages each). All hypothesis tests are two tailed. The models estimate robust standard errors. The certainty message is the excluded category. Town 1 is Miles City, Town 2 is Glendive, and the excluded category is Livingston. The model uses the variance-covariance structure of the random effects and uses maximum likelihood estimation.

*** $p \leq 0.001$ ** $p \leq 0.01$ * $p \leq 0.05$

Table 4. Wald Tests for Equivalence of Coefficients

Comparison (mean affective response for messages in parentheses)	χ^2	Prob. > χ^2
Probability vs. certainty science messages		
Probability (51.92) vs. certainty (51.80) [H_6]	0.00	0.978
Probability hero (64.97) vs. certainty hero (64.90) [H_6]	0.00	0.948
Probability victim (57.97) vs. certainty victim (59.04) [H_6]	0.08	0.777
Probability victim-to-hero (64.79) vs. certainty victim-to-hero (66.82) [H_6]	0.86	0.354
Probability message and associated narratives		
Probability (51.92) vs. probability hero (64.97) [H_2]	31.70***	0.001
Probability (51.92) vs. probability victim (57.97) [H_4]	6.31*	0.012
Probability (51.92) vs. probability victim-to-hero (64.79)	36.54***	0.001
Probability hero (64.97) vs. probability victim (57.97) [H_3]	7.08**	0.008
Probability hero (64.97) vs. probability victim-to-hero (64.79) [H_3]	0.00	0.964
Probability victim (57.97) vs. probability victim-to-hero (64.79) [H_3]	8.24**	0.004
Certainty message and associated narratives		
Certainty (51.80) vs. certainty hero (64.90) [H_2]	25.04***	0.001
Certainty (51.80) vs. certainty victim (59.04) [H_4]	6.50*	0.011
Certainty (51.80) vs. certainty victim-to-hero (66.82)	33.40***	0.001
Certainty hero (64.90) vs. certainty victim (59.04) [H_3]	4.82*	0.028
Certainty hero (64.90) vs. certainty victim-to-hero (66.82) [H_3]	1.08	0.298
Certainty victim (59.04) vs. certainty victim-to-hero (66.82) [H_3]	13.47***	0.001
Comparison for victim-to-hero arcs (difference in differences)		
PVH – P (12.87) vs. PH – P (13.05) [H_5]	0.00	0.964
PVH – P (12.87) vs. PV – P (6.05) [H_5]	8.24**	0.004
CVH – C (15.02) vs. CH – C (13.10) [H_5]	1.08	0.298
CVH – CV (15.02) vs. CV – C (7.24) [H_5]	13.47***	0.001

Notes. Results of Wald tests are based on specification #2 in Table 4, though the excluded category must change to obtain some of these results. The identity of the excluded category makes no difference to the results otherwise. Again, the variables are the overall evaluations provided by participants after completion of each message. For ease of interpretability, the numbers following each message are mean affective response values across the 90 participants rather than the coefficients from Table 4. Statistically significant results indicate that the coefficients for the two messages being tested are different from one another. The substantive conclusions here end up being identical to what would be obtained through two-tailed, paired-sample t-tests of the mean values for the message evaluations. However, the Wald test approach also allows for controlling for other independent variables, including the town of origin and other person-level variables.

*** $p \leq 0.001$ ** $p \leq 0.01$ * $p \leq 0.05$

Table 5. Paired sample t-tests for peaks and troughs in second-to-second data

Comparison	First Value	Second Value	Absolute Difference	P-value
Probability hero narrative				
Hero peak 1 (27.5%) > science trough 1 (75.8%) [H_2]	63.778	55.800	7.978***	0.001
Science trough 1 (75.8%) < hero peak 2 (90.1%) [H_2]	55.800	66.556	10.756***	0.001
Probability victim narrative				
Victim peak 1 (45.6%) > science trough 1 (76.7%) [H_4]	63.789	54.756	9.033***	0.001
Science trough 1 (76.7%) < victim peak 2 (92.2%) [H_4]	54.756	57.456	2.700	0.071
Probability victim-to-hero narrative				
Final victim peak (85.1%) to final hero peak (96.8%) [H_3]	54.067	67.344	13.278***	0.001
Certainty hero narrative				
Hero peak 1 (33.3%) > science trough 1 (74.2%) [H_2]	63.167	57.367	5.800**	0.005
Science trough 1 (74.2%) < hero peak 2 (88.2%) [H_2]	57.367	66.767	9.400***	0.001
Certainty victim narrative				
Victim peak 1 (54.7%) > science trough 1 (75.8%) [H_4]	64.300	57.589	6.711***	0.001
Science trough 1 (75.8%) < victim peak 2 (88.4%) [H_4]	57.589	58.022	0.433	0.583
Certainty victim-to-hero narrative				
Final victim peak (78.8%) < final hero peak (96.0%) [H_3]	58.133	69.344	11.211***	0.001
Probability hero-victim > hero-science [H_5]	13.278	10.756	2.522	0.138
Probability hero-victim > victim-science [H_5]	13.278	9.033	4.245	0.087
Certainty hero-victim > hero-science [H_5]	11.211	9.400	1.811	0.197
Certainty hero-victim > victim-science [H_5]	11.211	6.711	4.500*	0.034

Notes. The data used here come from the second-to-second affective responses of participants. This table excludes the first segment of science language for each message shown in Figure 3. The numbers in parentheses are the percentage across the message at which the peak or trough occurs (see Figure 3). The comparison is across mean scores for 90 participants at particular seconds in particular messages. The final four rows assess differences in differences. For example, the first test considers whether the victim-to-hero swing in the probability victim-to-hero narrative is statistically larger than the swing from science-to-hero language in the probability hero narrative. This analysis uses the peaks of victim language in comparisons.

*** $p \leq 0.001$ ** $p \leq 0.01$ * $p \leq 0.05$

Figure 1. Plot of polarity scores from hero corpus

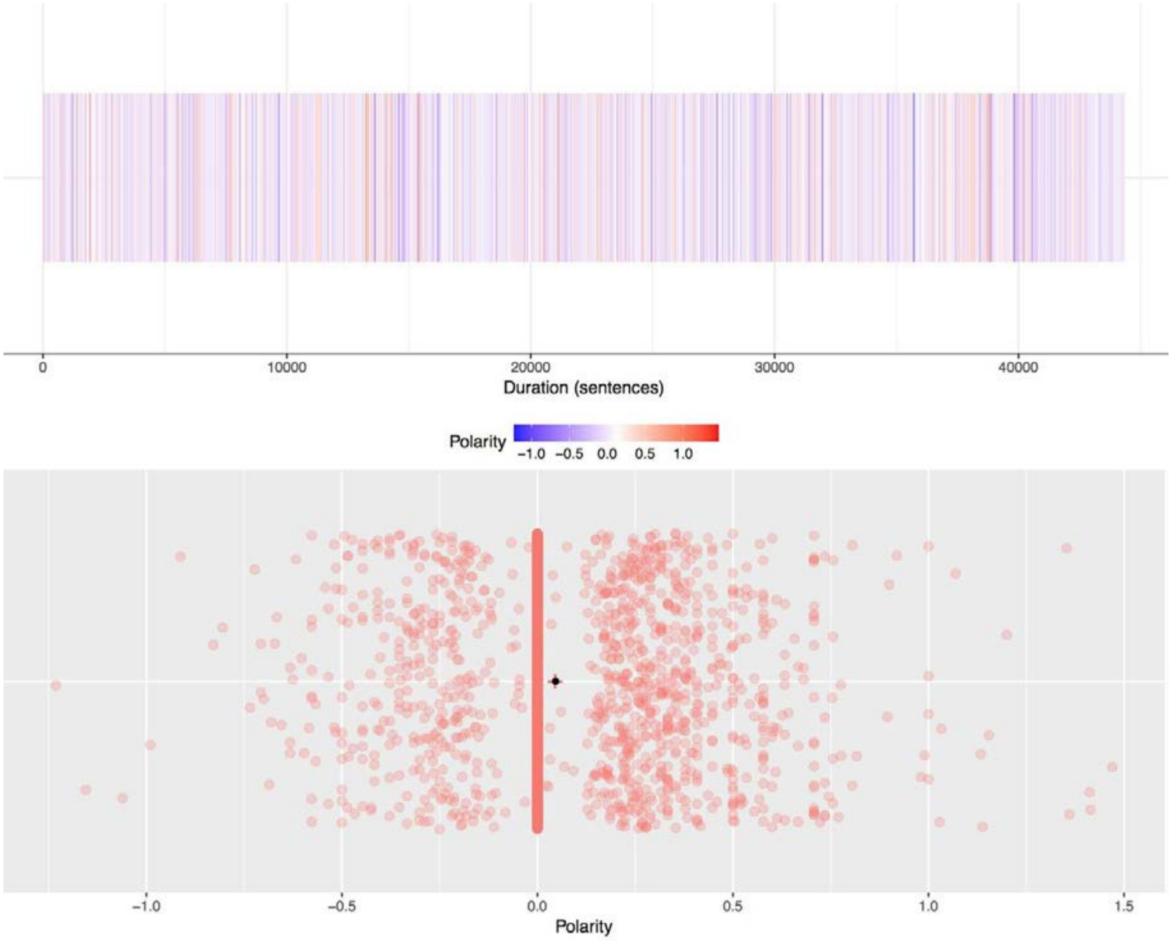


Figure 2a. Histogram for the probability hero narrative

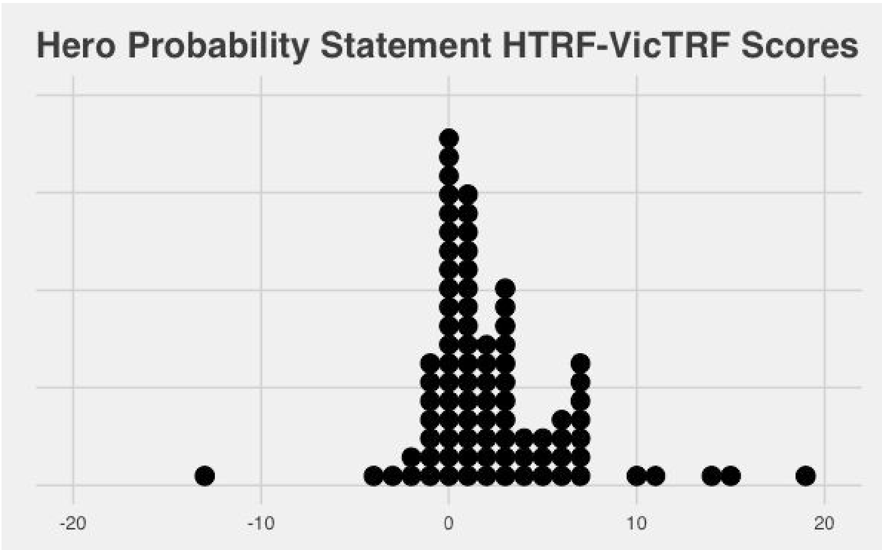


Figure 2b. Histogram for the probability victim-to-hero narrative

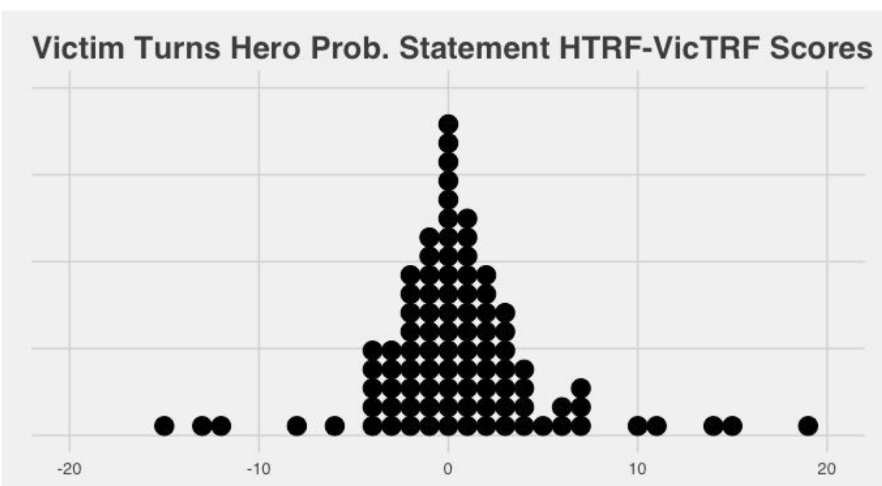
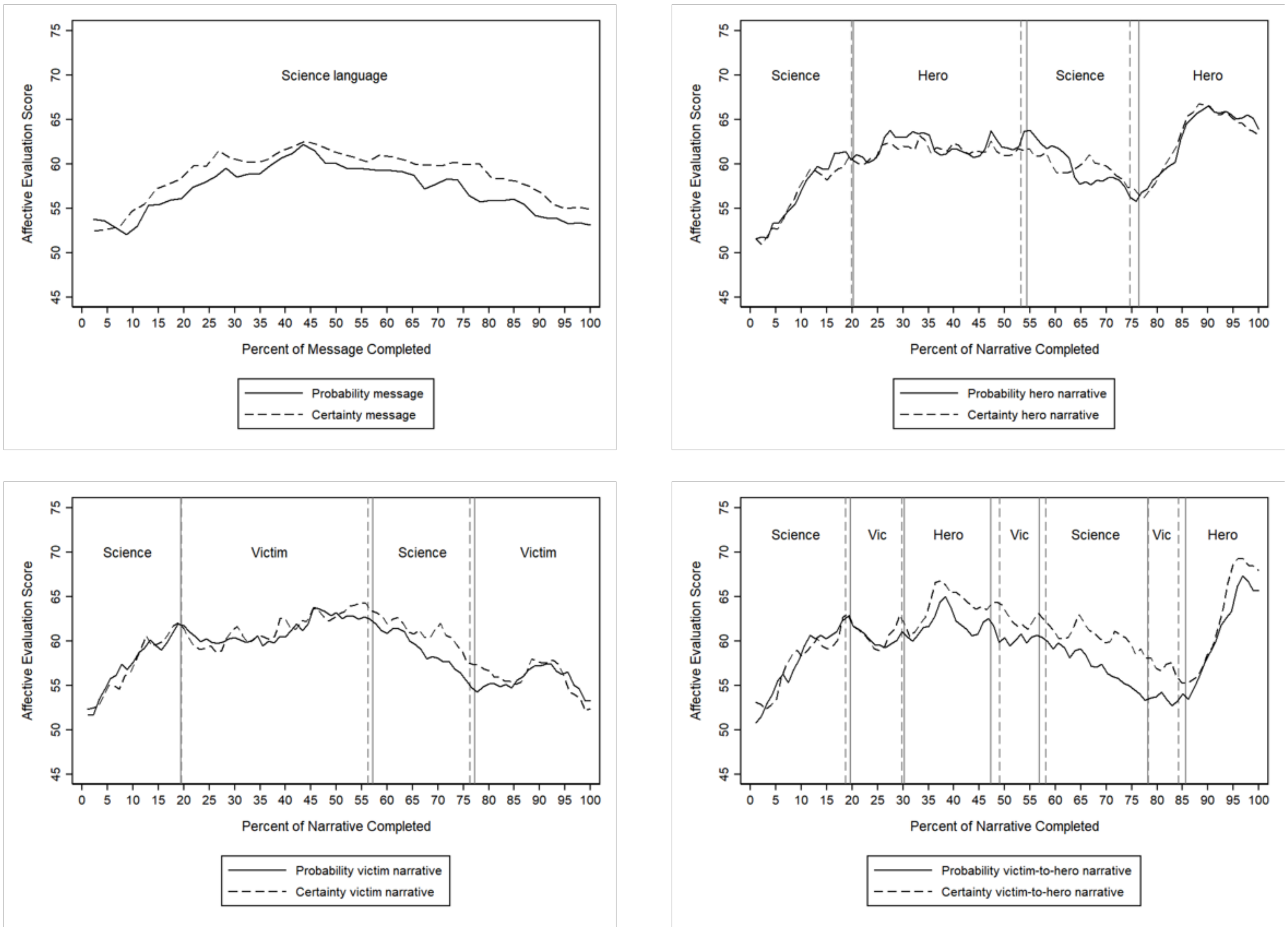


Figure 3. Average affective evaluation across duration of 8 messages for 90 participants



Appendix A. Interview protocol

Problem Definitions & Information Sources

1. What do you value about the Yellowstone River? *[Very open ended]*
2. What do you see as problems related to the Yellowstone River, if any? *[Build on #1 response]*
3. How would you describe a flood on the Yellowstone River? What happens or what are the signs? *[Probe for other sources of river flooding if only talk about rain and/or ice jams]*
4. What are aspects of Yellowstone River flooding that you see as problematic? *[If not answered in #2]*
5. Do you see any aspects of Yellowstone River flooding as beneficial?
6. To what extent do you think you are personally at risk from flooding on the Yellowstone River?
7. When you need information about Yellowstone River flooding, where do you go for that information?
8. What kinds of information about flooding do you pay attention to? *[If not addressed in #7]*
9. Do you wish you had other information available to you about flooding on the Yellowstone River? If so, what types or forms of information?

Flood Narratives: Heroes & Victims

10. What is your experience with river flooding events on the Yellowstone River or elsewhere? *[To the extent not covered earlier; looking for observations and adjectives]*
11. In what ways, if any, have you been harmed personally by river flooding events on the Yellowstone River or elsewhere? *[Victim (i.e., someone harmed)]*
12. In what ways, if any, has your community been harmed by river flooding events on the Yellowstone River or elsewhere? *[Victim]*
13. Who, if anybody, helped you personally to prepare for or recover from flooding events? How did they help? *[Probe for both before and after as necessary; heroes & decisions]*
14. Who, if anybody, helped your community to prepare for or recover from flooding events? How did they help? *[Probe for both before and after as necessary; heroes & decisions]*

Appendix B. Narrative language

Probability hero narrative

Flooding occurs when water flows over land that is usually dry. Flooding can result from rain, snowmelt, and high flows in waterways. Flooding can also result from waterways being blocked by debris or ice and from infrastructure failures. In Montana, good neighbors like you help when Yellowstone floodwaters rise. While many feel protected by the local dike, people also understand and respect the power of this river. Engineers provide the benefits of technical assistance to reduce flood risks. Yet, in the face of a large flood event, even the best-engineered solutions may not work. Under extreme flood conditions, the river could over-top your levee or bank. A flood large enough to qualify as a 100-year flood has a 1% chance of happening in any single year. Yet the chance of flooding also adds up over time. For example, a 100-year flood has a 26-percent chance of occurring in any 30-year period. Working together with your local emergency responders, you can think about and begin to implement individual and community strategies before a disaster occurs. By trying to protect from damages of extreme flooding, you will have really helped in a big way.

Probability victim narrative

Flooding occurs when water flows over land that is usually dry. Flooding can result from rain, snowmelt, and high flows in waterways. Flooding can also result from waterways being blocked by debris or ice and from infrastructure failures. Many homeowners and businesses along the Yellowstone River are concerned with having to pay a lot of money for insurance based on the latest federal flood map. While most respect the power of this river, your house or your friend's house and the economy of local business could be vulnerable. Even with engineered solutions to reduce flood worries, problems can happen quickly. Under extreme flood conditions, the river could over-top, leaving properties damaged and companies hit with expensive repair costs. A flood large enough to qualify as a 100-year flood has a 1% chance of happening in any single year. Yet the chance of flooding also adds up over time. For example, a 100-year flood has a 26-percent chance of occurring in any 30-year period. You, your friends, and your neighbor could be harmed or wiped out by high post-flood premiums and loss of valuable assets such as cattle and houses. Without preparation, your town could be lost as it faces difficult and sad times.

Probability victim-to-hero narrative

Flooding occurs when water flows over land that is usually dry. Flooding can result from rain, snowmelt, and high flows in waterways. Flooding can also result from waterways being blocked by debris or ice and from infrastructure failures. Many homeowners and businesses along the Yellowstone River are concerned with having to pay a lot of money for insurance based on the latest federal flood map. Yet, in Montana, good neighbors like you help when Yellowstone floodwaters rise. While many feel protected by the local dike, your house or your friend's house and the economy of local business could be vulnerable, as even the best-engineered solutions may not work. Under extreme flood conditions, the river could over-top, leaving properties damaged and companies hit with expensive repair costs. A flood large enough to qualify as a 100-year flood has a 1% chance of happening in any single year. Yet the chance of flooding also adds up over time. For example, a 100-year flood has a 26-percent chance of occurring in any 30-year period. Without preparation, your town could be lost, as it faces difficult and sad times. Working together with your local emergency responders, you can think about and begin to implement individual and community strategies before a disaster occurs.

Certainty hero narrative

Flooding occurs when water flows over land that is usually dry. Flooding can result from rain, snowmelt, and high flows in waterways. Flooding can also result from waterways being blocked by debris or ice and from infrastructure failures. Many homeowners and businesses along the Yellowstone River are concerned with having to pay a lot of money for insurance based on the latest federal flood map. Yet, in Montana, good neighbors like you help when Yellowstone floodwaters rise. While many feel protected by the local dike, your house or your friend’s house and the economy of local business could be vulnerable, as even the best-engineered solutions may not work. Under extreme flood conditions, the river could over-top, leaving properties damaged and companies hit with expensive repair costs. A flood large enough to qualify as a 100-year flood has a 1% chance of happening in any single year. Yet the chance of flooding also adds up over time. For example, a 100-year flood has a 26-percent chance of occurring in any 30-year period. Without preparation, your town could be lost, as it faces difficult and sad times. Working together with your local emergency responders, you can think about and begin to implement individual and community strategies before a disaster occurs.

Certainty victim narrative

Flooding occurs when water flows over land that is usually dry. Flooding can result from rain, snowmelt, and high flows in waterways. Flooding can also result from waterways being blocked by debris or ice and from infrastructure failures. Many homeowners and businesses along the Yellowstone River are concerned with having to pay a lot of money for insurance based on the latest federal flood map. While most respect the power of this river, your house or your friend’s house and the economy of local business could be vulnerable. Even with solidly engineered solutions to reduce flood worries, problems can happen quickly. Under extreme flood conditions, the river could over-top, leaving properties damaged and companies hit with expensive repair costs. The potential for flooding along waterways is greater than commonly understood. Towns are often situated on sand and gravel that was deposited along waterways during past large floods. Similar floods will occur in the future, flooding these towns. You, your friends, and your neighbor could be harmed or wiped out by high post-flood premiums and loss of valuable assets such as cattle and houses. Without preparation, your town could be lost as it faces difficult and sad times.

Certainty victim-to-hero narrative

Flooding occurs when water flows over land that is usually dry. Flooding can result from rain, snowmelt, and high flows in waterways. Flooding can also result from waterways being blocked by debris or ice and from infrastructure failures. Many homeowners and businesses along the Yellowstone River are concerned with having to pay a lot of money for insurance based on the latest federal flood map. Yet, in Montana, good neighbors like you help when Yellowstone floodwaters rise. While many feel protected by the local dike, your house or your friend’s house and the economy of local business could be vulnerable, as even the best-engineered solutions may not work. Under extreme flood conditions, the river could over-top, leaving properties damaged and companies hit with expensive repair costs. The potential for flooding along waterways is greater than commonly understood. Towns are often situated on sand and gravel that was deposited along waterways during past large floods. Similar floods will occur in the future, flooding these towns. Without preparation, your town could be lost as it faces difficult and sad times. Working together with your local emergency responders, you can think about and begin to implement individual and community strategies before a disaster occurs.