Emergency Management of Tomorrow Research: Artificial Intelligence Landscape Assessment

June 2024

Science and Technology

PNNL-36083

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Jonathan Barr, Pacific Northwest National Laboratory
Alexander Hagen, Pacific Northwest National Laboratory
Grant Tietje, Front Range Planning
Nicholas Betzsold, Pacific Northwest National Laboratory
Alex Greer, State University at New York Albany
Eric Best, State University at New York Albany

U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
under Contract DE-AC05-76RL01830

This report was prepared for the U.S. Department of Homeland Security under a Work-for-Others Agreement with the U.S. Department of Energy, contract DE-AC05-76RL01830, IA 70RSAT23KPM000025.

PACIFIC NORTHWEST NATIONAL LABORATORY
operated by
BATTELLE
for the
UNITED STATES DEPARTMENT OF ENERGY
under Contract DE-AC05-76RL01830

Printed in the United States of America

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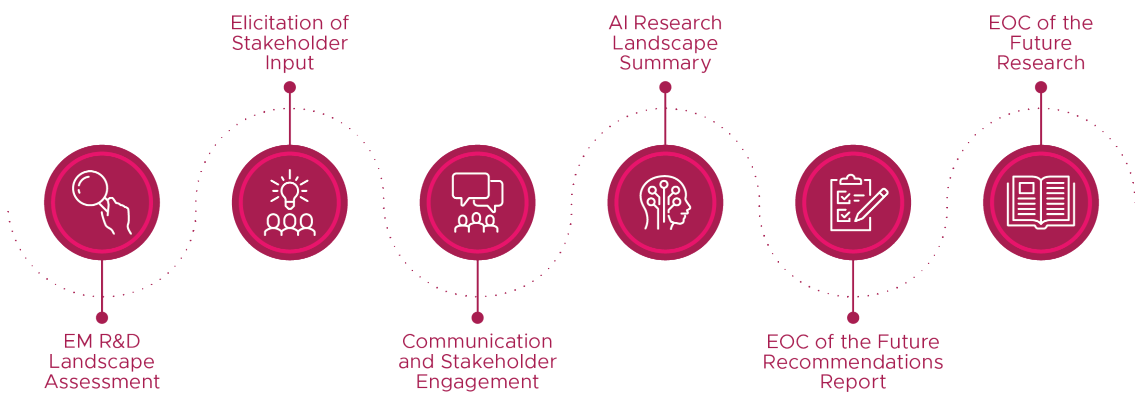
About the Emergency Management of Tomorrow Research

The Department of Homeland Security (DHS) Science and Technology Directorate (S&T) is partnering with Pacific Northwest National Laboratory (PNNL) to execute the Emergency Management (EM) of Tomorrow Research (EMOTR) program to identify current EM research, elicit capability needs from EM practitioners, and identify where technology, such as artificial intelligence (AI), may benefit the future of EM and emergency operations centers. The project is delivering a phased and iterative approach to inform future research and development (R&D) and investments for the EM community.

This report details the methodology, analysis, and insights of a landscape assessment of AI technologies and their potential application to EM. Feedback from this task will help shape future EMOTR research, analysis, and recommendations. To learn more about this task or others within the EMOTR scope, contact emotr@pnnl.gov.



Summary

The PNNL EMOTR team performed a landscape assessment of AI technologies and their potential application to EM. The landscape assessment began with an extensive literature review and tagging exercise to capture ideas, and curated and validated those ideas through discussions with emergency managers, university faculty, college students, national laboratory researchers, and federal staff.

With the resultant set of curated ideas, the team developed a list of 13 highlighted and enabling technologies that have a high probability of enhancing EM in the next 10 years.

Seven technologies had consensus from AI and EM stakeholders as to their optimistic future in EM:

- AI-Enabled Productivity Applications
- Public-Facing AI Communication
- AI-Enabled Planning
- AI-Filtered Domain Awareness
- AI-Enabled Disaster Prediction and Detection
- AI-Enabled Recovery and Prediction
- Risk Models for Optimal Asset Deployment.

Two additional technologies were included because of potential impact in the field, despite less interest from emergency managers:

- AI Embedding for Alternative Data Streams
- Modern Optimization for Asset Deployment.

Four enabling technologies must be in place for the previous technologies to provide impact:

- Security of AI Assets and Data
- Modeling, Simulation, and Digital Twin
- Information Technology Infrastructure for AI
- Governance and Public Perception of AI.

Of the highlighted technologies, improvement may be made through private industry and other public sector investment (such as from the Department of Defense or the intelligence community). Three have constraints and requirements specific to EM and may not progress without specific interest from the EM community: Risk Models for Optimal Asset Deployment, AI Embedding for Alternative Data Streams, and Modern Optimization for Asset Deployment. Finally, Governance and Public Perception of AI was identified as the most important enabling technology overall for AI, but Security of AI Assets and Data was identified as being the enabling technology with constraints and requirements most specific to the public sector, to DHS S&T, and to EM.

This report summarizes the methodology, analysis, and insights of the AI landscape assessment, highlighting an in-depth review of AI technologies and their potential application to EM. This information will inform future EMOTR research and outreach, which ultimately aims to assist DHS S&T in making informed decisions for future EM R&D.

Acknowledgments

The PNNL team would like to acknowledge appreciation for this work funded through DHS S&T. The State University of New York at Albany and their College of Emergency Preparedness, Homeland Security, and Cybersecurity were critical partners in validating and furthering the ideas presented in this report. The team also recognize Alex Greer, PhD, and Eric Best, PhD for their insightful discussions, organization of the faculty validation sessions, and conclusions; and Brandon Behlendorf, PhD, and his team at the Center for Advanced Red Teaming for organizing a successful sandpit exercise with students.

Acronyms and Abbreviations

AI	Artificial Intelligence
CEHC	College of Emergency Preparedness, Homeland Security, and Cybersecurity
DoD	Department of Defense
DHS	Department of Homeland Security
EM	Emergency Management
EMOTR	Emergency Management of Tomorrow Research
EOC	Emergency Operations Center
GIS	Geographic Information Systems
LLM	Large Language Models
ML	Machine Learning
MLOps	Machine Learning Operations
NLP	Natural Language Processing
NYS DHSES	New York State's Division of Homeland Security and Emergency Services
PNNL	Pacific Northwest National Laboratory
RAG	Retrieval Augmented Generation
TRL	Technology Readiness Level
UAlbany	University at Albany

Contents

1.0 Introduction

Since the start of the “deep learning revolution” in 2012, machine learning (ML) and artificial intelligence (AI) have been increasingly applied across domains.[i] Currently ML techniques in the United States are extensively used in the public and private domain, and tools based on these techniques are used knowingly or unknowingly daily by most individuals. Great opportunities exist for adoption and development of AI tools to assist emergency managers, law enforcement officers, support staff, and volunteers before, during, and after emergencies and disasters. With further development of AI and ML methods, as well as applied research and operationalization, AI and ML could become a crucial facet of emergency management (EM).[1-13, 208-210]

Artificial Intelligence or Machine Learning?

The nomenclature around data science, AI, and ML is extensive.[i] Each term has nuanced differences and general consensus does not exist regarding when each term is appropriate. For this report, the PNNL team sought to explore only those technologies that are enabled by emerging computational methods and not limit perspective to subsets within the broader field. Further, the team sought to communicate to stakeholders in a way that aligned to the communication from other sources, such as the popular media. To do this, the term AI is used to describe the broad field of emerging computational methods throughout this report.

As part of the EM of Tomorrow Research Program (EMOTR), sponsored by the Department of Homeland Security (DHS) Science and Technology Directorate (S&T), Pacific Northwest National Laboratory (PNNL) performed a landscape assessment of AI and ML technologies and their potential application to EM. This report summarizes the PNNL team’s scholarly work at the intersection of EM and ML, as of May 2024. Their approach takes the perspective of a data scientist seeking to find application areas for AI in EM. This perspective is counter to many reviews in the literature, which is typically that of an emergency manager, seeking to find a data science technique to solve specific problems.[1-16] This perspective allows for matching of emerging ML techniques to multiple different EM problems. Likewise, technology adoption lags behind technology development. Approaching this review from the perspective of data scientists accounts for the faster pace of research in ML as compared to the adoption of technology in EM.

This report details PNNL’s methodology, including assumptions and constraints, as well as a framework for the evaluating ML technologies for the overall EM information environment. The report describes 13 technologies that constitute the best-aligned AI technologies and AI-enabling technologies for supporting future EM needs and solving EM problems. The report concludes with an examination of which technologies may be realized through investment from other entities, both public and private.

Ultimately, this report provides a current understanding of the most promising AI research as applied to EM, along with insights regarding how additional research and development (R&D) could benefit the EM landscape of tomorrow.

2.0 Methodology

This task followed three key steps to perform a comprehensive and well-aligned landscape assessment for AI/ML research applicable to EM:

1. Develop a tagged bibliography.
2. Summarize and validate findings with experts in EM and ML.
3. Connect with college students with relevant expertise for new and radical ideas.

2.1 Tagged Bibliography

To capture the current state of EM and ML literature, the team conducted a multi-pronged review, analyzed the key concepts of each source, and developed a bibliography of sources tagged by these key concepts. This review paralleled the review in Sleiman, et al. 2024,[209] but with a restricted focus to only AI in EM. During expert elicitation early in the review process, EM applications were perceived as underrepresented in ML research. While this proved to be inaccurate, it still prompted use of diverse sources to find relevant publications.

The core resource in the tagged bibliography generation was keyword searching for conference and refereed publications. Search terms included “emergency management” or “disaster management” in conjunction with “machine learning” or “artificial intelligence.” To keep pace with ML advances, PNNL conducted equivalent searches on the preprint server arxiv.org for un-refereed manuscripts. To ensure that informal sources did not include additional content, the search included several other sources, including Reddit (www.reddit.com) and relevant subreddits like r/EmergencyManagement and r/MachineLearning, GitHub (www.github.com) with the same search terms as for journal articles, and other forms of media like internet-hosted videos and blogs. In general, these informal sources were duplicative or of low quality and were not included in the final tagged bibliography. Finally, the team elicited expert opinion from existing networks in the EM research, applications, and operations fields, and from the foundational and applied ML fields.

As in other fields, the majority of relevant research identified for EM and ML came from refereed and preprint manuscripts. Figure 1 shows the number of papers or preprints published in EM, ML, and their intersection since 1991. For reference, all publications are also shown on the figure. ML is a fast-growing and popular field in publishing, whereas EM is less so; however, these graphs show that the number of ML applications to EM is approximately as expected (the proportion of EM-ML publications is approximately the product of the proportion of EM and the proportion of ML articles).

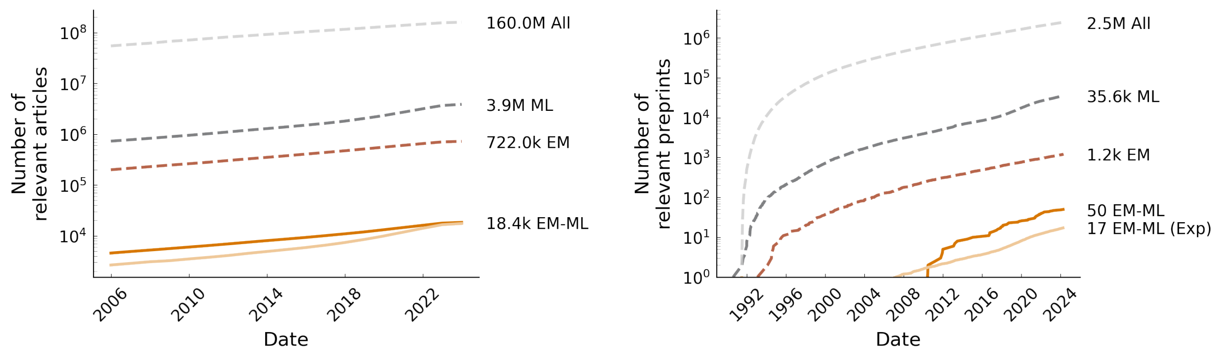


Figure 1. Number of articles[ii] and preprints[iii] published and corresponding subsets for EM, ML, and the combination of EM-ML since 1991.

To process these articles efficiently, the team generated a tagging process for each article based on an initial readthrough. One or more tags were applied to every article. The set of tags is outlined in Table 1.

Table 1. Bibliography Tags

Tag	Definition
Chatbots	Relating the use of natural language processing (NLP) to create an artificial agent that converses with humans to perform EM tasks.
Data Engineering	Relating to the networking, data storage, data format, and other details that enable data science for appropriate and timely routing of data.
Geospatial	Relating to geospatial information services, especially vector-based information about roads, land features, and asset locations.
Overhead Imagery	Relating to images of areas take from overhead flying or satellite-based assets.
Social Media Understanding	Relating to the use of social media networks and their posts to understand events occurring.
Decision Optimality	Relating to the use of mathematical or ML methods to make more optimal decisions, such as routing resources or minimizing risk to populations.
Disaster Prediction and Measurement	Relating to the use of incoming data to predict the future onset of a disaster or emergency, or the measurement of the severity of that event after it has started.
Natural Imagery	Relating to the use of images from visual light taken from approximately ground level, to include surveillance cameras and social media posts.
Robotics	Relating to the control or use of robots in emergencies.
Public Acceptance	Relating to how the public would accept ML technologies during emergencies.
Review	Review articles of many other articles.

Tag	Definition
Testing and Evaluation	Relating to how these techniques can be evaluated or tested to confirm reliability, accuracy, and effectiveness.
Security	Related to the security of algorithms from cyber or other forms of attack.
Online Learning	Related to the continuous learning of a ML system to better adapt to its environment.
Technical Data	Related to use of data that is technical in nature, such as spectroscopy or other chemical sensors.
Simulation	Related to the creation of data through physical or other forms of simulation.
Regulation	Related to the legal environment and how it affects the development and application of ML technologies.
Domain Awareness	Related to the presentation and distillation of information about the environment and situation to a human.
Governance	Related to the set of rules and regulations that will govern the creation and application of ML technologies in EM.

The nearly 200 articles evaluated are provided with their tags in the bibliography section of this document (see section 6.1). In addition, the PNNL team consulted with other national laboratory research staff who apply EM-relevant ML technologies to other domains. This report reflects their insight regarding the state of the art in geospatial and overhead imagery, change detection in imagery, denied communications, alternative optimization techniques, and threat identification with online learning.

2.2 Expert Validation

From this identification and categorization of articles, the team identified technologies that either are promising for solving EM problems in the future or are critical supporting technologies for using ML to solve EM problems in the future. To validate these technologies as well-aligned, non-trivial, and feasible, the team performed a validation exercise enabled by the University at Albany (UAlbany) College of Emergency Preparedness, Homeland Security, and Cybersecurity (CEHC) faculty.

During two sessions conducted on April 2 and 3, 2024, members of UAlbany's faculty and EM stakeholders from state agencies and city departments convened with the PNNL team to discuss the identified technologies. The faculty convened included those with expertise in EM, cybersecurity, ML, and traditional computer science. The EM stakeholders included representatives from the New York State Police, Albany Fire Department, and New York State's Division of Homeland Security and Emergency Services (NYS DHSES).

During these sessions, discussion of the 13 technology concepts was structured by an activity categorizing each technology by its Acceleration Toward Maturity and Potential for New Research. The combination of ratings in these two areas splits ideas into concepts that may be one of the following:

- Ideal for DHS investment (high potential but low acceleration)

- Impactful and have research support in other industries (high potential and acceleration)
- Having less impact (low potential).

These sessions helped ground results of this task in faculty and EM stakeholder-led feedback, and included digressions that informed results for enabling technologies. Additionally, these sessions indicated imperfect alignment between the AI art-of-the-possible and emergency managers' understanding of it, which presents an opportunity for further education.

2.3 Idea Generation

To bolster the diversity of sources for review, this task organized an opportunity to obtain outside ideas from a population less indoctrinated to the current state of the practice in EM. On April 5, 2024, a "sandpit" exercise was held at UAlbany, where UAlbany and Rensselaer Polytechnic Institute students competed to develop ideas to apply ML to an emergency operations center (EOC) (Figure 2). In this exercise, 17 student teams of 2-4 students each were introduced to the concept of an EOC and provided an exemplar emergency to seed their thinking. Students were asked to come up with a concept for ML use in such a situation that would improve EOC operations during the emergency. The students communicated their ideas through a three-minute, one-slide briefing and a two-page report. The student teams were judged by a panel composed of representatives from PNNL, DHS, NYSDHSES, and UAlbany faculty. The two best overall student teams and the most creative student team were awarded. The student concepts aligned predominantly with the tag of "decision optimality," which validated a previous conclusion that "decision optimality" is an unexpectedly visible and well-supported subfield within the AI and EM intersection.

Figure 2. Sandpit exercise at the UAlbany

3.0 Framework

The information environment that faces emergency managers, first responders, and other stakeholders during emergencies is challenging and complex. Information comes to those involved in myriad forms, through myriad channels, at varying speeds and with varying levels of veracity, uncertainty, and usefulness. Applying AI to EM could have high impact precisely because of this complex information environment. AI has proven its efficacy in processing data faster, more consistently, and more comprehensively than humans. AI (or data science more broadly) utilizes information as its most precious resource, so the literature is deep in how to solve the challenges inherent in complex data environments.

To understand better the EM challenges for which AI can be leveraged, an overarching framework is needed to capture that complex information environment. The team developed a framework to support capturing this complex information environment (outlined below and leveraged throughout this report). This framework was developed from overarching descriptions in the EM literature, from expert elicitation and context from emergency managers and other stakeholders. The goal of making a formal framework was the following:

- To identify cross-cutting challenges across many EM applications
- To identify gaps between well-supported challenges in EM
- To develop a vision for broader advancement after those gaps were closed
- To find underdeveloped subfields.

The EMOTR AI framework is based on many features that can be applied to each EM challenge or to available information. The framework comprised five categories of features, two of which relate to EM applications and three of which characterize the data available or needed. The EM application categories were the Stage of an incident during which an application is relevant and the Domain for which information is relevant.

Stage identified applications along a progression from the following:

- Mitigation before an incident
- Detection around the onset of the incident
- Response during the event
- Recovery after the event.

Domain identified that data may be available from the following:

- Public buildings
- Homes
- Private commercial buildings
- Private power infrastructure
- Private gas infrastructure
- Telecommunications infrastructure
- Transportation systems
- Natural environment
- Law enforcement systems
- Other emergency systems.

To characterize the relevant or available data, the framework characterizes its Modality, Uncertainty, and Structure. The Modalities are:

- Text (and transcribed text)

- Geospatial information (such as from geographic information systems [GIS]) and natural imagery
- Overhead imagery
- Climate and weather data
- Technical readings from the increasing number of sensors
- Metadata on the preceding modalities (for example, the time at which a transcribed phone call was received).

Uncertainty characterizes each piece of data as high, medium, low, or variable. Uncertainty includes a measure of the likelihood that the datum is mis- or disinformation, and how close the datum is to the true value (assuming it is intended to be true).

Structure of the data could be unstructured (such as geospatial information), structured, or mixed. All of these features may be dynamic. For example, a datum may have uncertain veracity at the start of an incident but be elevated as it is verified, or a system may be fully functioning at the start of an incident but become degraded due to damage.

The EMOTR AI framework allowed the team to bridge the gap between EM and AI. When presented with an EM application, it was possible to easily characterize its Stage and hypothesize all the Domains that contained relevant information. The team was able to further characterize the relative information by Modality, Uncertainty, and Veracity. This allowed for the selection of a data science technique that applied to those Modalities, Uncertainties, and Structures. In the converse, for a given AI technique, it was possible to determine which Modalities, Uncertainties, and Structures a given technique applied, and use that to step into EM applications that required applicable information. Two concrete examples are:

- EM Application – Civil Unrest Prediction and Mitigation: Prediction and mitigation happen before a civil unrest incident and are applicable to the Stage of mitigation. Civil unrest may affect public buildings, power or gas infrastructure, transportation, or law enforcement systems. It also may be coordinated through telecommunications infrastructure. It may be evident or coordinated through text and images on social media or other media. It may also be evident on overhead or natural imagery. NLP and computer vision may be applicable. The uncertainty of data informing this prediction is especially important, as dis- and misinformation is expected about civil unrest. Overall, the data is unstructured, although subsets of data such as images have inherent structure. Image-text models (and other forms of data fusion) may be useful in civil unrest prediction and mitigation, that techniques for verifying uncertain data may be useful, and that any such techniques must be flexible to unstructured data (many current techniques require highly structured data).
- AI Technology – Retrieval Augmented Generation (RAG): RAG is an emerging technique that helps large language models (LLM) ensure that their responses to prompts are accurate. As such, it improves the uncertainty/veracity of text generated by LLMs. Therefore, it is applicable to the text modality. The text modality is available from most Domains in EM and also available in most stages of an incident. Therefore, RAG may be a cross-cutting technology that enables better AI-generated responses. It may be useful in phone call summarization, social media trend understanding, writing of scripts for press conferences, writing of after-action and other types of reports, and for use in chatbots to respond to its users in an emergency.

With this EMOTR AI framework in hand, it was possible to match many EM applications to technologies and also map many AI technologies to EM applications. By generalizing beyond single applications and single AI technologies, this research can posit a small number of trends that will have an impact on AI for EM in the next 10 years.

4.0 Results

The results for the tag proportions for the evaluated articles are shown in Figure 3. Unsurprisingly, disaster prediction and measurement was a popular field of study. However, the second most prevalent topic addressed questions in Decision Optimality. This included resource routing during a disaster, placing sensors before disasters, and even risk model formulations of similar questions. This finding was validated by the emergency managers in the validation exercise and other reports[210] considering Decision Optimality as one of the core competencies of EM. Another notable prevalence value was the relatively small number of publications on the testing and evaluation of AI technologies for EM, echoing a conclusion from other recommendations reports.[208] This highlights a risk in the field but is unsurprising in the context of AI's broader problems with replication and generalization. Tag prevalence is dynamic and likely will evolve over time but are useful in understanding the inclusions and exclusions in current research in the field.

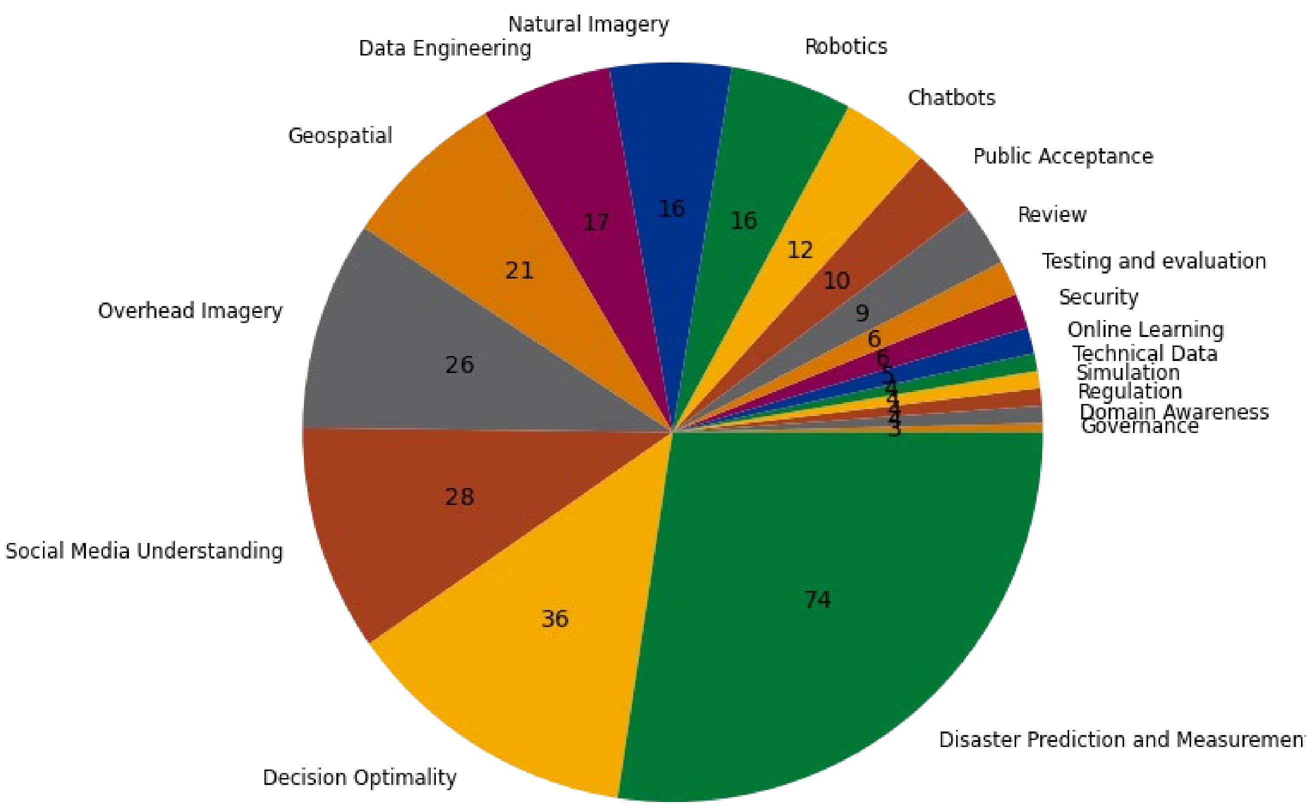


Figure 3. Number of articles tagged associated with each tag. Note, an article may have more than one tag.

The tag proportions and insights from the alignment and verification technologies were distilled into 13 highlighted technologies or enabling technologies that are summarized in one-page technology cards, or visual summaries, outlined in the sections 4.1-4.13. Each card represents an emerging AI technology with direct alignment to EM that may have the potential to affect the latter field within 10 years' time. Enabling technologies are those things that will constitute the infrastructure for AI technologies and without which progress in these the highlighted technologies may not be able to be used.

The following sections present the 13 highlighted or enabling technology cards (summarized in Table 2). Each technology card is a single page with a summary of the technology. This summary details relevant references available in section 6.1. Each summary is followed by a table that details the following:

- Type – Whether the concept is a highlighted or enabling technology
- Name – Technology name
- Status – Current status including a Technology Readiness Level (TRL) for each technology[xii] and EM-focused TRL (TRL_{EM})[1]
- Timing – Estimated time to maturity in years
- Concept – Key points of the technology
- Application to EM - Key points on technologies application to EM
- Research Status – Current state of the research
- Prediction – Prediction about the future of the technology.

Table 2. Highlighted and Enabling Technologies

Highlighted Technologies	Enabling Technologies
• AI-Enabled Productivity Applications • Public-Facing AI Communication • AI-Enabled Planning • AI-Filtered Domain Awareness • AI-Enabled Disaster Prediction and Detection • AI-Enabled Recovery and Prediction • Risk Models for Optimal Asset Deployment • AI Embedding for Alternative Data Streams • Modern Optimization for Asset Deployment	• Security of AI Assets and Data • Modeling, Simulation, and Digital Twin • Information Technology Infrastructure for AI • Governance and Public Perception of AI

From this set of technologies, several are deemed lower technical risk due to the technology's maturity associated with a relatively high TRL (see Table 3). These technologies present R&D opportunities that could be well suited for "quick wins" as much of the technical risk has been mitigated. Alternatively, Table 3 also presents two technologies with a low TRLs and therefore relatively higher risk R&D propositions. These technologies are well suited for investment to realize the potential effectiveness of early-stage concepts and technologies.

[1] The EM TRL, denoted as TRL_{EM} in the table, reflects the analysis on how mature the technology is relative to application in the EM domain.

Table 3. Technology Risk Profile from Associated Technology Readiness Levels

Lower Technical Risk Technologies	Higher Technical Risk Technologies
• AI-Enabled Productivity Applications	• AI-Filtered Domain Awareness
• Risk Models for Optimal Asset Deployment	• Modern Optimization for Asset Deployment
• AI Embedding for Alternative Data Streams	

4.1 AI-Enabled Productivity Applications

One idea from this review that excited the emergency managers was the idea of using modern NLP to reduce the workload of emergency managers during and after emergencies.[20,42,43,48,49,153,191] The emergency managers were interested and comfortable with the idea of AI converting bullet points into long-form text. This was extremely interesting to the emergency managers for finishing after-action reports, for conducting overall retrospectives of events, and for other reporting requirements.[208]

The underlying technology that would enable such applications are LLMs, which are trained to turn text into "semantic representations," which quantitatively describe an idea, and then to turn the semantic representations into human readable text. This underlying technology has enabled many private applications, most notably ChatGPT.[v] This technology is ready and mature to do text summarization, bullet to long-form conversions, and similar techniques. Unfortunately, LLMs rely on existing and learned knowledge from their training corpus, so dynamic fields are still a challenge for them. Specifically, they can "hallucinate" concepts when they try to process new concepts that were not in their training corpus. RAG is promising solution to hallucinations, but it is still somewhat immature.[iv]

An additional use to the same technology, with very different uses in EM, is the concept of a programming helper such as Github's CoPilot.[vi] This could help expedite during emergency access to new databases; it is ideal for time critical programming, but its quality is not up to the quality of human written code. The very limited applicability to EM may be due to the hallucination problem, legislative restrictions, and because the training corpuses of the largest LLMs are likely both insecure and in violation of information use licenses.[v] The security issue is likely to be resolved, as several national laboratories have deployed LLMs within their Official Use Only environments; however, licenses remain an ongoing legal concern. With growing trust in AI and governance regarding training datasets, and with better security around use, these types of technologies could be deployed at scale in 5-7 years.

<table>
<tr><td colspan="2">HIGHLIGHTED TECHNOLOGY:
AI-ENABLED PRODUCTIVITY APPLICATIONS</td><td></td><td>6-8
TRL</td><td>1-3
TRL_{EM}</td><td>5-7
YEARS</td></tr>
<tr><td colspan="2"></td><td></td><td colspan="2">CURRENT STATUS</td><td>READY IN</td></tr>
<tr><td>Concept</td><td>Use AI for administrative tasks such as:
- Knowledge summarization
- Report writing
- SQL query writing
- Code writing</td><td colspan="3">- Very little applied focus from EM
- Hallucination problem
- Questionable regulation status</td><td>Research Status</td></tr>
<tr><td colspan="2">Application to Emergency Management
- After-action reports
- During emergency queries for status
- Retrospective for performance review
- Press reports</td><td colspan="3">- With growing trust in AI, AI-Enabled Productive Applications will be applied in general and bespoke ways to EM.</td><td>Prediction</td></tr>
</table>

4.2 Public-Facing AI Communication

Like the concept of AI-Enabled Productivity Applications, NLP could perform public-facing communication. This could drastically reduce the amount of time needed for press releases, phone answering, requests from media, and similar tasks. Emergency managers were interested in the time savings of using AI for this type of communication but were concerned about the public perception of using an AI to perform this kind of communication as well as the current lack of legal guidance.

The underlying technology for using AI to perform public-facing communication is the same as AI-Enabled Productivity Applications, again using LLMs to convert concepts into human readable text. As such, it is susceptible to the same hallucination problems and requires the same solutions. Further, LLMs perform an action more like “association” in their conversion of concepts into text than “planning”—they provide a mix of previously encountered scripts instead of planning from a framework.[vii] This makes long text written by AI less likely to be coherent and self-consistent than that written by a human. Solutions to the planning question are under development (see AI-Enabled Planning).

An additional benefit to using AI for public-facing communication is the ability to train the AI to perform best practices in communication. This has already been approached in the literature—some research has been performed into how to communicate to indigenous populations with cultural differences.[43,44] This could be especially beneficial during long-running and stressful situations where an AI would be completely immune to the fatigue or emotions of the situation. More enthusiasm was observed for systems in which humans would review final versions of messages, pointing to utility as a decision support system.

Given the underlying technology is the same as AI-Enabled Productivity Applications, AI-enabled public-facing communication in EM could be ready to be deployed responsibly in 5-7 years. However, it is likely that journalists already use AI to draft their public communications, and it may be used before it is pushed out officially by the agencies.

<table>
<tr><td colspan="2" rowspan="2">HIGHLIGHTED TECHNOLOGY:
PUBLIC-FACING AI COMMUNICATION</td><td rowspan="2"></td><td>5-7
TRL</td><td>1-3
TRL_{EM}</td><td>1-2*
YEARS</td></tr>
<tr><td colspan="2">CURRENT STATUS</td><td>READY IN</td></tr>
<tr><td>Concept</td><td>- AI can generate coherent scripts based on several bullet points for public dissemination.
- Certain objectives can be rewarded during training.</td><td colspan="3">- AI methods can “hallucinate” facts and insert them into text.
- AI methods currents do more association than planning, which makes long communications less coherent.
- Solutions for both above are in development.</td><td>Research Status</td></tr>
<tr><td colspan="2">Application to Emergency Management</td><td colspan="3" rowspan="2">- AI may already be used by journalists for public communications.
- Governance and the public trust landscape are potential barriers to use in EM.
- As with journalists, likely will be used informally, even if not approved or ready.</td><td rowspan="2">Prediction</td></tr>
<tr><td colspan="2">- Use for press reports and newspaper interviews to ease the burden on emergency managers.
- Research backed communication methods can be rewarded in training for consistent and optimal tone.</td></tr>
</table>

4.3 AI-Filtered Domain Awareness

As described in the framework, the information environment for emergency managers is already and increasingly growing more complex. Unstructured, mixed quality, and overwhelming amounts of information is provided through video feeds, social media, phone communications, sensors, and additional sources. Simply tending to all these sources is difficult, much less filtering, weighting, and verifying the data. As is becoming common in defense, intelligence, and other security situations, domain awareness facilities or applications can use ML techniques to determine the appropriate and optimal information to display to the emergency managers.[14]

Several ML technologies could play a role in information filtering, weighting, and display. The first and most crucial is the “encoding” of text, video, images, and other information into a semantic representation that can be computationally manipulated. Techniques for doing this abound, although contrastively learning has only recently enabled the ability to compare information from across data types (i.e., image to text comparison). Then, data fusion is an important technology needed to ensure that all information available is presented, not just the information available solely in each data stream.[175] Data fusion, despite its long history of research, still has major challenges.

A concern in filtering information through AI techniques is the “echo chamber” effect, where AI simply chooses the same information even when other information is available. Emerging explore-exploit tradeoff techniques may be able to modulate the proportion of new and previously shown information displayed.

Given the relatively easy regulation environment and low public visibility, domain awareness filtering and weighting may be deployed relatively quickly, in 2-5 years. However, it will take quite a bit longer to deploy data fusion-enabled systems with proper testing and evaluation. This highlighted technology seems especially ripe for incremental improvements, and the defense and intelligence sectors are actively developing solutions.

<table>
<tr><td colspan="2" rowspan="2">HIGHLIGHTED TECHNOLOGY:
AI-FILTERED DOMAIN AWARENESS</td><td rowspan="2"></td><td>1-3
TRL</td><td>1-3
TRL_{EM}</td><td>2-5
YEARS</td></tr>
<tr><td colspan="2">CURRENT STATUS</td><td>READY IN</td></tr>
<tr><td>Concept</td><td>- An information-rich environment like an emergency needs information filtering and weighting.
- Data fusion techniques can more judiciously show and remind humans information.</td><td colspan="3">- Operations centers are evolving and have an appetite for advanced techniques.
- Issues exist with the “echo chamber” effect, and an explore-exploit tradeoff is needed for viewpoints on information.
- Human-machine teaming and perception issues will be critical to overcome.</td><td>Research Status</td></tr>
<tr><td colspan="2">Application to Emergency Management</td><td colspan="3" rowspan="2">- The regulation environment is relatively simple for showing information to emergency managers, so near-term opportunities to deploy exist.
- Most of the underlying technology exists and other fields are deploying similar systems.</td><td rowspan="2">Prediction</td></tr>
<tr><td colspan="2">- Operations center visuals
- Reminders to emergency managers and first responders
- Follow-up for task completion in chaotic environments</td></tr>
</table>

4.4 AI-Enabled Planning

Planning for emergencies or planning next steps within emergencies is an exceedingly difficult task. Especially in generalized or all-hazards approaches, the number of considerations and their sometimes-competing effects can overwhelm human planners. While traditionally not associated with high performance in planning, AI is promising as a planning technology because of its wide bandwidth for attending to many pieces of information. Emergency managers already outsource components of pre-event planning and were interested in using AI techniques to perform the same.

As discussed in Public-Facing AI Communication, the planning performance of current ML techniques are not of a high standard. They often associate current situations with past situations and use plans from past situations, without regard to new constraints or past plans' success. Several new techniques have been proposed and implemented, including Chain-of-Thought reasoning, Tree-of-Thought reasoning, and neural A-star, which are promising planning technologies for neural networks.[viiix] Coupled with data fusion, neural network planning could perform consistent, fast, and close-to-optimal planning for a variety of situations.

Emergency managers were interested in using this technology to ease their burden of planning for specific emergencies and creating time-consuming reports that are required. The opportunity may be larger than that: neural planning could be used to improve current methods to quickly create evacuation plans under changing road conditions, to route autonomous vehicles, and to plan new resource allocations with dynamic resource availability[183-210]. This technology had more practitioner support as a decision support system rather than as an unchecked decision system.

Theoretical barriers may persist in the nascent technologies like Chain-of-Thought, thus this technology will take 7-10 years to fully adopt and deploy. The testing and evaluation of this technology may be especially challenging, as it must either require numerous full-scale exercises or rely on simulated (and therefore imperfect) data. The constraints that make this technology interesting to emergency managers are unique, and, as a result, DHS (along with the Department of Defense [DoD]) may have an outsized impact on this technology.

<table>
<tr><td colspan="2" rowspan="2">HIGHLIGHTED TECHNOLOGY:
AI-ENABLED PLANNING</td><td rowspan="2"></td><td>**4-6**
TRL</td><td>**1-3**
TRL$_{EM}$</td><td>**7-10**
YEARS</td></tr>
<tr><td colspan="2">CURRENT STATUS</td><td>READY IN</td></tr>
<tr><td>**Concept**</td><td>- Emerging techniques can ingest multiple data streams to process situation context (e.g., surveillance footage, overhead imagery, and microblogs).
- Planning steps using this full context can provide more optimal solutions.</td><td colspan="3">- Fusing multiple data streams is currently developed for pairs and triplets, moving toward more.
- Several nascent concepts such as Chain-of-thought, tree-of-thought and neural A-star are promising.</td><td>**Research Status**</td></tr>
<tr><td colspan="2">**Application to Emergency Management**
- Resource routing under uncertain road status
- Autonomous vehicle routing
- Resource allocation during an emergency</td><td colspan="3">- Possible theoretical barriers in neural planning.
- It will be difficult to test and evaluate these technologies.
- DHS and DoD may have a large influence in this space.</td><td>**Prediction**</td></tr>
</table>

4.5 AI-Enabled Disaster Prediction and Detection

The most popular topic of the ML in EM literature is that of disaster prediction and detection. Current researchers apply it to flood prediction,[154-182] infrastructure failure,[162] security emergencies, and famines.[137] They use overhead imagery, geospatial information systems, tabular data such as soil densities, and graph techniques to perform this prediction. These techniques are well supported by the ML literature—the classifiers underlying disaster prediction and detection are one of the first thing to which any ML student is exposed. The value proposition for using ML to perform these tasks, and not human-based agents, is the constant vigilance possible with AI, the consistency and speed, and the wide bandwidth to digest many data streams. Overall, AI has proven to be better at prediction and detection than humans in a wide variety of fields.[i]

Some concerns exist with AI-enabled prediction and detection, specifically in generalizability. Many neural networks are trained on one dataset representing one disaster in one location. It is very unlikely that those networks are applicable to other situations or locations. The field has found several ways to alleviate this issue, such as data diversity. Using many different locations and different disasters in a training set (at least 100,000) creates robust, generalizable models. Fortunately, disasters are not that prevalent, resulting in an inherent lack of data. Few-shot learning is a subfield of ML dedicated to learning on smaller amounts of data than traditional techniques and therefore will likely have a high impact in disaster prediction and detection.

Based on the existing literature, these techniques are ready for deployment in certain cases. The ML operations (MLOps) surrounding those cases are engineering concerns that should be considered, such as how to monitor the models to ensure they are not failing and how to alert when they are failing.[208] For fully generalizable all-hazard type models, a sizable amount of data and resource allocation is required before training and deploying; therefore, this research will continue throughout the next 10 years.

<table>
<tr><td colspan="2">HIGHLIGHTED TECHNOLOGY:
AI-ENABLED DISASTER PREDICTION AND DETECTION</td><td></td><td>1-7
TRL</td><td>1-7
TRL_{EM}</td><td colspan="2">1-10
YEARS</td></tr>
<tr><td colspan="3"></td><td colspan="2">CURRENT STATUS</td><td colspan="2">READY IN</td></tr>
<tr><td>Concept</td><td>- Given input data streams (e.g., overhead imagery), onset of events can be predicted or detected.
- AI has consistently proven to predict better and detect sooner than traditional prediction/detection in many other fields.</td><td colspan="4">- Single-modality single-threat examples abound.
- Issues persist with generalizability (i.e., does model for site A apply to site B?).
- Few-shot learning is an important topic for future work.</td><td>Research Status</td></tr>
<tr><td colspan="2">Application to Emergency Management
- Earlier prediction and detection can enable better responses.
- Prediction can enable proactive responses.
- Consistent AI vigilance can ease burden on public servants.</td><td colspan="4">- Wide ecosystem will be developed and deployed over the next decade.
- MLOps (the art of training, retraining, alerting, and monitoring models) will become paramount.</td><td>Prediction</td></tr>
</table>

4.6 AI-Enabled Recovery and Prediction

Evaluation of the recovery of locations after a disaster, prediction of their progress, and the second order actions to help speed or change that recovery are historically an underrepresented area of EM. AI holds promise to perform measurement of recovery, prediction thereof, and enable those future decisions to speed recovery in the same way that it holds promise to detect disasters before they happen.[27,80,177,178,198,199]

The underlying technology for recovery prediction and measurement is very similar to that underlying AI-Enabled Disaster Prediction and Detection: regression is a fundamental technique in data science and a large section of literature is devoted to using it to measure and predict recovery.

Similar conclusions to AI-Enabled Disaster Prediction and Detection also apply. Generalization and MLOps are areas of focus, and properly performing those will result in highly performant and useful systems. The area of recovery prediction and measurement may need more deliberate focus because of the historically lower interest given from EM research perspectives. Overall, some technologies that prediction and measurement are ready to be deployed today, but research in techniques will evolve throughout the next 10 years.

HIGHLIGHTED TECHNOLOGY: **AI-ENABLED RECOVERY AND PREDICTION**		1-7 TRL	1-7 TRL_{EM}	1-10 YEARS
		CURRENT STATUS		READY IN
Concept	- Given a data stream, AI can measure and predict aspects of the environment. - AI has consistently proven to measure with lower mean absolute error and predict with the same compared to other methods.	- Single-modality, single-emergency type solutions exist in the literature. - Issues persist with generalizability (i.e., does a model at time X work for time Y?). - Data fusion is growing in popularity.	**Research Status**	
Application to Emergency Management	- Automated measurement of vegetation or building recovery after disaster. - Many data modalities currently used (overhead imagery, geospatial information systems, social media posting).	- From an AI perspective, this does not differ from AI-Enabled Disaster Prediction – similar conclusions apply.	**Prediction**	

4.7 Risk Models for Optimal Asset Deployment

As previously stated, optimal decision-making was a surprising focus of ML in EM research, at least to the team conducting this task. However, emergency managers are consistently thinking about how they can organize and manage their assets in optimal ways. Included in this are different, risk-based ways to think about costs of each decision.[64,65,69,72,90,119,140] The intersection of these two considerations is a field with many opportunities and broader than simply resource allocation during an emergency. Risk-based optimization can be used to place sensors in a way that reduces the risk (not probability) of not detecting a disaster during its onset and help route vehicles or other assets, which reduces the risk to either the assets or the population under risk, and similarly for evacuation routes.

Both supporting technologies, optimization techniques and risk modeling, are well understood and have significant supporting literature in their own right. The connections between the two have already been established, and application studies have already been created in the ML in EM literature. A broad variety of underlying technologies exist and have relevance, from gradient-free optimization, stochastic optimization, partial-differential equation-based optimization, and risk assessment models. This area of research is highly developed and may be deployable within the next 1 to 5 years.

Potential concerns with the governance and public perceptions surround the confluence of these two fields. The public perception concerns from AI-Enabled Planning repeat, with the additional consideration that risk models are also somewhat controversial in their own right.[143,144] Governance and responsible use of these two technologies may hinder or even limit its adoption and deployment. Further, testing and evaluation of these technologies is difficult, especially from a mission-level perspective. Counterfactuals to the taken resource allocation are difficult to assess except in exercises or simulation. DHS may have a large influence in furthering this field as it seeks to overcome those large challenges.

HIGHLIGHTED TECHNOLOGY: **RISK MODELS FOR OPTIMAL ASSET DEPLOYMENT**			**6-9** TRL	**4-6** TRL$_{EM}$	**1-5** YEARS
			CURRENT STATUS		READY IN
Concept	- With limited resources, optimizing risk of events (as opposed to minimizing probability) is important. - Modern risk modeling methods paired with optimization can guide the deployment of assets in a risk-optimal way.	- Risk modeling and optimization methods are well understood, the connections between the two are already well established. - Application studies to EM are numerous in the literature.			**Research Status**
Application to Emergency Management	- Sensors may be placed to detect disasters with the lowest risk to the population of missed disasters. - Vehicles may be routed in a way that minimizes the overall risk. - Evacuation routes can be calculated in a risk-optimal way.	- Wide governance and public perception of machine-generated plans is a concern for the future. - Mission-level assessment of risk ontologies will be important. - DHS may have a large influence in combining these two technologies.			**Prediction**

4.8 AI Embedding for Alternative Data Streams

The emergence of the Internet of Things and Smart Cities add complexity to an already difficult information environment for emergency managers. Some emergency managers have long needed to understand technical sensor readings such as seismic sensors or at facilities such as chemical or nuclear plants,[171,184] but the proliferation of additional sensors has expanded this need to most localities. AI enables a unified approach to use each sensor reading and contextualize it with other information, unlike current techniques which require bespoke analyses for each sensor type.

Emergency managers were less interested in this technology than the rest of the technologies; the effects of it are indirect and the benefits will be realized in a longer time frame. It has been chosen for inclusion as the theory that underlies embedding alternative data streams is the same theory that enabled computer vision and NLP, both of which were largely ignored by applied researchers until they reached a certain level of maturity.

Encoding is a set of techniques in ML that transforms a datum (e.g., text, image, video, computed tomography, spectra, or other type) into a single semantic representation, on which further computational manipulation can be performed. Contrastive, diffusive, reconstructive, and supervised learning have enabled the theoretical ability to compare data from the same modality and between modalities.[x] This is fundamental to the downstream tasks such as planning, predicting, and detecting.

While challenges persist with adoption, data scale, and nuisance information, the techniques to encode almost any data type are currently available. Large-scale training, testing, and evaluation will help applications researchers use these for in their technologies. These will likely be applied more commonly in applied research such as in EM within the next 3 years. Because homeland security, defense, and intelligence sectors are more likely to use alternative sensors, they may have a large role to play in furthering this technology.

<table>
<tr><td colspan="2" rowspan="2">HIGHLIGHTED TECHNOLOGY:
AI EMBEDDING FOR ALTERNATIVE DATA STREAMS</td><td rowspan="2"></td><td>6-9
TRL</td><td>2-4
TRL$_{EM}$</td><td colspan="2">1-3
YEARS</td></tr>
<tr><td colspan="2">CURRENT STATUS</td><td colspan="2">READY IN</td></tr>
<tr><td>Concept</td><td>- Every new data type traditionally requires bespoke analysis solutions (e.g., peak fitting for spectra).
- Modern contrastive learning and neural architectures allow a unified approach for all data types.</td><td colspan="4">- Embedding is well understood and implemented for vision and text.
- Embedding is still emergent for audio, video, and some technical data streams.
- The applied research follows the above distribution.</td><td>Research Status</td></tr>
<tr><td colspan="2">Application to Emergency Management
- Allows utilization of alternative data modalities for detection, prediction, and assessment of emergencies.
- Vastly increases the amount of data available for computational use in making decisions.</td><td colspan="4">- Use of these methods is increasing to find data streams with the most useful signals.
- DHS and the intelligence community may have a large influence in this field.</td><td>Prediction</td></tr>
</table>

4.9 Modern Optimization for Asset Deployment

Many EM tasks naturally fit into an optimization regime: the minimization of risk of certain emergencies or the minimization of cost when deploying assets. Performing an optimization in a realistic information environment, amid continuous and discrete values, uncertainty about those values, missing data, and possible constraints on the solution (such as the number of assets or budget) has historically been challenging. ML has both re-invigorated investigation into optimization methods and provided new methods.[1] Like AI Embedding for Alternative Data Streams, modern optimization for asset deployment is a foundational technology included in this task despite less interest from EM practitioners.

Several advancements in optimization techniques enable different possibilities. Reinforcement learning and other gradient-free enables optimization in a situation where the derivative of the optimization target has undefined gradients, constraints such as when assets cannot cross a boundary, or budget limitations. Stochastic Gradient Descent methods used in ML[32] can also enable the minimization of very high dimensional functions, such as optimizing the public perception of a speech, where public perception is measured by some neural network on social media posts. Finally, partial-differential equation-focused optimization, as is used in the power grid optimization sector, have added techniques that can enable security of their solutions or other discrete considerations in what is otherwise a continuous problem.[xiii]

The overall field of optimization is robust, but the applied literature is almost non-existent. Therefore, it will take at least 7 to 10 years before deployment of such methods are affected. In the interim, emergency managers should be involved with the applied researchers such that the appropriate mission objectives are sought in the optimization problem.

HIGHLIGHTED TECHNOLOGY: **MODERN OPTIMIZATION FOR ASSET DEPLOYMENT**		**1-4** TRL	**1-2** TRL$_{EM}$	**7-10** YEARS
		CURRENT STATUS		READY IN

Concept	- New optimization techniques can find optimal solutions for problems impossible before, such as: o Discrete-continuous sets o Problems with undefined gradients o Large dimensional outputs	- Separate fields are investigating aspects of this technology: o Differential equation-focused optimization o Reinforcement learning o Genetic and other gradient-free methods	**Research Status**
	Application to Emergency Management - Enables resource routing and deployment plans with additional constraints (e.g., security). - Enables planning with predictions with uncertainty. - Allows for resource routing using simulation as part of the data stream.	- Applied research is needed to map separate methods to appropriate applications. - EM subject matter experts will need to guide optimization targets in the field.	**Prediction**

4.10 Security of AI Assets and Data

As in all fields that rely on digital technologies, cybersecurity is a crucial aspect for AI in EM.[28,45,46,47] Further, the data used to train the AI is also a critical asset that must be protected by cybersecurity practice. The requirements for cybersecurity in ML-enabled applications are not unique and most practices used by the broader software deployment industry will appropriately protect AI-enabled assets. As AI expands into autonomous vehicles[71,80,83,92,103,104,186] and edge-based computing,[73,75,84] cybersecurity will be needed on more and lower-power systems, which will need to be addressed by the defense, security, and EM communities.

Data security has more unique facets than the cybersecurity of deployed AI assets. Currently, datasets utilized by ML practitioners are large, monolithic, and curated sets of measurements for specific purposes. They may be susceptible to intentional or unintentional biases, as well as synthetic data and possibly backdoors. With the improvement of synthetic data generation through simulation and ML-based techniques, risks increase for inclusion or insertion of data to purposely affect downstream AI techniques' training.

Procedures for handling such data assets should be created and should consider:

- How or whether to handle a dataset from a third party for which the data veracity cannot be verified?
- How to verify a dataset or dataset creator?
- How to protect a government-owned dataset from insertion of synthetic or biased data?

Maintaining the security of AI-enabled assets and data used to train AI techniques is crucial—the alternative is untrustworthy AI techniques and vulnerable assets.

ENABLING TECHNOLOGY: **SECURITY OF AI ASSETS AND DATA**			
Concept	- Connected assets require advanced cybersecurity to enable their proper and ethical use. - Datasets on which AI is trained also require adversarial security.	- Standard cybersecurity approaches abound for asset security. - Dataset security (and entitlement) is a topic of current debate in popular and technical media. - Few systems-level analyses are available in the open literature.	**Research Status**
Application to Emergency Management			
- Future autonomous vehicles may be vulnerable to cyberattack. - Future datasets may be vulnerable to inclusion of mis- and disinformation as well as engineered backdoors.		- The requirements will change based on the development of AI technologies, both standard and adversarial.	**Prediction**

4.11 Modeling, Simulation, and Digital Twin

AI-enabled technologies require large amounts of data to develop and train. In a field such as EM, where there is an inherent imbalance or dearth of data about the events of interest and little possibility to perform experiments, simulation broadly is of interest to help alleviate the data gaps. As such, modeling and simulation and their more data-driven relative, digital twins, have received significant interest for their use in the AI development pipeline.

Significant literature exists about modeling, simulation, and digital twin techniques, and some specifically for EM.[79,89,160] Some successful use cases highlight the use of simulated data for training disaster predictors. The emergency managers polled were interested in digital twin created data for working with overhead images or chatbots.

In other fields, the utility of synthetic data to AI training has come into question. While simulation or other synthetic data is easier to generate than data from real events, it may not exactly follow the distribution of data from real events. That fact, coupled with AI's current issues in generalization, can cause the AI to learn to use features in the simulated data that do not exist in real data. This debate is ongoing and may not be resolved soon. The consensus in high-energy physics is that synthetic data does not benefit AI training,[xi] whereas in materials science the opposite seems to be accepted. Further, digital twins, which are based on combining physical and data-driven techniques, require data in their own right. Thus, they are less appealing as a way to alleviate data size concerns for training neural networks. Modeling, simulation, and digital twin technologies hold a huge promise; however, their utility should always be tested before large investment.

<table>
<tr><td colspan="2">ENABLING TECHNOLOGY:
MODELING, SIMULATION, AND DIGITAL TWIN</td><td colspan="2"></td></tr>
<tr><td>Concept</td><td>- Training AI requires large amounts of data.
- The amount of available data may be able to be augmented with simulation, modeling, or digital twins.</td><td>- Significant literature is available on many different modeling, simulation, and digital twin modalities.
- Open debate persists about whether synthetic and simulated data helps downstream trained AI. The field of high-energy physics and materials science are notable fields exploring synthetic data.</td><td>Research Status</td></tr>
<tr><td colspan="2">Application to Emergency Management</td><td rowspan="2">- Applied EM research in simulation, modeling, and digital twin for AI is nascent, emerging in climate modeling.
- Iteration will show whether it is helpful to downstream trained AI.</td><td rowspan="2">Prediction</td></tr>
<tr><td colspan="2">- Climate modeling may be used to train disaster predictors for climate disasters.
- Synthetic overhead images, or their analogs in other fields, can be used to train other disaster predictors.
- Synthetic text can be used to train, test, and evaluate chatbots.</td></tr>
</table>

4.12 Information Technology Infrastructure for AI

One major assumption applied throughout this report is the assumption that data will be delivered to the AI-enabled EM solution at the right speed and with the right quality. That assumption relies on a robust and pervasive information technology infrastructure, and requires tight integration between enterprise-level system architects, emergency managers, and data scientists, as well as the software engineers and data engineers implementing the architecture solutions.[66] Advanced techniques for solving the problem of scaling data pipelines (sometimes called "data gravity") have emerged for AI and other fields. Notable among those are data mesh, where data is shared to only the assets in the local proximity, and data fabric, which combines different layers for different aspects of the data ingestion and utilization process but enables centralized data access because of the process. Hybrid solutions are also promising, such as data mesh combined with a slower centralized data archiving process.

Another aspect of information technology to impact EM is the interoperability and entitlements between the many heterogeneous organizations that comprise the EM enterprise. Future systems will need to operate continuously with many other systems.[73,75,84] Future data owners will need to adjudicate access to data to new users at increasing speed. Standards may help solve some of these problems, but flexible technologies to help bridge the gaps between systems or adjudicate data access (such as zero trust systems) may also have a significant impact.[208,209] DHS is exploring these questions, such as with the open architecture concepts being explored for Transportation Security Administration or the "client domains" being delivered to Customs and Border Protection.

ENABLING TECHNOLOGY: **IT INFRASTRUCTURE FOR AI**			
Concept	- Current IT infrastructure may not support AI at scale. - Data mesh and data fabric are increasingly deployed for commercial and defense applications. - If unsolved, infrastructure may severely limit AI applications.	- Most AI utilizes centralized static datasets and assumes instantaneous high-quality data delivery during the event. - Use of streaming, incomplete, and online data has only started to be investigated. - MLOps research discusses these issues but is siloed from the main body of AI research.	**Research Status**
Application to Emergency Management		- Issues persist for bridging the divide between data engineers and data scientists. - DHS has already started to show interest and focus on operationalizing AI and ML.	**Prediction**
- With increasing data availability, better data routing and data discovery is needed. - Smart Cities expand the amount of data and complicate the above. - Better data routing would get the data to the right emergency managers, first responders, or volunteers at the right time.			

4.13 Governance and Public Perception of AI

Possibly the largest issue in all modern AI is that of fairness, trustworthiness, responsibility, and public perception of AI. The legal environment surrounding ethics and laws for collecting data and using AI to act are changing quickly and sometimes unpredictably. The requirements for responsibility are especially important for fields like EM, where life and property are at risk.[208]

The literature includes some examples of investigations into the public perception and governance around AI tools.[15,16,50,51,93,115] Additionally, risk-based computations of the same have been performed.[143] Foundational to those, articles seek to codify and validate measurement techniques for the public perception of AI techniques and resultant decisions.

While the literature and other explorations will likely continue at scale due to this issue's visibility, concerns persist about how this will affect the development and adoption of AI for EM.[210] High-profile failures of deployed AI in EM will likely cause renewed questions about the ability of AI to approach questions where life and property are at risk, even if they occur at a lower probability or with lower consequences than human decisions.

DHS has already approached many of the governance and public perception questions and has internal guidance to the acceptance, approval, and deployment of AI systems.[13,51] With the relatively small number of deployed AI-enabled DHS applications, this system has a good performance history. It remains to be seen whether it will scale. Continued diligence, updated guidance, and retrospectives will likely be necessary to enable governance and public perception of AI that strikes the right balance between ensuring fair and trustworthiness of AI-enabled tools and ease of adoption and deployment.

<table>
<tr><td colspan="2">ENABLING TECHNOLOGY:
GOVERNANCE AND PUBLIC PERCEPTION OF AI</td><td colspan="2"></td></tr>
<tr><td>**Concept**</td><td>- Humans' decision-making power comes through public trust and public mandates.
- How can we empower AI to make decisions legally and ethically?
- How can we communicate that process to the public?</td><td>- Limited, single-use investigations have been published.
- Risk-based considerations have been investigated.
- Measurement techniques have been explored.</td><td>**Research Status**</td></tr>
<tr><td colspan="2">**Application to Emergency Management**</td><td rowspan="2">- Governance and public perception are likely the most important uncertainty for AI in the next decade.
- DHS components are already engaging in determining the governing processes of AI.
- High-profile failures of AI will be a challenge to mitigate and clean up.</td><td rowspan="2">**Prediction**</td></tr>
<tr><td colspan="2">- Many actions must be—and must be perceived to be—fair and equitable, including:
o Resource routing
o Proactive actions
o Risk-based decisions</td></tr>
</table>

5.0 Conclusions

Following a nearly year-long study into AI applications for EM, this report describes the detailed landscape of AI and its applications in EM. PNNL conducted a structured collection and curation of EM applications and AI technologies and aligned them to each other, followed by validation exercises with EM stakeholders, university faculty, college students, national laboratory researchers, and federal research staff. This work developed a framework that supports aligning the technologies between technologies in AI and their applications EM and the applications of EM with technologies in AI. Finally, the team curated a set of technologies and enabling technologies with the potential to greatly impact EM in the next 10 years. Highlights include:

- The resulting technologies were diverse, ranging from text-based tools that may improve the everyday life of emergency managers and other stakeholders (like AI-Enabled Productivity Applications), to tools that may minimize cost and life loss in disasters (like AI-Enabled Recovery and Prediction), to technologies that may be foundational to the next stage of AI in EM toward the end of the next decade (such as AI Embedding for Alternative Data Streams).
- Six technologies (AI-Enabled Productivity Applications, Public-Facing AI Communication, AI-Enabled Planning, AI-Enabled Disaster Prediction and Detection, AI-Enabled Recovery and Prediction, Risk Models for Optimal Asset Deployment) had consensus from AI and EM stakeholders as to their optimistic future in the field.
- One technology was viewed as useful, but misconceptions persisted about the extent to which it already existed (AI-Filtered Domain Awareness).
- Two technologies were included because of the high impact possible, despite less interest from emergency managers specifically (AI Embedding for Alternative Data Streams, and Modern Optimization for Asset Deployment).
- Four enabling technologies were identified that must be in place for the previous technologies to provide impact:
  - Security of AI Assets and Data
  - Modeling, Simulation, and Digital Twin
  - Information Technology Infrastructure for AI
  - Governance and Public Perception of AI.

While improvement may be achieved through private industry and other public sector investment (such as from DoD or the intelligence community), several technologies have constraints and requirements specific to EM and may not progress without specific interest from the EM community, specifically the following:

- Risk Models for Optimal Asset Deployment
- AI Embedding for Alternative Data Streams
- Modern Optimization for Asset Deployment.

Governance and Public Perception of AI was identified as the most important enabling technology overall for AI, and as being the enabling technology with constraints and requirements most specific to the public sector, DHS, and EM.

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Pacific Northwest National Laboratory

902 Battelle Boulevard
P.O. Box 999
Richland, WA 99354

1-888-375-PNNL (7665)

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Some EM-specific barriers to adoption should be considered when evaluating new AI technologies, such as the critical nature of EM applications. As coordinating agencies, EM organizations need to be aware of many domains and communicate with experts in all of them. This makes the negative outcomes from misclassifications or hallucinations much greater in EM than many other fields and is likely to lead to slower adoption in the critical and regulated EM and EM-adjacent fields compared to organizations not focused on public safety. Additionally, emergency managers frequently must communicate with entire communities, including those that are not technologically literate, meaning that many market-based tools may be less useful.

Finally, the landscape of AI for EM is likely to change drastically in the next decade and may prove or disprove some of the conclusions provided from this report. However, the methodology and framework provided can be re-used to iterate toward future conclusions whenever a field-changing event occurs or on another specified timescale.