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Human Wildlife Conflict Monitoring: Understanding Human Wildlife Conflict Through Big Data

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Executive Summary

This research examines global methodologies for understanding community attitudes and tolerance regarding Human Wildlife Conflict. Both traditional and future-focused approaches are examined for use in the World Wildlife Fund's 13 tiger landscapes. Traditional methodologies are resource intensive and limit the ability for longitudinal studies and timely indication of attitudinal shifts. This research uses the Safe System Approach to explore innovative ways of understanding community attitudes toward human tiger conflict. We argue that improved monitoring of conflict areas will improve conflict management in all areas. This research uses policy analysis tools to evaluate the effectiveness of various big data techniques, including trend and sentiment analysis, network analysis and community leader identification. Piloting innovative approaches to understanding attitudes has great potential to expand knowledge of human tiger conflict and lead to conflict responses that can eliminate retaliatory killings of tigers globally.

Keywords: human wildlife conflict, big data, data mining, attitudinal awareness, tiger conservation, policy analysis

Introduction

Human Wildlife Conflict (HWC) refers to all cases in which interactions between humans and wildlife lead to negative impact at both sides through fear, injuries, death, and loss of property or livelihoods (WWF Network HWC Working Group definition). HWC is increasing worldwide due to human population growth and habitat loss and, in some instances, increased wildlife populations as a result of conservation success (Carter, Riley, & Liu, 2012). Humans are using more land, which limits habitats for wildlife. The result is increased negative interactions and, oftentimes, intensifying conflict between humans and wildlife. Humans frequently respond to HWC in ways that threaten animal life. When dealing with large carnivores, the common responses tend to be eradication or regulated hunting due to the animals being seen as a threat to both humans and their assets (Treves & Karanth, 2003). These retaliatory responses to HWC, combined with diminishing habitat and prey, and poaching of large carnivores, have severely decreased populations of large conflict related wildlife species globally. Notable affected species include lions, wolves, jaguars, polar bears, tigers and elephants.

In many instances the acute and reactive responses by local communities or government to conflict is unexpected or is disproportionate to the HWC event itself. First, wildlife managers are often unprepared for or surprised by a retaliatory incident, or when community tolerance is breached by conflict events. And second, the perceived risk often outweighs the actual risk of conflict, and local attitudes and emotions therefore dictate responses that far outweigh the severity or extant of the original incident. Understanding and tracking community attitudes is therefore a critical component of HWC management as it can allow managers to track and measure community sentiment and be better prepared as and when community tolerance is breached, and retaliatory killing may occur (Brooks, pers. comm.).

Monitoring and tracking community attitudes in human wildlife conflict contexts is typically done via qualitative surveys and Knowledge, Action Perception (KAP) surveying delivered at the village or community level. Invariably such methods involve many enumerators, take multiple days to undertake to achieve adequate sampling, and require extensive data collation and analysis. As such, where community attitudes surveying for HWC has been undertaken, it is often only done once due to the effort and costs involved. As understanding community attitudes is a critical ingredient in managing tiger conflict and therefore avoiding local extinction, then more agile and replicable methods for monitoring attitudes must be developed (Brooks, pers. comm.).

The purpose of this research is therefore to explore innovative methods to increase understanding of community attitudes and tolerance regarding human tiger conflict. Our research attempts to overcome the barriers to community attitude tracking by proposing pilot testing of innovative approaches that could enable better deployment of programs and resources to enhance management of HWC.

Why managing human tiger conflict matters

Wild tigers are in jeopardy. Significant habitat loss, poaching, and deficient conservation initiatives have led to a 95% population decrease of the species over the past century (Dinerstein et al., 2007). Immense human population growth, increased spending on major infrastructure, and the fragmentation of tiger landscapes increase and intensify conflicts between tigers and humans (Dinerstein et al., 2007; WWF, 2016). Human tiger conflicts may be triggered by several different factors. Illegal tiger killings are often motivated by loss of human life or injury, loss of livestock, loss of crops, and damage to property (Acharya, Paudel, Neupane, & Köhl, 2016).

Local communities living near tiger landscapes are the key stakeholders in the debate about tiger conservation. A better understanding of community attitudes and practices toward human tiger conflicts in local communities is vital for the success of HWC interventions. Social engagement and positive community attitudes towards conservation are essential to creating safeguards for humans and tigers as conflict increases. These relationships can be improved by enhanced management of HWC (WWF, 2018). Finding cost and time-efficient methods of collecting longitudinal data about the attitudes of communities that deal with human tiger conflict may drastically improve understanding of conflicts, potentially leading to improved policies for prevention, response and mitigation of conflict.

The importance of understanding community perceptions

Community attitudes in tiger landscapes have direct influence on tiger populations. Communities want to feel safe and know their assets are protected, and managers want to understand local sentiments and what the triggers are that lead to a change in local attitudes toward wildlife. For instance, Carter et al. (2012) found that a desire for fewer tigers is associated with perceived risk to humans and assets, as well as a lack of confidence in government to manage those risks. Negative attitudes toward tigers impact the number of retaliatory and preemptive killings that occur and reduce community support for conservation programs on the ground.

For most people, attitudes toward human wildlife conflicts are shaped by indirect interactions with conflicts, rather than direct interactions with animals themselves (Carter et al., 2012). Examples of indirect interactions include hearing news reports, reading social media posts, or word-of-mouth anecdotes. Innovative monitoring of community attitudes will help conservationists understand the extent of negative attitudes and inform potential interventions, such as geographically targeted messaging campaigns about the important of animal and habitat conservation.

Information deficiency

Understanding and addressing HWC is especially challenging because data regarding HWC is not always collected and the data that is collected is often spread across multiple agencies, not always accurate or unavailable to outside sources. The effectiveness of HWC interventions are frequently uncertain because of this dearth of data. In addition, HWC has been largely studied at the site level, but patterns of conflict at the national and international level have not been significantly addressed, making it difficult to determine if global interventions are feasible (Acharya, Paudel, Neupane, & Köhl, 2016).

To date, current efforts to monitor and track community attitudes of tigers and HWC fall short. Monitoring frameworks must be established that provide for accurate, timely and longitudinal data collection to inform these interventions.

Methodology

This report approaches the challenge of understanding community attitudes to HWC from a policy analysis perspective. Policy analysis is designed to be client-focused, basing its approach on the needs and interests of decision-makers. Policy analysis as an approach is designed to support policy decision-making by providing the tools and information needed for policymakers to make effective, informed decisions. This approach may include the crafting, comparison and ranking of policy options as a tool to help policymakers process large amounts of information efficiently and effectively (Weimer & Vining, 2011). The field of policy analysis provides the ideal framework to assess community attitudes to HWC, as the process and the goal is the same: both are client-focused to ensure decision-makers' needs are met, and that information is used to help inform more effective management decisions. Three main questions guided this project:

1. What methodologies exist globally for understanding community attitudes, tolerance and tipping points regarding Human Wildlife Conflict?
2. What are innovations in the field of attitudinal awareness that could provide accurate, timely and longitudinal monitoring?
3. What future-focused framework(s) are suitable to pilot and test across selected sites?

To address these questions, a set of literature reviews were conducted. Information regarding the Safe Systems Approach adopted by WWF guided the larger literature review. This review provided both direction on answering the subsequent questions and criteria for evaluating traditional and innovative attitudinal awareness methodologies. A set of peer-reviewed journal articles and practitioner reports regarding existing approaches to measuring and understanding community attitudes and attitudinal changes were collected by following recommendations of highly published scholars in the field and conducting literature searches of online databases. Citations within key pieces of research and case studies were used to guide the collection of additional literature until saturation of current methodological practices was reached. Attributions associated with the Safe Systems Approach were utilized to evaluate current practices and identify deficiencies. Deficiencies identified, along with the Safe Systems Approach attributes, were used to guide literature collection on innovations in attitudinal awareness methodologies. Such methodological innovations were not bound by cost, current technological capabilities or academic discipline. Rather, they were future focused. The next section reviews elements of human tiger conflict management.

Framing human tiger conflict management

Safe System approach to human wildlife conflict

WWF Tigers Alive Initiative has adopted an approach to HWC known as the Safe System Approach (Brooks, 2015). The goal of the approach is to design systems that are intrinsically safe to all stakeholders. In the case of HWC, stakeholders include people, their assets, wildlife, and habitat. The approach was first developed to eliminate road deaths in Sweden's Vision Zero project and several other countries. Vision Zero assumed that "the providers and enforcers of the road transport system are responsible to citizens and must guarantee their safety in the long term" (Organisation for Economic Co-Operation and Development, 2008, p. 110). System designers are responsible for the safety of those involved in the system, whether human or wildlife.

The Safe System Approach shifts blame of system outcomes from individuals to the system itself. Individuals have a right to survive in complex systems and are unable to bear the entire burden of blame when conflicts or injuries occur (Organisation for Economic Co-Operation and Development, 2008, p. 110). "Within a safe system framework, managing a set of interventions that still leaves open the opportunity for fatality or serious injury is not enough" (Organisation for Economic Co-Operation and Development, 2008, p. 107). Approaches that place blame on individuals making day-to-day decisions are unable to increase long-term safety because they only have the ability to mitigate the symptoms of conflict rather than address systemic faults that result in negative outcomes. The Safe System Approach must work to improve upon the societal values of human and wildlife health, individual rights and economic development (Organisation for Economic Co-Operation and Development, 2008, p. 109). The Safe System Approach aims to shift the blame for tiger conflict events, from the tigers themselves, to the systemic faults that make human tiger interactions occur in the first place.

Six elements of human wildlife conflict

The management of human wildlife conflict is comprised of six basic elements (Table 1): monitoring, understanding the conflict, policy, prevention, response and mitigation (Brooks 2015).

Table 1: Elements of human wildlife conflict management

ELEMENT OF MANAGEMENT	DEFINITION
MONITORING	Measuring the performance and effectiveness of HWC management interventions over time
UNDERSTANDING THE CONFLICT	Research into all aspects of the conflict profile
POLICY	Protocols, principles, provisions and measures undertaken by authorities which are stipulated in legislation and governmental plans
PREVENTION	Stopping or preventing HWC before it occurs
RESPONSE	Measures taken to alleviate a specific or ongoing HWC incident
MITIGATION	Reducing the impacts of HWC after it occurs

Tools and actions from each element play a critical role in the development of the Safe System Approach to HWC management in that they are all interlinked. For example, innovative monitoring of conflict helps stakeholders and policymakers improve on best practices for prevention. In this case, both the policy and prevention elements benefit when monitoring is continuously improved.

Monitoring is also inversely influenced by the other elements (Brooks, 2015). Unraveling the complex and nuanced relationships between these elements leads to comprehensive knowledge of the conflict.

Our research is primarily concerned with unpacking the community attitudes component of the monitoring element. Given that current methods of understanding community attitudes are limited, better monitoring is needed to strengthen HWC management overall. The shortfalls of current policies, responses, prevention, and mitigation efforts create a need for more innovative methods of monitoring. The Safe System Approach creates a feedback loop which allows for trial, error and correction, ultimately leading to less conflict. Once innovative approaches are developed and incorporated into new policies or prevention measures, future monitoring techniques will require further adjustment.

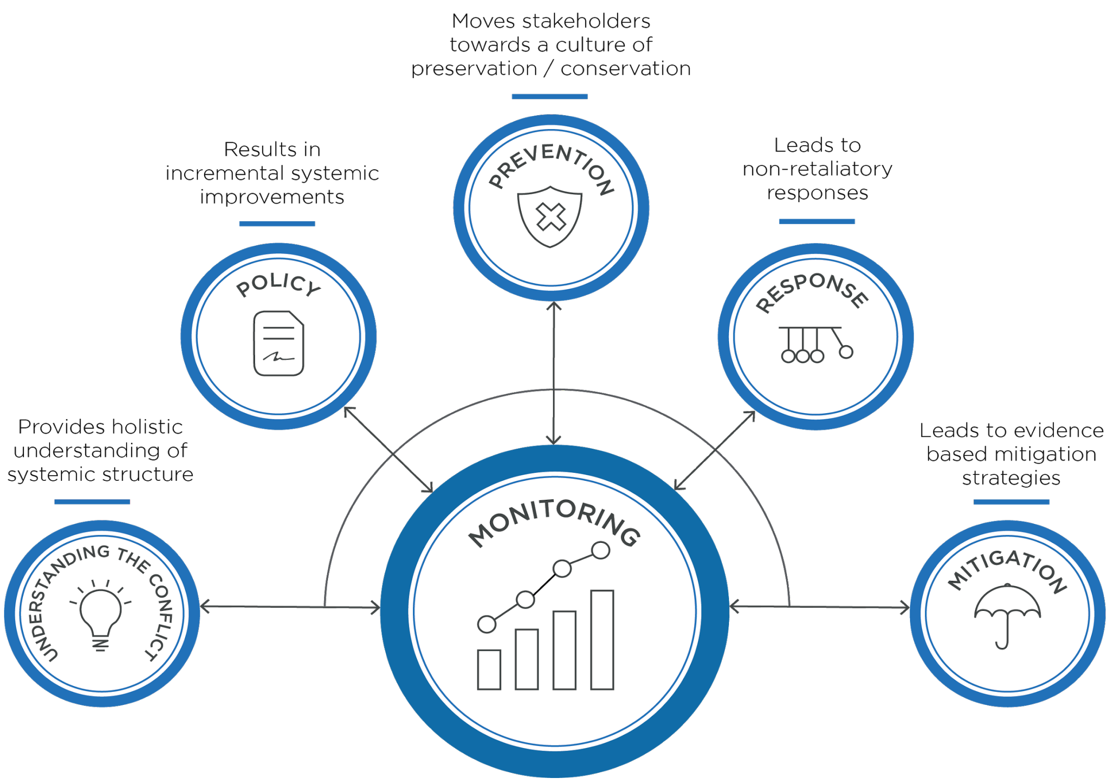
Table 2 provides examples of how innovative monitoring benefits each element of the Safe System Approach to human tiger conflict.

Table 2: Results of Monitoring's Interaction with Other Safe Systems Approach Elements

UNDERSTANDING THE CONFLICT	Enables awareness of the magnitude of conflict
	Identifies trends and changes of conflicts overtime
	Provides holistic understanding of systemic structure
POLICY	Provides feedback on policy outcomes
	Informs evidence based policymaking
	Leads to the creation of best practices
	Results in incremental systemic improvements
PREVENTION	Identifies conflict tolerance tipping points
	Improves rapid response capabilities
	Identifies systemic faults that lead to conflict
	Moves stakeholders towards a culture of preservation/conservation
RESPONSE	Determines the effectiveness/efficacy of current responses
	Determines willingness of local communities to participate in response
	Develops innovative responses to conflict
	Leads to non-retaliatory responses
MITIGATION	Determines the effectiveness/effectiveness of mitigation efforts
	Determines willingness of local communities to participate in mitigation efforts
	Results in innovations in mitigation approaches
	Leads to evidence based mitigation strategies

Figure 1 depicts the ultimate outcome of monitoring's impact when utilized in the Safe System Approach. Figure 1 and Table 2 both illustrate how innovative monitoring results in improvement throughout an entire HTC management system.

Figure 1 : Ultimate Outcome of Monitoring's Interaction within the Safe System Approach



Current methodological approaches in measuring attitudes and attitudinal changes

Methodologies for understanding local attitudes are not new, and global lessons from other sectors provide valuable insight for application in HWC management. The concept of understanding networks and mapping complex sets of relationships is a common goal in studies that measure attitudes and attitudinal changes (Bicchieri & Noah, 2017; Keys, Thomsen, & Smith, 2016; Paluck, Shepherd, & Aronow, 2019). Attitudes are formed, spread and changed through the relationships of the people within in a community, and knowing and understanding those relationships is key to measuring and even creating changes in attitudes (Keys, Thomsen, & Smith, 2016). Community mapping can be done in both quantitative and qualitative ways. For example, community members can be asked to list their relationships in a survey or connections can be determined during focus group discussions (Keys, Thomsen, & Smith, 2016; Paluck, Shepherd, & Aronow, 2019).

Surveying is the most common quantitative method used to measure community attitudes toward HWC (Struebig et al., 2018; Carter et al., 2012; Kansky, Kidd & Knight, 2016; Inskip et al., 2016). Some examples of recent research utilizing surveys to examine dimensions of HWC include a study by Kansky, Kidd and Knight (2016) that used surveys to identify causes and motivations for human baboon conflict in South Africa, and a study by Inskip et al. (2016) that used surveys and focus groups to identify attitudes about human tiger conflict in Bangladesh.

The most common qualitative method used to measure attitudes and attitudinal changes is the creation of focus groups (Mackie et al., 2014; van den Ent et al., 2017). Focus group discussion allows for clarification between participants and administrators that is not available on a survey (van den Ent et al., 2017). In the event of a mixed methods approach, focus group discussions can help inform what questions need to be asked in a survey and how those questions should be written to best create understanding for the respondents (Creswell, 2013). Another qualitative method often used is participatory action research (Mackie et al., 2014). This method is more formal than a focus group, requiring participants to work together to complete an action. This allows for easy recreation and provides rich qualitative content.

Each of these methods used to understand attitudes, while different in approach, aim to collect similar data from their population. The data collection is meant to measure an individual's reference networks, personal behavior, anticipated personal behavior, empirical expectations, factual beliefs, personal normative beliefs, normative expectations and beliefs in the presence of sanction (Bicchier & Noah, 2017; Mackie et al., 2014). However, surveying and focus group data collection methods face limitations that impede accurate longitudinal analysis of community attitudes.

Limitations of current practice

Current approaches to measuring attitudes and attitudinal change can be resource intensive and inefficient. Surveys and focus groups can be time and cost intensive. They may require translators to be hired in addition to survey administrators or focus group moderators. After the necessary people are hired, it can take weeks to months to gather the necessary data. Once data is collected, it needs to be coded and then compiled together before it can be fully analyzed (Creswell, 2013; Mackie et al., 2014). This makes it difficult for these methods to produce instantaneous observations of human beliefs and attitudes.

Given these limitations, researchers are turning to methods of attitudinal data collection without surveys or focus groups. For example, the field of socio-hydrology created a model to calculate a quantitative variable that predicts the attitudes of a community without having to administer surveys (Chen, Wang, Tian, & Sivapalan, 2016; Elshafei, Coletti, Sivapalan, & Hipsey, 2015). This model uses standardized measurements of "ecosystem services" and "economic returns" along with climate, developmental and political context variables to create what is called the "Community Sensitivity Variable" (Elshafei et al., 2015). Although this example is unique to individual communities and their attitudes toward water regulation, it demonstrates a way to mathematically quantify human attitudes without the use of surveys, saving time and money (Chen et al., 2016). However, such innovations have not been integrated into measuring attitudinal awareness regarding HWC. The next section examines innovative strategies to such monitoring.

Innovation in monitoring public attitudes and change

This section focuses on innovative ways that researchers dealing with complex processes use technology to build systems for feedback. These approaches rely on the analysis of big data and are not only systematic, but also scalable, affordable, and timely. The process of design should connect the creation of a product (or policy) with the users of that product through an ongoing feedback process. This process is meant to yield quality data that can extend the design timeline both backwards and forwards, for historical context as well as future prediction and change.

The phrase “big data” refers to massive, complex sets of data that are constantly generated through autonomous systems, such as social media websites. One example is the Twitter API (application programming interface) that gives researchers access to an ongoing stream of millions of tweets continually generated by Twitter users. Due to their size and complexity, these data sources cannot easily be analyzed using traditional methods.

Another source of big data is termed “web scraping”. Web scraping involves the use of computer scripts to automate the collection of information (often textual data) from websites. This technique (or set of techniques) can be scaled from hundreds to hundreds of thousands of websites, providing a wealth of data for analysis (Landers, Brusso, Cavanaugh, & Collmus, 2016).

The analysis of big data to generate useful information is known as “data mining”. Data mining uses techniques drawn from statistics and machine learning (artificial intelligence models that apply the power of computers to “learn” patterns from data). Outlined below, and detailed in Appendix 1, are a selection of general methods that researchers use to glean useful insights from big data, as well as smaller datasets. These methods are reactive, meaning they can be used to respond to issues more quickly and with more information. Ultimately these methods enable limited predictive power by identifying issues before they start or before they become more serious.

> Trend analysis: Seeks to identify patterns that can indicate or predict certain trends. Trend analysis is essentially the counting of data over time. It can be applied to a wide range of quantifiable data, including social media posts and comments, web searches and phone calls.
>
> Sentiment analysis: Seeks to classify text sources related to a certain topic, such as tweets about an environmental policy, into positive, neutral and negative buckets. These buckets are used to determine public sentiment on an issue and thus to address or predict public responses to that issue. Sentiment analysis can be applied to a narrower range of data than trend analysis because it requires data that can be used to gauge sentiment. It may not be possible to ascertain a person’s feelings about tigers from a Google search for “tigers,” but a Twitter post about tigers may more likely contain textual clues about user sentiments.

Network analysis: Can be applied to social media networks by using comments, shares, likes, retweets and mentions to identify central and peripheral actors in a network. This method identifies outliers and influential figures, as well as patterns of influence, information sharing and learning between network actors. Network analysis can be applied in any scenario where the participants of a network and their relationships with each other are known. On a large scale, network data is most commonly collected from social networking websites, like Facebook and Twitter.

Community leader identification: When mapping networks, key "community leaders" can be identified (Bicchieri & Noah, 2017; Keys et al., 2016; Paluck et al., 2019; Pettifor et al., 2015). Community leaders are not necessarily the people who draw obvious attention to themselves, meaning they are not always the same as political leaders (Keys et al., 2016; Paluck et al., 2019). Community leaders are the people observed most by members of the community. Essentially, they have the most amount of connections with the population (Paluck et al., 2019). A potential innovation in community leader identification is the use of social media data to identify larger, more fragmented networks than surveys are typically capable of measuring.

Spatial analysis: uses geographic information systems (GIS) to analyze spatial relationships between different features or events as laid out on a map. This approach has been in use for some time, but increased computer processing power and available machine learning techniques now allow for more in-depth spatial analysis on larger scales. Spatial analysis uses geotagging from photos or posts on social media to identify geographical hotspots where an event might happen or crucial zones where action might be taken to prevent conflict.

Combining methods

While each of the methods above allows for in-depth analysis by itself, there is significant innovative potential in combining them. Research that combines methods can yield multidimensional insights that allow for better understanding of patterns and the development of stronger predictive models. For example, Chen et al. (2015) use sentiment analysis, trend analysis and spatial analysis of Twitter data in combination with spatial weather data to build a model that is able to better predict crime in Chicago. Sluban et al. (2014) also use sentiment analysis and network analysis on Twitter data to identify different environmental belief networks and their leaders, helping to explain how information is generated and shared across the environmental debate as a whole.

Box: Benefits of big data

These big data driven methods share similar advantages. The cost for development of data mining and analysis algorithms is quite accessible, as nearly all of the examples mentioned above were completed by small, academic research teams. In addition, these methods are highly scalable. Once a framework is developed, the amount of data that it can handle is limited only by data accessibility and computing power. Likewise, these methods can be accessed on-demand and applied to all existing past longitudinal data. These methods can be used in conjunction with predictive algorithms to yield timely probabilistic analyses of potential future trends and outcomes, allowing for proactive responses to pressing issues.

Big data in the developing world

In the past, limited access to technology in developing countries has made it hard to collect and analyze big data, since the data has not existed. Even in the developed world, big data was vastly less available in the recent past. However, as technology and the ability to transmit and communicate information becomes more accessible, this difficulty is diminishing. According to Protopop and Shanoyan (2016), between 2005 and 2015, mobile broadband (smartphone) usage increased by 30 times in developing countries, while the percentage of people using internet increased by up to 40%. While internet penetration in developing countries remained relatively low at 35.3% (in 2015), these numbers point to a rapid expansion of network access and infrastructure in these areas. This growth will undoubtedly be accompanied by a rapid increase in the production of big data from these areas.

Amankwah-Amoah (2016) provides an example of multi-method big data usage in developing countries by looking at the techniques used to combat and contain the Ebola outbreak in West Africa, particularly in the countries of Guinea, Liberia and Sierra Leone. Given the limited medical capacity of these countries, big data analysis was seen as a solution to "help ensure that resources are deployed in a timely and efficient manner" (Amankwah-Amoah, 2016, p.8). To do this, researchers applied sentiment and trend analysis to data from social media including blogs, Twitter, Facebook and online forums to both inform public policy and develop early-warning systems to detect potential outbreaks (Amankwah-Amoah, 2016, p.10-11). Researchers also applied spatial and network analysis to cell phone records in order to identify areas where calls were being made to certain helplines, which allowed them to see potential hotspots. Phone data was also used to track population movements, in order to predict where the virus might spread. This information helped set up new treatment centers in ideal locations and to restrict travel from dangerous areas (Amankwah-Amoah, 2016, p. 11).

Researchers point out some constraints to using big data in the developing world, including a potential demographic bias since technology adaptation is led by younger people, and older people might not be represented in the data. There is also an issue with data ethics and privacy. Big data reveals a depth of information about people and their relationships and behaviors without explicit individual consent, which can lead to unintended consequences (Amankwah-Amoah, 2016; Desouza & Smith, 2014). When utilizing big data, researchers must use caution to protect privacy and any sensitive information contained in the data.

Lack of infrastructure, including human resources, for analyzing big data is another significant challenge for developing countries. Governments, NGOs and private businesses might be incentivized not to make data available, in order to avoid security threats, or to maintain a competitive advantage for funding or market share. Integrating data from multiple siloed and proprietary sources represents another challenge (Desouza & Smith, 2014; Luna, Mayan, García, Almerares, & Househ, 2014).

Recommendations for the use of big data

Desouza and Smith (2014) use big data for social innovation to emphasize the importance of coordination, collaboration and openness. To support this theme, a number of steps to facilitate innovative big data usage are highlighted (Desouza and Smith, 2014, p.43):

Building global data banks for critical issues (encourage data sharing)
Engaging citizens and citizen science

Building a cadre of data curators and analysts (investing in technical human expertise)
Promoting virtual experimentation platforms (encouraging collaboration)

Comparing methods

Table 3 analyzes each of the methods listed in this report according to six criteria. Accurate monitoring requires timeliness, longitudinal application, accuracy of results, scalability of application, cost effectiveness and political feasibility. Judgement-based choice, a methodology commonly used in policy analysis, informs which methods are best applied under different criteria preferences (Weimer& Vining, 2011). Each method is ranked by these criteria from one to five: one being "not at all effective" and five being "very effective." Each criterion column has pros and cons, and the relevance of a method depends on the weight assigned to individual criterion relative to the others.

Timeliness refers to the ability of a method to yield actionable results quickly. Methods that require more time or more difficult data collection receive a lower score for timeliness. Spatial analysis, for example, receives a lower score than other innovative methods because it often requires the collection or development of geographical map files, as well as regionally specific data.

Table 3: Analysis of standard and innovative methods

	Timeliness	Longitudinal	Accuracy	Scalability	Cost effectiveness	Political feasibility
Current Methods						
Surveys	2	1	5	2	2	3
Focus Groups	3	2	4	1	1	3
Participatory Action Research	3	2	4	2	2	4
Innovative Methods						
Trend Analysis	5	4	3	5	5	5
Sentiment Analysis	4	4	3	5	4	4
Network Analysis	4	2	4	4	4	3
Community Leader Identification	3	2	4	4	3	3
Spatial Analysis	3	3	4	3	3	4

Longitudinal application refers to the ability of a method to extend its timeline both forward and backward. Surveys and network analysis receive lower scores here because they are primarily point-in-time methods, although they have some predictive potential. Trend and sentiment analysis receive higher scores because they can extend as far back as data exists in addition to having predictive potential.

Accuracy of results refers to the validity and trustworthiness of data collected with a method. Surveys receive a higher score here because they measure individual preferences, which are generally more reliable than group sentiments. Trend analysis and sentiment analysis receive the lowest scores because they use algorithms to sort and analyze large amounts of highly diverse information, resulting in a somewhat higher error rate. However, the error rate decreases to some degree with larger amounts of data.

Scalability refers to the ability of a method to process increasing amounts of data easily. There tends to be a slight trade-off between accuracy and scalability—methods that are more easily scalable are also less in-depth, leading to somewhat less contextual reliability in the data. Focus groups have low scalability because they are expensive and time-consuming to conduct but yield rich contextual data. Data mining methods are generally more scalable but tend not to yield contextual data at the individual or small-group level.

Cost effectiveness is related to timeliness, as a method that takes longer to develop and apply is likely to cost more. Current methods tend to be more expensive than data mining methods, although more in-depth spatial and network analysis can cost more time and money.

Finally, political feasibility refers to the ease at which a method can be conducted without facing political resistance. All of the methods in this report receive high scores in this category, although focus groups/surveys and network analysis/community leader identification have the potential to be more politically obtrusive, depending on the questions being asked and the personal data being collected.

Piloting innovative approaches

The ultimate goal of this research is to eliminate retaliatory killings of conflict species through innovative data collection techniques to better understand community attitudes, as well as tipping points where tolerance is lost. This research identifies the limitations of current methodologies used to monitor community attitudinal awareness across the tiger range. Namely, they are resource intensive, limit the ability for longitudinal studies and do not provide timely indication of attitudinal shifts occurring within individual communities. Innovations in the field of attitudinal awareness research can help mitigate these limitations. The combination of big data and network methodologies leads to a more nuanced understanding of community attitudes, across geographic regions and over time.

The first step in piloting innovative approaches is to perform an evaluation of potential innovative measures. The methodologies chosen to pilot across selected tiger sites should be evaluated for their effectiveness based on a specific set of criteria, as illustrated in Table 3. The criteria included in this research are common in studies of policy analysis. However, criteria can be adjusted based on value judgements of different organizations or objectives. The criteria and scoring used in this proposal can be altered based on recommendations from other experts within and outside WWF.

Based on this evaluation, trend analysis is an ideal starting focus for a pilot. Trend analysis scores highly for several imperative criteria including timeliness, scalability and cost. The innovative methods above can be thought of as a set of increasingly complex steps. Trend analysis is the first of these steps because it can be used relatively quickly and easily as an exploratory tool for identifying rough patterns in the data. As methodological complexity increases, deeper and more complex data can be collected, although this can increase cost and difficulty.

Trend analysis can inform sentiment analysis. Sentiment analysis is closely related to trend analysis, but requires the data scientist to know what kind of attitudes are relevant for analysis. For example, if trend analysis shows that a particular hashtag is trending on Twitter and is relevant to HWC, then sentiment analysis can be deployed to test community attitudes related to that hashtag. Care should also be taken during trend analysis to identify related terms that refer to the same topic. Communities often use different terms to refer to similar topics, which in turn might reflect differing sentiments.

Trend and sentiment analysis add layers of depth for network and spatial analysis. For example, sentiment analysis can be used to identify networks of people and community leaders that share similar attitudes, while trend analysis can be used to identify hotspots of activity on a map. Network and spatial analysis are the most complex methods mentioned in this report, because they are able to accommodate multiple layers of context. They are also able to provide very valuable results and predictions if done well and informed thoroughly by other methods.

Feedback from pilot tests informs continuing adjustments to both traditional and innovative methods of understanding community attitudes. The exploratory nature of these methodologies means that additional gaps in knowledge concerning human tiger conflict are likely to appear after initial piloting. Thus requiring future methodological adjustments, such as additional search terms or even primary variables that influence community perceptions and conflict tipping points. The innovative methods mentioned in this report are not a replacement for the methods currently being employed, but an expansion. To be effective, these approaches require the application of context-specific knowledge. Although data mining seeks to identify trends from massive datasets, it requires some contextual knowledge about the specific trends and variables that are being searched for. Specific knowledge about human tiger conflict is also necessary to interpret the identified data trends and to identify which key terms or trends need to be searched in the first place.

Big data analytical techniques are utilized in part through the hiring of relevantly experienced data analysts and in part, through the application of previous research on HWC mentioned in this report. Surveys, focus groups and participatory action research inform data scientists about the variables and trends that should be searched for in the big data. As a result, data mining and the development of predictive algorithms is best done through an iterative process that is continuously informed and re-informed by data collected through traditional, on-the-ground methods. This kind of regular feedback helps to ensure that these innovative methods stay accurate, relevant, scalable and optimally predictive.

Conclusion

HWC management is increasingly complex due to human population growth, the human footprint and land use change. The vast landscapes that tigers formerly inhabited have been reduced to noncontiguous patches of suitable habitat. Thus, approaches to human tiger conflict management must continuously improve and adapt to face the grim reality of tiger preservation. The Safe System Approach supports a system-wide analysis of issues in order to pinpoint major systematic faults leading to retaliatory killing of tigers. Integrating this approach with policy analysis methodologies illuminates innovative ways to better understand community attitudes, social tolerance and more broadly addressing HWC. This research proposes a pilot test of innovative big data approaches to understanding community attitudes toward human tiger conflict. These include trend and sentiment analysis, which can then inform the more complex methods of network analysis, community leader identification and spatial analysis. Innovations in monitoring lead to better understanding of the conflict and comprehensive policies, as well as targeted prevention, response and mitigation – ultimately decreasing retaliatory killings of tigers.

Appendices

Appendix 1: Innovations in monitoring public attitudes and change

Trend analysis

Trend analysis seeks to identify patterns that can indicate or predict certain trends. For example, Kallus (2014) designed an algorithm that counts the number of times protest is mentioned on social media and uses those counts as part of a model to predict actual events of civil unrest. He tested the model by predicting the 2013 Egyptian coup d'état, ahead of news coverage. Researchers might also look at Google Trends search data to gather similar information. Google's trend analysis has been shown to be better than the U.S. Center for Disease Control's traditional approach for predicting flu outbreaks (Amankwah-Amoah, 2016).

Natural Language Processing (NLP) is a field often used for trend analysis. NLP makes use of algorithms designed to recognize, predict and categorize text from multiple sources, often by using contextual analysis, machine learning and probabilities based on common word and phrase usage.

Applied trend analysis

Trend analysis is essentially the counting of data over time. It can be applied to a wide range of quantifiable data, including social media posts and comments, web searches and phone calls. Trend analysis can be implemented very quickly and inexpensively. Google Trends is a publicly available trend analysis tool that allows users without any knowledge of coding or data mining to quickly view Google search trends worldwide.

More advanced trend analysis requires the development of data mining code to quantify large amounts of data (such as Twitter hashtag mentions) over time, but this code can generally be scaled to similar data over varying time scales. Kallus (2014) put together a comprehensive trend analysis method that can be tested and applied in multiple scenarios over varying times and geographies. This was done with the help of only a small research group.

Sentiment analysis

Sentiment analysis also relies on NLP techniques, for classification as much as quantification. Sentiment analysis seeks to classify text sources related to a certain topic, such as tweets about an environmental policy, into positive, neutral and negative buckets. These buckets are used to determine public sentiment on an issue and thus to address or predict public responses to that issue. Sluban et al. (2014) used sentiment analysis of Twitter data to examine user attitudes toward different environmental terms, including "solar," "recycling" and "fracking."

Applied sentiment analysis

Sentiment analysis can be applied to a narrower range of data than trend analysis because it requires data that can be used to gauge sentiment. It may not be possible to ascertain a person's feelings about tigers from a Google search for "tigers," but a Twitter post about tigers may more likely contain textual clues about user sentiments. Therefore, sentiment analysis requires existent and accessible textual data.

Sentiment analysis shares methodological and practical overlap with trend analysis. However, sentiment analysis requires more advanced data mining techniques (such as NLP) to deploy. Once a method has been developed, it shares many of the same advantages and disadvantages as trend analysis methods: it can be scaled, tested and redeployed easily. Like trend analysis, sentiment analysis can be developed by a small team of researchers. In the example given above, Sluban et al. (2014) and four other researchers developed a scalable sentiment analysis platform that informs a network analysis project.

Network analysis

Network analysis can be applied to social media networks by using comments, shares, likes, retweets and mentions to identify central and peripheral actors in a network. This method identifies outliers and influential figures, as well as patterns of influence, information sharing and learning between network actors. Ranganath et al. (2016) use this approach to look at social media user interactions to examine the probability of a user "declaring protest as other users reach out to him over time" (p.208). This probability is then used in an algorithm to help predict user involvement in protests.

Applied network analysis

Network analysis can be applied in any scenario where the participants of a network and their relationships with each other are known. This data is collected from surveys, interviews or larger sources of data. On a large scale, network data is most commonly collected from social networking websites, like Facebook and Twitter. Network analysis can be combined with trend analysis and sentiment analysis to look at how trends and sentiments spread across networks.

Like trend and sentiment analysis, network analysis can be deployed inexpensively and does not require significant investment to develop. In the above example, Ranganath (2016) and five other researchers built and deployed a scalable network analysis platform.

Community leader identification

When mapping networks, key "community leaders" can be identified (Bicchieri & Noah, 2017; Keys et al., 2016; Paluck et al., 2019; Pettifor et al., 2015). Community leaders are not necessarily the people who draw obvious attention to themselves, meaning they are not always the same as political leaders (Keys et al., 2016; Paluck et al., 2019). Community leaders are the people observed most by members of the community. Essentially, they have the most amount of connections with the population (Paluck et al., 2019). Community leader identification is traditionally done by surveying a population regarding the people who most influence their perceptions. This survey data can be used to understand HWC.

Once community leaders are identified, they can assist conservationists in the work of intervention. This can include having them play a role in implementation, acting as a liaison between the community and conservationists or assisting in administering surveys (Keys et al., 2016; Paluck et al., 2015; Pettifor et al., 2015). Currently, community leaders are used to help community members receive reimbursement for livestock after a tiger attack in Bhutan (Sangay and Vernes, 2008).

A potential innovation in community leader identification is the use of social media data to identify larger, more fragmented networks than surveys are typically capable of measuring. This approach is valuable because the use of community leaders in the work of intervention helps validate the implementation of the intervention to community members (Miller & Prentice, 2016). This validation creates better community attitudes and supports the intervention and the authority figures attached to it (Miller & Prentice, 2016).

Spatial analysis

Spatial analysis uses geographic information systems (GIS) to analyze spatial relationships between different features or events as laid out on a map. This approach has been in use for some time, but increased computer processing power and available machine learning techniques now allow for more in-depth spatial analysis on larger scales. Spatial analysis uses geotagging from photos or posts on social media to identify geographical hotspots where an event might happen or crucial zones where action might be taken to prevent conflict.

Of the four methods listed here, this method has seen perhaps the most use so far in the analysis of HWC. Mateo-Tomás et al. (2012) use spatial analysis of veterinary clinic reports and other related data to identify zones where illegal poisoning of wild fauna occurred. This data was then compared with other available data to determine risk factors like perceived predation of livestock. Similarly, Sitati et al. (2003) use GIS data to identify risk factors for geographical conflict between humans and elephants, which they use to build a predictive model for identifying high-risk areas. Baldwin (2009) provides an overview of one of the most common forms of machine learning analysis (Maximum Entropy Modeling, or Maxent) for studying wildlife distributions and habitat selection.

Applied spatial analysis

Spatial analysis requires spatial data for the area to be researched, at the level that it will be researched. For example, a researcher hoping to model wildlife distributions across a populated county might want spatial files detailing the physical geography, the human population and the political boundaries of that county.

In addition to the foundational spatial files that a map will be based on, data can be plotted with geographic coordinates, such as longitude and latitude. Some posts on Twitter are “geotagged” with coordinates that allow the location of the user when they made that post to be located on a geographic map. Events and encounters can be geotagged through the use of a cell phone with GPS, or some other GPS locator.

The need to collect and build geographic files increases the cost and labor of spatial analysis projects, but this method is still able to accommodate and analyze big data at a reasonable scale, with reasonable labor. In a group of only four researchers, Mateo-Tomás et al. (2012) implemented a scalable hot-spot detection model, capable of incorporating new and diverse data related to human wildlife conflict.

References

Acharya, K. P., Paudel, P. K., Neupane, P. R., & Köhl, M. (2016). Human-wildlife conflicts in Nepal: Patterns of human fatalities and injuries caused by large mammals. *PLOS ONE*, *11*(9), e0161717. https://doi.org/10.1371/journal.pone.0161717

Amankwah-Amoah, J. (2016). Emerging economies, emerging challenges: Mobilizing and capturing value from big data. *Technological Forecasting and Social Change*, *110*, 167–174.

Baldwin, R. (2009). Use of maximum entropy modeling in wildlife research. *Entropy*, *11*(4), 854–866.

Bicchieri, C., & Noah, T. (2017). *Applying social norms theory in CATS programming*. University of Pennsylvania - UNICEF.

Brooks, A. (2015). *Safe Systems: Revolutionizing human wildlife conflict*. WWF.

Carter, N. H., López-Bao, J. V., Bruskotter, J. T., Gore, M., Chapron, G., Johnson, A., & Treves, A. (2017). A conceptual framework for understanding illegal killing of large carnivores. *Ambio*, *46*(3), 251–264. https://doi.org/10.1007/s13280-016-0852-z

Carter, N. H., Riley, S. J., & Liu, J. (2012). Utility of a psychological framework for carnivore conservation. *Oryx*, *46*(4), 525–535. https://doi.org/10.1017/S0030605312000245

Chen, Xi, Wang, D., Tian, F., & Sivapalan, M. (2016). From channelization to restoration: Socio-hydrologic modeling with changing community preferences in the Kissimmee River Basin, Florida. *Water Resources Research*, *52*(2), 1227–1244. https://doi.org/10.1002/2015WR018194

Chen, Xinyu, Cho, Y., & Jang, S. Y. (2015). Crime prediction using Twitter sentiment and weather. In *2015 Systems and Information Engineering Design Symposium* (pp.63–68). IEEE.

Creswell, J. (2013). Research Design: Qualitative, quantitative, and mixed methods approaches. New York, NY: SAGE Publications.

Desouza, K. C., & Smith, K. L. (2014). Big data for social innovation. *Stanford Social Innovation Review*, *12*(3), 38–43.

Dinerstein, E., Loucks, C., Wikramanayake, E., Ginsberg, J., Sanderson, E., Seidensticker, J., & Songer, M. (2007). The fate of wild tigers. *BioScience*, *57*(6), 508–514. https://doi.org/10.1641/B570608

Elshafei, Y., Coletti, J. Z., Sivapalan, M., & Hipsey, M. R. (2015). A model of the socio-hydrologic dynamics in a semiarid catchment: Isolating feedbacks in the coupled human-hydrology system. *Water Resources Research*, *51*(8), 6442–6471. https://doi.org/10.1002/2015WR017048

Inskip, C., Carter, N., Riley, S., Roberts, T., & MacMillan, D. (2016). Toward Human-Carnivore Coexistence: Understanding Tolerance for Tigers in Bangladesh. *PLOS ONE*, *11*(1), e0145913. https://doi.org/10.1371/journal.pone.0145913

Kallus, N. (2014). Predicting crowd behavior with big public data. In *Proceedings of the 23rd International Conference on World Wide Web* (pp. 625–630). ACM.

Kansky, R., Kidd, M., & Knight, A. T. (2016). A wildlife tolerance model and case study for understanding human wildlife conflicts. *Biological Conservation*, *201*, 137–145. https://doi.org/10.1016/j.biocon.2016.07.002

Keys, N., Thomsen, D. C., & Smith, T. F. (2016). Adaptive capacity and climate change: The role of community opinion leaders. *Local Environment*, *21*(4), 432–450. https://doi.org/10.1080/13549839.2014.967758

Landers, R. N., Brusso, R. C., Cavanaugh, K. J., & Collmus, A. B. (2016). A primer on theory-driven web scraping: Automatic extraction of big data from the Internet for use in psychological research. *Psychological Methods*, 21(4), 475–492. https://doi.org/10.1037/met0000081

Luna, D., Mayan, J., García, M., Almerares, A., & Househ, M. (2014). Challenges and potential solutions for big data implementations in developing countries. *Yearbook of Medical Informatics*, *23*(01), 36–41.

Mackie, G., Moneti, F., Denny, E., & Shakya, H. (2014). *What are social norms? How are they measured?* (Working Paper). San Diego: University of California at San Diego-UNICEF.

Mateo-Tomás, P., Olea, P. P., Sánchez-Barbudo, I. S., & Mateo, R. (2012). Alleviating human–wildlife conflicts: identifying the causes and mapping the risk of illegal poisoning of wild fauna. *Journal of Applied Ecology*, *49*(2), 376–385.

Miller, D. T., & Prentice, D. A. (2016). Changing norms to change behavior. *Annual Review of Psychology*, *67*(1), 339–361.https://doi.org/10.1146/annurev-psych-010814-015013

Mobile cellular subscriptions (per 100 people) | Data. (n.d.). Retrieved February 22, 2019, from https://data.worldbank.org/indicator/IT.CEL.SETS.P2?end=2017&locations=ID

Organisation for Economic Co-Operation and Development. (2008). *Towards zero: Ambitious road safety targets and the safe system approach*.

Paluck, E. L., Shepherd, H., & Aronow, P. M. (2019). Changing climates of conflict: A social network experiment in 56 schools. *Proceedings of the National Academy of Sciences*, *116*(3), 566–571. https://doi.org/10.7910/DVN/29199

Pettifor, A., Lippman, S. A., Selin, A. M., Peacock, D., Gottert, A., Maman, S., & MacPhail, C. (2015). A cluster randomized-controlled trial of a community mobilization intervention to change gender norms and reduce HIV risk in rural South Africa: Study design and intervention. *BMC Public Health*, *15*(1). https://doi.org/10.1186/s12889-015-2048-z

Protopop, I., & Shanoyan, A. (2016). Big Data and smallholder farmers: Big data applications in the agri-food supply chain in developing countries. *International Food and Agribusiness Management Review*, *19*(1030-2016–83148), 173.

Ranganath, S., Morstatter, F., Hu, X., Tang, J., Wang, S., & Liu, H. (2016). Predicting online protest participation of social media users. In *Thirtieth AAAI Conference on Artificial Intelligence*.

Sangay, T., & Vernes, K. (2008). Human–wildlife conflict in the Kingdom of Bhutan: Patterns of livestock predation by large mammalian carnivores. *Biological Conservation*, *141*(5), 1272–1282. https://doi.org/10.1016/j.biocon.2008.02.027

Sitati, N. W., Walpole, M. J., Smith, R. J., & Leader-Williams, N. (2003). Predicting spatial aspects of human–elephant conflict. *Journal of Applied Ecology*, *40*(4), 667–677.

Sluban, B., Smailovic, J., Juric, M., Mozetic, I., & Battiston, S. (2014). Community sentiment on environmental topics in social networks. In *2014 Tenth*

International Conference on Signal-Image Technology and Internet-Based Systems (pp. 376–382). IEEE.

Struebig, M., Linkie, M., Deere, N., Martyr, D., Millyanawati, B., Faulkner, S., Le Comber, S., Mangunjaya, F., Leader-Williams, N., McKay, J., & St. John, F. (2018). Addressing human-tiger conflict using socio-ecological information on tolerance and risk. *Nature Communications*, 9:3455, 1-9. DOI: 10.1038/s41467-018-05983-y

Treves, A., & Karanth, K. (2003). Human-carnivore conflict and perspectives on carnivore management worldwide. *Conservation Biology*, *17*(6), 1491–1499.

van den Ent, M. M. V. X., Mallya, A., Sandhu, H., Anya, B. P., Yusuf, N., Ntakibirora, M., & Eggers, R. (2017). Experiences and lessons from polio eradication applied to immunization in 10 focus countries of the polio endgame strategic plan. *The Journal of Infectious Diseases*, *216*(suppl_1), S250–S259. https://doi.org/10.1093/infdis/jix047

Weimer, David L., & Vining, Aidan R. (2011). *Policy Analysis* (5th ed.). New York: Routledge.

World Wildlife Fund. (2008). *Common Ground: Solutions for reducing the human, economic, and conservation costs of human wildlife conflict*.

World Wildlife Fund. (2016). *Annual Report 2015*. WWF. Retrieved from http://tigers.panda.org/reports/

World Wildlife Fund. (2018). *Annual Report 2017 – Doubling Wild Tigers*. WWF. Retrieved from http://tigers.panda.org/reports/