

Permafrost thaw-related infrastructure damage costs in Alaska are projected to double under low and medium emission scenarios

Corresponding Author: Mr Elias Manos

This file contains all editorial decision letters in order by version, followed by all author rebuttals in order by version.

Version 0:

Decision Letter:

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Dear Mr Manos,

Your manuscript titled "Deep learning-based building and road detection reveals higher permafrost thaw-related damage costs than previously estimated for Alaska" has now been seen by 2 reviewers, whose comments are appended below. You will see that they find your work of some potential interest. However, they have raised quite substantial concerns that must be addressed. In light of these comments, we cannot accept the manuscript for publication, but would be interested in considering a revised version that fully addresses these serious concerns. Additionally you need to address carefully following editorial thresholds;

***Provide novel and firmly supported insight into the projected cost of building and road damages due to permafrost degradation in Alaska.

***Provide methodological details, explain and justify the suitability of applying empirical equations to determine bearing capacity for soils in Alaska.

***Discuss the validation process, integration of social vulnerability into the economic damage estimates, and consider adding low-emission scenarios.

We hope you will find the reviewers' comments useful as you decide how to proceed. Should additional work allow you to address these criticisms, we would be happy to look at a substantially revised manuscript. If you choose to take up this option, please either highlight all changes in the manuscript text file, or provide a list of the changes to the manuscript with your responses to the reviewers.

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Please do not hesitate to contact us if you have any questions or would like to discuss the required revisions further. Thank you for the opportunity to review your work.

Best regards,

Sadia Ilyas
External Editor
Communications Earth & Environment

Martina Grecequet, PhD
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REVIEWER COMMENTS:

Reviewer #1 (Remarks to the Author):

This manuscript presents an important topic of economic consequences of infrastructure damages caused by permafrost degradation in Alaska. The scope of the research is adequate. The conclusions can be useful references for policy and decision makers. Yet, there are some key deficiencies in the methodology, which may affect the validity of the results. These issues are presented below.

1. Novelty and insufficient validation of the deep learning model

The manuscript claims novelty in using deep learning for infrastructure detection. However, machine learning techniques for satellite image analysis have been widely applied in various fields, including infrastructure detection in Alaska (e.g., Kaiser et al. 2024). The manuscript states that the HABITAT deep learning pipeline achieved a 94% accuracy in detecting buildings and roads, but the validation process is not sufficiently discussed in either the manuscript or supplementary materials. The accuracy metrics (e.g., producer's accuracy and user's accuracy) are mentioned, but there is no explanation of potential false positives or false negatives that could skew the results.

2. Weak integration of social vulnerability analysis

While the manuscript mentions the use of the social vulnerability index (SVI), it does not effectively integrate this analysis with the economic damage estimates. The discussion of social vulnerability is superficial, and the supplementary materials do not provide any additional insights to this analysis.

3. Oversimplified assessment of bearing capacity reduction

The bearing capacity model used in the manuscript was based on a geotechnical model that accounts for skin resistance

and tip resistance. The dimension of the pile foundation is predetermined, and the bearing capacity is calculated based on soil properties, including soil texture, ice content, and peat content. A series of empirically derived equations were applied to relate soil properties with skin and tip resistance. However, these empirical equations were not established based on soil sampled from Alaska. The use of these empirical equations to model Alaskan permafrost clearly involves extrapolation. For example, the empirical models are developed for sand, clay, loam, and peat with ice content ranging from 0.05 to 0.5 (Streletskiy et al. 2012). Indeed, the soil is predominantly silty soil with ground ice content higher than 80%, taking Alaska's Arctic Coastal Plain as an example.

4. Discrepancies in estimated future cost

The calculations provided in the manuscript do not specify the time period over which these costs are projected. This ambiguity makes it difficult to compare the results with other studies.

References

Kaiser, S., Boike, J., Grosse, G. and Langer, M., 2024. Multisource Synthesized Inventory of CRITICAL Infrastructure and HUMAN-Impacted Areas in ALASKA (SIRIUS). *Earth System Science Data*, 16(8), pp.3719-3753.

Streletskiy, D.A., Shiklomanov, N.I. and Nelson, F.E., 2012. Permafrost, infrastructure, and climate change: a GIS-based landscape approach to geotechnical modeling. *Arctic, Antarctic, and Alpine Research*, 44(3), pp.368-380.

Reviewer #2 (Remarks to the Author):

In this paper, a deep-learning AI method is proposed to identify Alaskan roads, buildings and storage tanks by remote sensing images, and the stability of roads, buildings and storage tanks is simulated using a permafrost geotechnical model, and the cost of infrastructure damage is estimated under the SSP5-8.5 climatic scenario. Based on deep-learning to identify infrastructure by remote sensing images, this provides us with a new method, which is a well reference. However, the cost estimation of simulated infrastructure stability and infrastructure damage based on a permafrost geotechnical model is not a new, and a lot of research work has been carried out in this area. In terms of simulated infrastructure security for a geotechnical engineering models, it is more important to provide risk zoning of infrastructure for future climate change. Therefore, it is recommended that the authors focus

on infrastructure identification and geotechnical simulation, and delete the cost estimate of infrastructures damage. This allows for a more detailed discussion of the stability and reliability of Alaska's infrastructure under future climate change. There are still some questions:

1. Whether all the buildings in Alaska are pile foundations or whether they are elevated pile foundations, there is a huge difference in the response of permafrost to climate change under these two types of pile foundations. Please explain whether the article considers pile foundation and elevated pile foundation uniformly. How are damage standards for infrastructures obtained?

2. Road in towns is basically covered with asphalt pavement, and road is gravel pavement in other permafrost regions. There is a big difference in permafrost changes under these two types for the response to climate change. In this paper, whether gravel pavement or asphalt pavement is used, how to obtain the standard of road damage in permafrost regions, annual settlement deformation or cumulative deformation?

3. In this paper, the results of three GCM models are used. Whether the SSP5-8.5 climate scenario employ the ensemble average of three GCM or the SSP5-8.5 output of each model? Please explaining. Why does the author only use the SSP585 high-emission scenario? At least one low-emission scenario should be considered. Suggesting that the authors add a low-emission SSP2-4.5 scenario.

Here is some specific suggesting:

1. Ref 1 seems too old. The climate is changing dramatically, and the permafrost is shrinking. Therefore, new literature is recommended.
2. Table 1 does not seem to be needed and is recommended as additional information if it must be listed.
3. Lines 133-134, this sentence is not well understood. It is suggested to modify it more clearly.
4. Lines 1365-143, whether the difference in the amount of infrastructure identified is related to time. Because there may be new roads, houses, etc., different times may make a difference.
5. How to obtain the accuracy evaluation and what factors are used as the basis for accuracy evaluation.
6. Whether the permafrost geotechnical model can simultaneously simulate the stability of road, building, and storage tank?

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Dear Mr Manos,

Your manuscript titled "Deep learning-based building and road detection reveals higher permafrost thaw-related damage costs than previously estimated for Alaska" has now been seen by our reviewers, whose comments appear below. In light of their advice we are delighted to say that we are happy, in principle, to publish a suitably revised version in Communications Earth & Environment.

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We hope to hear from you within two weeks; please let us know if you need more time.

Best regards,

Sadia Ilyas, PhD

Editorial Board Member
Communications Earth & Environment

Martina Grecequet, PhD
Senior Editor,
Communications Earth & Environment
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REVIEWERS' COMMENTS:

Reviewer #1 (Remarks to the Author):

The authors provided thorough responses and made significant revisions. They have satisfactorily addressed my previous four major comments. I agree with their explanations and the revisions. The results are now well supported and their limitations are clearly identified. I believe the revised manuscript has scientific merit and contributes to the permafrost community in both science and engineering fields.

Reviewer #2 (Remarks to the Author):

Although authors does not agree my suggestion about excluding the assessment of the cost estimation of infrastructures damage, I agree with their ideas. Authors clearly clarified my doubts and made changes. I have no further comments or suggestions. I agree to publish this article in Communication Earth & Environment.

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<Reviewer's response: Black font color >

<Author response: Blue font color. *Copied revised text from the manuscript is in italics.* >

Reviewer #1

We thank the reviewer for their constructive comments in helping us elevate the manuscript. We have made major changes to the manuscript based on each point, which can be found below:

1. Novelty and insufficient validation of the deep learning model. The manuscript claims novelty in using deep learning for infrastructure detection. However, machine learning techniques for satellite image analysis have been widely applied in various fields, including infrastructure detection in Alaska (e.g., Kaiser et al. 2024). The manuscript states that the HABITAT deep learning pipeline achieved a 94% accuracy in detecting buildings and roads, but the validation process is not sufficiently discussed in either the manuscript or supplementary materials. The accuracy metrics (e.g., producer's accuracy and user's accuracy) are mentioned, but there is no explanation of potential false positives or false negatives that could skew the results.

We appreciate the reviewer identifying the need for clarification on the novelty of the ML techniques used for detecting Arctic infrastructure from high-resolution Maxar imagery. The work by Kaiser et al. (2024) was published after we submitted our manuscript, so we were at the time unable to include their work in our discussion. The reference is now added. To clarify, the SIRIUS dataset presented by Kaiser et al. is a compilation of various existing datasets, no machine learning-based infrastructure detection was conducted in that study. Rather, they utilized the already existing SACHI dataset (Bartsch et al., 2020, 2021). SACHI is based on analysis from Sentinel 1 and Sentinel 2 imagery, which has a 10 m spatial resolution. A 10 m spatial resolution is too coarse to reliably delineate most individual building footprints or detect small/unpaved roads -most of which are relatively small in the Arctic region. The SACHI dataset is technically a land use/land cover map, not an individual building footprint or road centerline map. Thus, the SACHI dataset is limited in supporting risk assessment studies that seek to estimate infrastructure losses related to permafrost thaw. The infrastructure dataset we developed is based on Maxar imagery (0.5 m spatial resolution) and can support the outlining of individual structures. The only existing dataset with such a spatial resolution and coverage is the OpenStreetMap (OSM). Our new dataset is detecting 17 M m² (+47%) more infrastructure coverage in Alaska than OSM, as OSM is based on manual delineation and visual interpretation of remote sensing imagery which is not efficient across large areas.

Revisions in the manuscript to clarify this novelty include the following:

Introduction (pages 5-6, lines 98-123):

“Currently, the Sentinel ½-derived Arctic Coastal Human Impacts dataset (SACHI) is the first and only published circumpolar dataset of roads, buildings, and other human-impacted area

within 100 km of Arctic coasts^{29,31}. SACHI was produced with gradient boosting machines and a UNet deep learning model applied on Sentinel 1 and 2 satellite imagery, which has a 10 m spatial resolution. SACHI was also used to compile the Multisource Synthesized Inventory of CRITICAL Infrastructure and HUMAN-Impacted Areas in AlaSka (SIRIUS), which also consists of OSM, as well as an existing watershed database and permafrost data³². A 10 m spatial resolution may not be sufficient to resolve many small buildings, roads, and other infrastructure across the Arctic. For example, Kumpula et al.^{33–35} compared the applicability of satellite imagery with varying spatial resolutions in identifying visible anthropogenic impacts within the Bovanenkovo gas field on the Yamal Peninsula in Siberia. It was found that very high resolution (<5 m spatial resolution) satellite imagery, such as QuickBird-02, is needed to effectively resolve industrial impacts such as barracks and built-up areas, paved roads, and off-road tracks, while 10 – 15 m resolution imagery such as ASTER and SPOT can only moderately resolve such impacts. Proulx-Bourque et al. (2019) found that the accuracy of visually identifying urban residential buildings significantly decreases when the spatial resolution of imagery decreases from a range of 0.3 m - 0.7 m to 1 m or coarser³⁶. This is further demonstrated by the low user's and producer's accuracy of the SACHI road class when validated in Prudhoe Bay, Alaska, which were 69% and 26%, respectively. The user's accuracy of the SACHI building class was also considerably low in Prudhoe Bay at 28%. Further, the 10 m spatial resolution of Sentinel imagery is likely too low to resolve the many small, unpaved roads characteristic of the Arctic region. It also likely does not provide machine learning algorithms with enough information to effectively distinguish buildings from non-building features, resulting in many false positives. Accordingly, the Arctic human footprint remains poorly represented in high-resolution digital geospatial data, which is the foundational dataset for hazard preparedness, response, and mitigation.”

Introduction (page 7, lines 142-145):

“To the best of our knowledge, there are no published publicly available studies in the peer-reviewed literature on automated infrastructure detection from sub-meter spatial resolution satellite imagery on a pan-Arctic, nationwide, or statewide scale (Supplementary Table 2).”

Discussion (pages 17-18, lines 301-309):

“Infrastructure risk assessments depend on accurate geospatial measurements (e.g., building footprint area, road centerline length) to estimate losses due to permafrost hazards. Therefore, products from Sentinel imagery (10 m spatial resolution) may not be suitable for cost analyses. However, human footprint datasets such as SACHI are still a valuable land use product that establishes a tradeoff between spatial resolution and temporal resolution. The short revisit frequency of the Sentinel 1 and 2 satellites (10 days and 12 days for a single satellite, respectively) could enable the SACHI workflow to be used in efficiently monitoring various spatiotemporal expansions in human footprints across the circumpolar Arctic. Sub-meter scale snow-free imagery is, at best, currently available once a year.”

Supplementary information (pages 18-19):

Supplementary Table 2. Literature survey on satellite-based Arctic built infrastructure mapping efforts.

<i>Reference</i>	<i>Study Area</i>	<i>Data</i>	<i>Spatial Resolution (in Order of Listed Data, “Field Survey” Omitted)</i>	<i>Method</i>	<i>Feature(s) of Interest</i>
<i>Kumpula et al. (2006)⁵</i>	<i>Bovanenkovo gas field, Yamal Peninsula (West Siberia)</i>	<i>Field survey, QuickBird-2 (panchromatic, multispectral), ASTER VNIR, Landsat (TM, MSS)</i>	<i>0.61 m, 2.5 m, 15 m, 30 m, 80 m</i>	<i>Manual digitization</i>	<i>Quarries, power lines, roads, winter roads, drill towers, barracks</i>
<i>Kumpula et al. (2010)⁶</i>	<i>Bovanenkovo gas field, Yamal Peninsula (West Siberia)</i>	<i>Field survey, QuickBird-2 (pan, multi), ASTER VNIR, SPOT (pan, multi), Landsat (ETM7, TM, MSS)</i>	<i>0.63 m, 2.4 m, 15 m, 10 m, 20 m, 30 m, 30 m, 80 m</i>	<i>Manual digitization</i>	<i>Roads, impervious cover, barracks, winter roads, settlements, quarries</i>
<i>Kumpula et al. (2011)⁷</i>	<i>Bovanenkovo gas field and Toravei oil field, Yamal Peninsula (West Siberia)</i>	<i>Field survey, QuickBird-2 (pan, multi), ASTER VNIR, SPOT (multi), Landsat (ETM7, TM, MSS)</i>	<i>0.63 m, 2.4 m, 15 m, 10 m, 20 m, 30 m, 30 m</i>	<i>Manual digitization</i>	<i>Buildings, roads, sand quarries, pipelines</i>
<i>Kumpula et al. (2012)⁸</i>	<i>Bovanenkovo gas field, Yamal Peninsula (West Siberia)</i>	<i>Field survey, QuickBird-2 (pan, multi), GeoEye, ASTER VNIR, SPOT (multi), Landsat (ETM7, TM, MSS)</i>	<i>0.63 m, 2.4 m, 1.65 m, 15 m, 20 m, 30 m, 30 m, 70 m</i>	<i>Manual digitization</i>	<i>Pipelines, powerlines, drilling towers, roads, impervious cover, barracks,</i>

					<i>settlements, quarries</i>
<i>Raynolds et al. (2014)⁹</i>	<i>Prudhoe Bay Oilfield, Alaska</i>	<i>Aerial photography (B&W, color, color infrared)</i>	<i>1 ft resolution for two images. Map scale was then used to describe the rest of the imagery. Scales are as follows: 1:3000, 1:6000, 1:12,000, 1:18,000, 1:24,000, 1:60,000, 1:68,000, 1:120,000</i>	<i>Manual digitization</i>	<i>Roads, gravel pads, excavations, pipelines, powerlines, fences, canals, gravel and construction debris</i>
<i>Gadal and Ouerghemmi (2019)¹⁰</i>	<i>Yakutsk, Russia</i>	<i>SPOT-6 (pan, multi), Sentinel-2 (multi)</i>	<i>1.5 m, 6 m, 10 m</i>	<i>Semi-automated (object-based image analysis)</i>	<i>Houses, other structures</i>
<i>Ourng et al. (2019)¹¹</i>	<i>Surgut, Russia</i>	<i>Sentinel-1 (SAR), Sentinel-2 (multi), Landsat (TM, MSS)</i>	<i>10 m, 10 m, 30 m, 60 m</i>	<i>Automated (machine learning)</i>	<i>Built-up area</i>
<i>Bartsch et al. (2020)¹²</i>	<i>Pan-Arctic, within 100 km of the Arctic coast</i>	<i>Sentinel-1 (SAR) and Sentinel-2 (multi)</i>	<i>10 m, 10 m</i>	<i>Automated (machine learning and deep learning)</i>	<i>Buildings, roads, other human-impacted areas</i>
<i>Ardelean et al. (2020)¹³</i>	<i>Bovanenkovo gas field, Yamal Peninsula (West Siberia)</i>	<i>QuickBird-2 (pan, multi), GeoEye-1 (pan, multi)</i>	<i>0.6 m, 2.4 m, 0.4 m, 1.8 m</i>	<i>Manual digitization</i>	<i>Buildings, roads</i>

Manos et al. (2022) ¹⁴	North Slope of Alaska	WorldView-2, QuickBird-2	0.5 m – 0.87 m	Automated (deep learning)	Buildings (public, commercial, residential, industrial, roads)
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We have expanded the description of the validation process. This was achieved by expanding the analysis to include an increased sampling area in order to include a more representative range of the built environments (e.g., rural village, medium-sized city, large city) found in Alaska. Accuracy assessment across a range of built environments, each with unique challenges to building and road detection, gave us the proper basis upon which to discuss possible false positives and negatives and to recognize the strengths and weaknesses of the map.

The edits to the manuscript include:

Results (pages 10-12, lines 203-237):

“The HABITAT map was found to have an overall accuracy of 82% by visually validating the ground truth of 1,373 randomly selected building, storage tank, road, and background predictions. Data used in accuracy assessment included the communities of Bethel, Fairbanks, Hooper Bay, and Noorvik (Table 1). The user’s accuracy of 0.58 for the background class is due to the compounded effect of false negatives (i.e., missed detections) of buildings and roads, reflected by their respective producer’s accuracies of 0.83 and 0.77. These false negatives of buildings and roads mostly occur due to how satellite image scenes are split into tiles for model training and subsequent mapping. Firstly, large buildings oftentimes cannot fit within the dimensions of 256×256 pixels (approximately 128 by 128 m at 0.5 m resolution), which is the input image size that we chose for the deep learning model. In these cases, the model must detect a single building that has been split across multiple tiles, resulting in partially completed, fragmented building footprints (Supplementary Fig. 2). Within the accuracy assessment, this particular cause of false negatives is almost exclusively found in Fairbanks, which is the largest city in Alaska located on continuous or discontinuous permafrost. Fairbanks has large buildings whose areas extend well beyond the dimensions of the images input to our deep learning model. Conversely, the small buildings in the rural villages do not lead to this type of misclassification. Secondly, satellite image scenes are split into non-overlapping tiles, which can be problematic in the detection of roads as they are spatially continuous features that interconnect with each other. Splitting satellite image scenes into tiles with some degree of overlap ultimately forces a deep learning segmentation model to repeat predictions of the same road at the same location. This not only increases the chances that the road will be predicted to begin with, but also that roads will be connected across space.

The user's accuracies of the building, road, and storage tank classes reflect false positives (i.e., detected instance of an object that does not exist in reality) that are mostly due to the deep learning model being confused by miscellaneous impervious cover or anthropogenic features in urban communities (e.g., Fairbanks and Bethel) with visual properties that may appear similar to the classes of interest (Supplementary Fig. 2). However, based on the user's accuracy values, these false positives were limited. For example, part of a paved parking lot may be confused for a paved road. Built anthropogenic features with distinct edges that are not buildings, such as an ice-skating rink, may be confused for buildings. Circular patterns marked in the ground may be confused for storage tanks, which are themselves circular structures. On the other hand, false positives due to natural land cover features were minimized (see Methods section Postprocessing of detected buildings and roads). The model displays minimal confusion between different types of infrastructure (Methods sections Deep-learning-based building and road detection and Thematic map accuracy assessment for details on how this map was created and validated)."

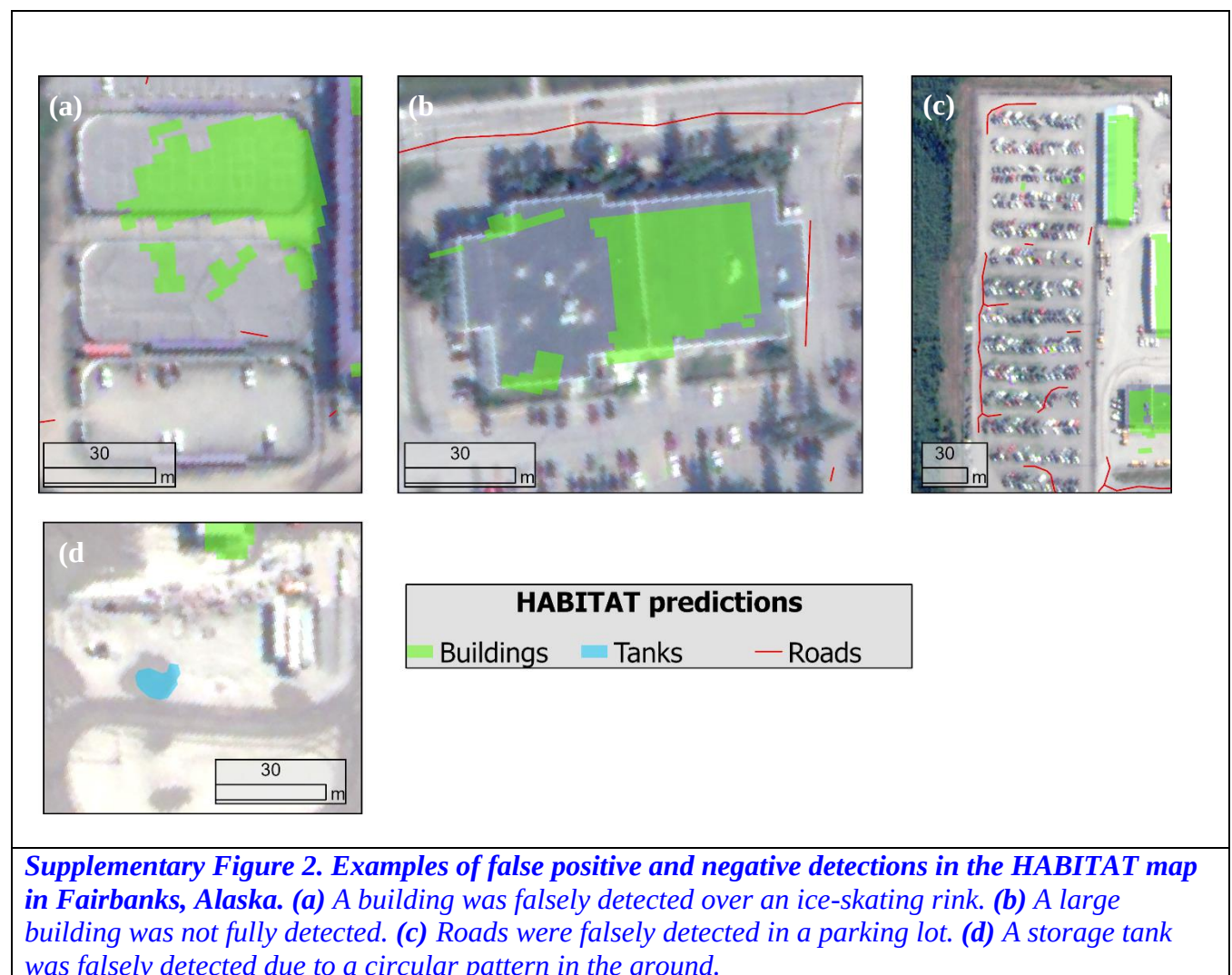
Results (page 12):

Table 1. Thematic map accuracy assessment of HABITAT (see Methods section Thematic map accuracy assessment for details on the applied metrics).						
	Background	Building	Road	Storage tank	Total	User's accuracy
Background	213	81	72	0	366	0.58
Building	40	438	6	0	484	0.90
Road	24	7	262	0	293	0.89
Storage tank	19	0	0	211	230	0.92
Total	296	526	340	211	1373	
Producer's accuracy	0.72	0.83	0.77	1		
					Overall accuracy	0.82

Methods (pages 27-28, lines 518-548):

“Following best practices outlined by Olofsson et al.⁶² and Congalton and Green⁶³, we conducted thematic accuracy assessment of the HABITAT map. We selected four Alaskan communities that represent the various built environment settings relative to Alaska. Noorvik and Hooper Bay were selected to represent rural villages, Bethel was selected to represent medium-sized cities, and Fairbanks was selected to represent the largest of Alaskan cities. Each of these settings are characterized by buildings and roads of various geometries, spatial distributions, construction materials, and topologies that are evident from satellite imagery. Fairbanks, for example, is a highly developed urban environment notably characterized by larger buildings that can often take on irregular geometries, which is typical of non-residential development associated with a larger economy (office buildings, industrial buildings, retail centers, etc.) Urban road networks are generally dense, with many interconnected roads that are long compared to those of rural communities. Additionally, urban roads are mostly paved. Conversely, rural villages, such as Hooper Bay and Noorvik, that rely on mixed cash-subsistence economies⁴¹ have little non-residential development. Therefore, rural villages are mostly composed of small, detached houses and sparse networks of unpaved roads.

For each of the four communities, we randomly sampled 300-350 predicted polygons from the HABITAT map representing buildings, storage tanks, and roads, as well as locations with no prediction (i.e., background) using stratified random sampling. This sampling scheme randomly distributes points across polygons of each class, in which each class has a number of points proportional to its relative area. This was done using the Create Accuracy Assessment Points tool in the ArcGIS Pro software. Because roads are represented as line features in the HABITAT map, a 10 m buffer was applied in order to convert them to polygon features that cover the footprint of the road. For each community, we constrained the random sampling to the footprint of the Maxar satellite image scene used to map it. In total, there were 1,373 random selections. For each sampled location, we visually interpreted the underlying Maxar satellite imagery at that location to identify the true class label. If infrastructure is present, we identified the specific infrastructure class; if there is no infrastructure, the ground truth label is considered to be “background”. Then, we computed the error matrix using the ArcGIS Compute Confusion Matrix tool, which is a cross-tabulation of the class labels allocated in the remote sensing-derived map against the true data collected from sampled validation sites. From the error matrix with q classes, we computed the following accuracy metrics:”



2. Weak integration of social vulnerability analysis. While the manuscript mentions the use of the social vulnerability index (SVI), it does not effectively integrate this analysis with the economic damage estimates. The discussion of social vulnerability is superficial, and the supplementary materials do not provide any additional insights to this analysis.

We appreciate the comment. Considering that the U.S. Federal Emergency Management Agency's (FEMA) National Risk Index (NRI) does not address permafrost thaw hazards, we revised the manuscript by creating a "Permafrost thaw risk index (PTRI)", which integrates the U.S. Center for Disease Control and Prevention's Social Vulnerability Index (CDC SVI) with our estimated infrastructure damage costs. We hope that this initial definition of a permafrost thaw risk index may inspire and raise awareness of permafrost thaw hazards in the national

conversation around geohazards and the compounding of multiple stressors on Alaska's remote communities. The intention behind including CDC SVI together with our estimated infrastructure losses is that the situation in many remote communities in Alaska is heightened because they each amplify the other. The sum is greater than its parts, i.e., an example of a polycrisis (see definitions of polycrisis here: <https://polycrisis.org/lessons/what-does-the-term-polycrisis-mean/>), because risk is largely defined by many authoritative organizations (e.g., United Nations) as being an interaction of all three factors.

See the following changes to the manuscript:

Abstract (page 2, lines 42-44):

“National risk and hazard assessments, which currently exclude permafrost thaw, need to include permafrost as its own category to properly integrate the Arctic region into the United States of America’s preparedness and resilience.”

Introduction (pages 6-7, lines 124-142):

“People living on permafrost are affected by most of the 18 natural hazards acknowledged by the United States federal government (flooding, wildfire, winter weather, etc.)³⁷ which are all exhibited under a relative rapid emergence (hours to weeks). Weather and climate hazard damages to the United States are estimated to range annually from \$20B to \$165B with an annual average of \$57.7B (1980-2022)³⁸ However, the national cost estimates do not include permafrost hazards, which are developing within decadal timescales. Permafrost is also not included in the National Risk Index developed by the United States Federal Emergency Management Administration³⁷. Most of the permafrost-affected communities in Alaska are remote (not connected to the road system) and are represented by a high Native population that holds a disproportionately high burden of stress³⁹. Accordingly, many people living in permafrost-affected landscapes are experiencing a polycrisis with a major stressor (the permafrost hazard) poorly recognized by the federal government. To top it off, Alaska has received the lowest rating (D) of all states in the 2023 United States Geospatial Maturity Assessment⁴⁰ with most remote communities lacking digital maps of infrastructure and property ownership/addresses that are required to seek FEMA funding. Few communities have completed or started site-specific erosion, flooding, or permafrost risk assessments needed to assess unmet funding needs for hazard adaptation and mitigation projects⁴¹. Obtaining refined cost estimates of the permafrost hazard via a comprehensive infrastructure inventory can help elevate this nationally ignored stressor alongside the 18 acknowledged natural hazards.”

Discussion (pages 19-20, lines 336-350):

“This study may serve communities, boroughs or census areas in assessing cost estimates that are needed when applying for funding assistance. Extensive barriers exist among federal programs that prevent rural Alaskan communities from receiving the funds they need to prepare for threats caused by permafrost hazards⁴¹. We here highlighted exclusion of permafrost hazards

in authoritative federal programs aimed at assessing and responding to natural hazards (e.g. National Risk Index and weather and climate hazard assessments under the NOAA National Centers for Environmental Information). The cost of not accounting for the damages caused by permafrost hazards in the coming ~two decades is on par with the total annual cost of all weather and climate hazards in the United States of America. Furthermore, the lack of digital infrastructure and property ownership data (survey grade) further prevents most Alaska communities from applying for FEMA funding. Previous estimates of losses due to permafrost thaw^{15–18} were not organized and presented according to communities. Accordingly, the results presented here may provide remote Alaska communities, which often lack geospatial tools and expertise, with cost estimates of permafrost damage to buildings and roads that can assist in their assessments and planning efforts.”

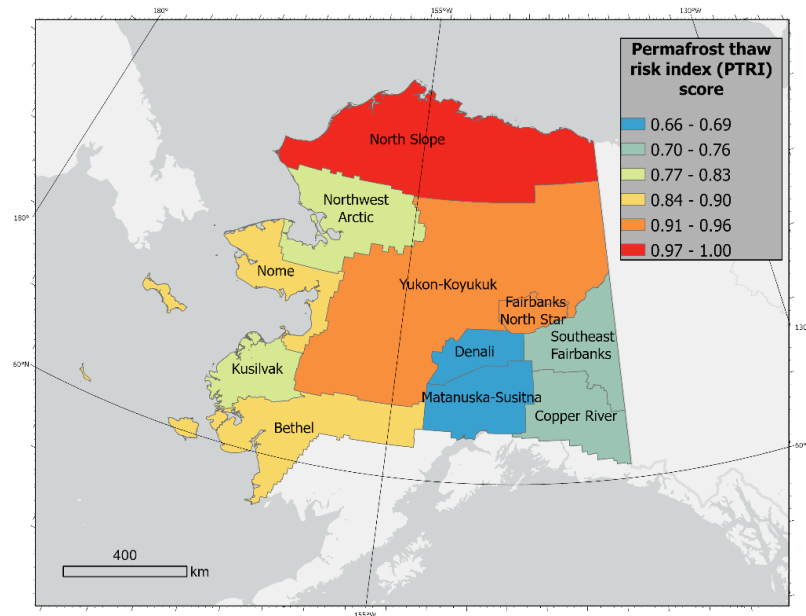
Methods (page 25, lines 483-487):

“We include in the supplementary material a first order attempt to integrate our permafrost damage cost estimate to the National Risk Index and the U.S. Center for Disease Control and Prevention’s Social Vulnerability Index (Permafrost thaw risk index in Supplementary Results and Supplementary Methods).”

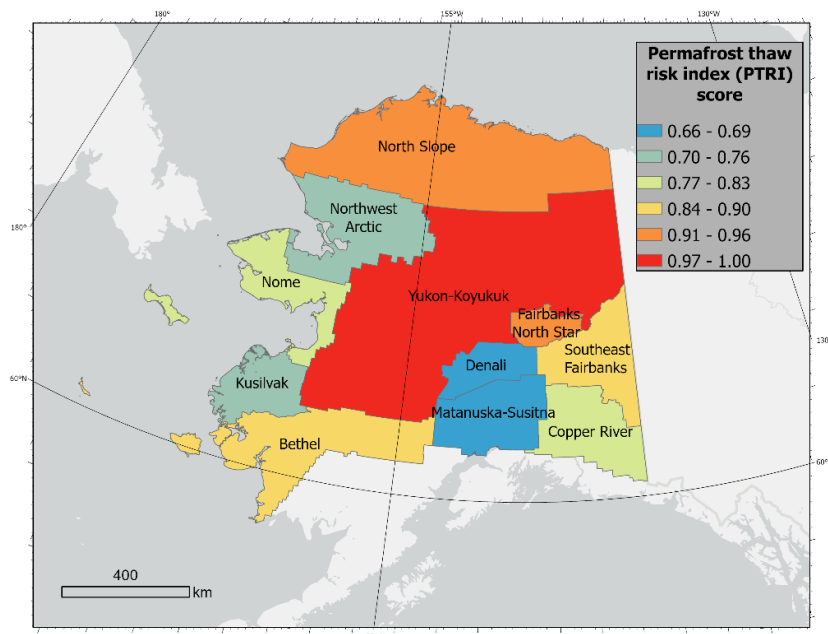
Supplementary information (page 22, lines 83-94):

*“Considering the five highest PTRI scores under the SSP245 scenario, North Slope Borough has a PTRI score of 1, indicating that its communities have higher risk to permafrost thaw hazards than those in all other boroughs or census areas, followed by Fairbanks North Star Borough with 0.96, Yukon-Koyukuk Census Area with, 0.93, Bethel Census Area with 0.90, and Nome Census Area with 0.86 (Supplementary Fig. 15a). Considering the five highest PTRI scores under the SSP585 scenario, Yukon-Koyukuk Census Area has a PTRI score of 1, followed by North Slope Borough with 0.96, Fairbanks North Star with 0.93, Southeast Fairbanks Census Area with 0.90, and Bethel Census Area with 0.86 (Supplementary Fig. 15b). For both climate scenarios, Matanuska-Susitna Borough and Denali Borough have the lowest PTRI scores out of those counties that are subject to permafrost thaw hazards between 2015-2064, receiving 0.69 and 0.65 respectively. For details regarding the PTRI calculation, see **Permafrost thaw risk index.**”*

a)



b)



Supplementary Figure 15. Permafrost thaw risk index (PTRI) scores. PTRI scores are given for the (a) SSP245 and (b) SSP585 climate scenarios. PTRI scores are computed for each county under each scenario by multiplying expected cumulative building and road damage costs between 2015-2064 by a county's community risk factor. This score is a state percentile ranking for a given county in comparison to all other counties. Under SSP245, North Slope Borough has the highest PTRI score, having higher risk to permafrost thaw than all other counties. Under SSP585, Yukon-Koyukuk Census Area has the highest PTRI score.

Supplementary information (page 24, lines 103-125):

“In a January 2024 report outlining the needs of Alaskan native villages threatened by environmental hazards, the Alaska Native Tribal Health Consortium and the State of Alaska stated that few communities have completed or started site-specific erosion, flooding, or permafrost risk assessments needed to assess unmet funding needs for hazard adaptation and mitigation projects¹⁵. Community-specific risk assessments provide vital information needed to meet the requirements of many funding programs, such as FEMA’s Hazard Mitigation Assistance programs. However, these assessments are costly to perform, and most existing risk datasets or assessments developed for the contiguous U.S. (e.g., FEMA’s National Risk Index) do not account for hazards specific to Alaskan communities, such as permafrost thaw¹⁵. These gaps are highlighted when comparing the results of the PTRI to the NRI scores for Alaska. For the entire state of Alaska, the NRI estimates expected annual building losses of \$157M due to various hazards not directly related to permafrost thaw¹⁶. This would amount to cumulative building losses of \$8B over fifty years (assuming the annual loss does not change), which is the period of time over which we estimated building losses in this study. Compared to this study’s estimate of \$37B - \$51B of building losses due to permafrost thaw, it is clear that the NRI is largely underestimating disaster risk in Alaska by not including permafrost thaw hazards. Also, the NRI identifies Matanuska-Susitna Borough, Anchorage Municipality, and Kenai Peninsula Borough as having the highest risk scores out of all counties in Alaska¹⁶. This risk is mostly attributed to hazards such as earthquake, tsunami, avalanche, and wildfire. Comparatively, Matanuska-Susitna has a PTRI score of 0.69, and Anchorage and Kenai Peninsula are not even located on continuous or discontinuous permafrost. Ultimately, the lack of permafrost thaw hazard occurrence data likely makes including permafrost thaw hazards in the NRI currently unfeasible¹⁷.”

Supplementary information (pages 29-31, lines 228-271):

“We extend the U.S. Federal Emergency Management Agency’s National Risk Index (NRI) to the two permafrost thaw hazards considered in this study, that is, bearing capacity loss and ground subsidence. In this section, the NRI equation and each component is briefly described. For a detailed technical explanation, please see the technical documentation¹⁶ and the associated study which presents the methodology¹⁷. The NRI measures the risk of every U.S. census tract and county to 18 natural hazards (not including permafrost-related hazards) through the following equation:

$$\text{Risk} = \text{Expected Annual Loss} \times \text{Community Risk} \quad (4)$$

$$\text{where Community Risk Factor} = f\left(\frac{\text{Social Vulnerability}}{\text{Community Resilience}}\right)$$

The function $f(\cdot)$ is a transformation that maps the ratio of social vulnerability and community resilience to a triangular distribution which ensures that higher social vulnerability and lower

community resilience, relative to all other counties or census tracts, result in higher NRI values for a given level of expected annual loss. The expected annual loss (EAL), quantified as a dollar amount, for each census tract or county is the average economic loss in dollars resulting from 18 natural hazards each year. EAL is computed for each hazard type and only quantifies loss for consequence types (i.e., buildings, population, or agriculture) relevant to a given hazard. This component determines the expected consequence of a given hazard. However, we replace the expected annual losses from the 18 considered hazard types with our estimated cumulative building and road damage costs due to bearing capacity loss and ground subsidence between 2015-2024 and 2055-2064. We name this modified version of the NRI the permafrost thaw risk index (PTRI).

The community risk factor (CRF) determines the degree to which the expected consequence will be enhanced or reduced, depending on the ratio of social vulnerability to community resilience. In the NRI, the social vulnerability score is a consequence-enhancing factor that represents the national percentile ranking of social vulnerability for a given county or census tract in comparison to all other counties or census tracts. A higher social vulnerability score results in a higher NRI score. This component uses the U.S. Center for Disease Control and Prevention's Social Vulnerability Index (CDC SVI), which utilizes 16 socioeconomic variables deemed to contribute to a community's reduced ability to prepare for, respond to, and recover from hazards³⁵. The community resilience score is a consequence-reducing factor that represents the relative level of community resilience within a county or census tract in comparison to all other counties or census tracts. A higher community resilience score results in a lower NRI score. This component uses the University of South Carolina Hazards Vulnerability & Resilience Institute's Baseline Resilience Indicators for Communities (HVRI BRIC)³⁶. The HVRI BRIC quantifies community resilience by identifying the ability of a community to prepare and plan for, absorb, recover from, and more successfully adapt to the impacts of natural hazards. It is based on a set of 49 indicators that represent six categories of resilience: social, economic, community capital, institutional capacity, housing/infrastructure, and environmental.

Based on the NRI equation, we compute the PTRI by multiplying estimated total (not normalized by population) building and road damage costs for all thirty Alaskan counties by their corresponding CRF as given by the NRI dataset. Then we compute the percentile rank of each county's raw PTRI value to produce the PTRI score. Therefore, the final PTRI score is a state percentile ranking for a given county in comparison to all other Alaskan counties. This is done for both SSP245 and SSP585-derived damage cost estimates.”

3. Oversimplified assessment of bearing capacity reduction. The bearing capacity model used in the manuscript was based on a geotechnical model that accounts for skin resistance and tip resistance. The dimension of the pile foundation is predetermined, and the bearing capacity is calculated based on soil properties, including soil texture, ice content, and peat content. A series of empirically derived equations were applied to relate soil properties with skin and tip resistance. However, these empirical equations were not established based on soil sampled from Alaska. The use of these empirical equations to model Alaskan permafrost clearly involves extrapolation. For example, the empirical models are developed for sand, clay, loam, and peat with ice content ranging from 0.05 to 0.5 (Streletskiy et al. 2012). Indeed, the soil is predominantly silty soil with ground ice content higher than 80%, taking Alaska's Arctic Coastal Plain as an example.

The reviewer expresses significant concerns that we agree are necessary to address. Indeed, the empirical equations are established based on data acquired from Russian and not Alaskan permafrost. We should clarify that the role of our study was not to improve geotechnical modelling of permafrost thaw hazards. Rather, the role of our study is to investigate how more complete infrastructure data can impact findings of infrastructure risk in direct comparison to past studies that have used the same thaw hazard modelling approach. Thus, we selected a validated, well-documented, readily-available existing methodology from the literature and did not manipulate it in any way. Still, we recognize the limitations of this hazard model, which uses calculations of pile bearing capacity from Russian engineering standards, when ideally American engineering standards based on Alaskan permafrost should be used instead. However, U.S. Arctic construction guidelines and federal standards are scarce or outdated and based primarily on mid-latitude engineering practices. Russian construction standards provide more information to calculate bearing capacity across a sufficiently wide range of ground temperatures. Additionally, recently published studies have also used the Russian-based empirical equations for infrastructure risk assessments outside of Russia, such as Faki et al. (2022) (Canada) and Yin et al. (2023) (China and Mongolia).

Ultimately, this discussion allows our study to express the extensive opportunity that exists in refining pile bearing capacity modelling for Alaska. We have made several changes to the manuscript in order to: (1) clarify the role of our study, (2) provide more details on the bearing capacity calculations in the supplementary information, (3) discuss limitations/assumptions of the bearing capacity calculations, as well as a justification for its use in the context of the current available methods.

The following revisions were made:

Introduction (page 7, lines 146-152):

“The main contributions of this study are:

1. *An improved baseline geospatial digital inventory of individual building and storage tank footprints and road centerlines for Alaska communities, and*
2. *A refined cost estimate of infrastructure damages caused by permafrost hazards between 2015-2024 and 2055-2064 using (a) our new Alaska infrastructure inventory and (b) existing permafrost thaw hazard maps developed from geotechnical engineering methods.”*

Introduction (page 8, line 165-167):

“We applied already published results by Streletskiy et al. (2023) from a stressor-response model¹⁸ that considers changes in pile bearing capacity loss and ground subsidence over Alaska under projected climate forcings”

Discussion (pages 20-21, lines 360-391):

“According to Wang et al. (2023)⁴⁴, the permafrost geotechnical model used in this study is currently the only approach to model infrastructure damages caused by specific thaw hazards across Alaska. While other hazard indices do exist^{13,45}, these have only been used to assess the exposure of infrastructure to hazard potential zones (e.g., high, moderate, low) in a generalized fashion, not to assess monetary losses. Findings of building and road damages reported in this study (and previous studies) should be interpreted alongside the assumptions and limitations surrounding the approach to pile bearing capacity estimation and road surface material. First, the approach assumes one type of piling foundation for all buildings, while in reality there is a wide variety of pile materials, lengths, installation methods, and local soil properties. Secondly, bearing capacity was calculated using stress values prescribed by the Russian construction standard⁴⁶. This is due to the limited range of values prescribed by U.S. standards⁴⁷ (see Pile bearing capacity estimation in Supplementary Methods) and the fact that U.S. Arctic construction guidelines and federal standards are scarce or outdated and based primarily on mid-latitude engineering practices⁴⁸. Thus, bearing capacity loss estimates based on Russian standards were most feasible for our study. Other recently published studies have also used the same equations and parameters to estimate bearing capacity for infrastructure risk assessments outside of Russia (Canada⁴⁹, China and Mongolia⁵⁰). Similarly, Faki et al.⁴⁹ used the Russian procedure for estimating pile bearing capacity in Canada since the provided parameters cover a wider range of ground temperatures and soil types compared to Canadian standards. Nevertheless, the Russian standard suggests relatively conservative values of shear stress (compared to U.S. standards⁴⁷), which likely leads to conservative estimates of pile bearing capacity presented here. Furthermore, the Russian standard does not provide stress values for piling foundations built in silt soils, which are common in Alaska⁵¹. The clay and loam soils, which are included in the Russian method, are to be expected to have lower adfreeze bond strength compared to silt⁴⁷. Finally, while paved and unpaved roads can have different responses in terms of permafrost thaw, we do not distinguish between roads of different surface materials in this study. Accordingly, there is clearly a need to improve engineering-informed modelling of

permafrost hazards. Engineers who may develop such refined maps of bearing capacity loss or ground subsidence in Alaska may use our HABITAT infrastructure map to support more detailed assessments. The contribution of our study was aimed to improve one aspect of the permafrost risk modelling framework, that is, by building the geospatial inventory of infrastructure exposed to permafrost hazards and to update cost estimates accordingly.”

Methods (page 23, lines 429-432):

“Results from the permafrost geotechnical modeling were obtained from Dmitry Streletskiy and previously published^{18,53}. Accordingly, we did not perform any new geotechnical calculations. Description of the permafrost geotechnical modeling done by Streletskiy and others is provided in Supplementary Methods Permafrost geotechnical model.”

Supplementary information (page 25, lines 127-135):

“Permafrost geotechnical model

Spatial equilibrium permafrost model

To calculate potential bearing capacity loss and the amount of ground subsidence, PT (permafrost temperature) and ALT (active layer thickness) are first estimated by the spatial equilibrium permafrost model developed by Streletskiy et al. (2012)¹⁸, which is based on the Kudryavstev solution of Stephan’s problem of heat conduction in a porous medium with phase transition. The model was validated by earlier publications at varying scales, including at the landscape scale for sites representative of generalized landcover categories on the North Slope of Alaska¹⁹.”

Supplementary information (pages 26-28, lines 153-210):

“Pile bearing capacity estimation

In the approach developed by Streletskiy et al. (2012)¹⁸, the capacity of permafrost-affected ground to bear square cement piling foundations ($0.35 \times 0.35 \times 10$ m) with vertically loaded friction piles is calculated as the sum of normal stresses at the base of the pile and shear stress at the pile sides in contact with permafrost. This calculation is a function of PT and ALT. The model was previously used to calculate pile bearing capacity changes on the North Slope of Alaska and was shown to be effective at facilitating the general depiction of locations where changes in bearing capacity can create hazardous conditions¹⁸. To spatially assess the impact of pile bearing capacity changes across Alaskan permafrost, we have assumed that all buildings are constructed with this piling foundation (such was also assumed in various similar studies^{3,4,24,25}). Most buildings on the North Slope and northwest coast of Alaska, and many in southwestern Alaska and interior rural communities, are indeed constructed on pilings²⁶. This ‘passive principle of permafrost construction’ aims to maintain thermal stability of the underlying ground across the lifespan of the building by disconnecting the building from the ground²⁷. As defined in Russian standard SP 25.13330.2012, “Basements and Foundations on

Permafrost”²⁸, Equation 1 is used to calculate bearing capacity for vertically loaded friction piles in permafrost with low ice content and equation 2 for high ice content.

$$F_u = \gamma_t \gamma_c (RA + \sum_{i=j}^n R_{af,i} A_{af,i}) \quad (1)$$

$$F_u = \gamma_t \gamma_c (RA + \sum_{i=j}^n ((1 - i_j) R_{sh,j} + i_j R_{sh,i,j}) A_{sh,j}) \quad (2)$$

In both equations, γ_t is a temperature coefficient accounting for potential changes in the ground thermal regime after construction ($\gamma_t = 1.0$ used in this study); γ_c is a production coefficient ($\gamma_c = 1.0$ used in this study); n is the number of different layers of permafrost in contact with the pile; i_j is ice content of the j th layer; R represents normal stresses generated at the base of the pile (kPa); A is bottom area of the bearing post or pile at its contact with the ground (m^2). In equation 1, $R_{af,i}$ represents shear stresses generated along the pile at a contact with layer i (kPa); $A_{af,i}$ is the area of the side contact of a pile with frozen ground (m^2). In equation 2, $R_{sh,j}$ and $R_{sh,i,j}$ are shear stresses on a pile with special cement solution at a side contact for the j th layer (kPa); and $A_{sh,j}$ is the area of side contact of pile with ground in layer j (m^2).

Experimental values of the normal (R) and shear stresses ($R_{af,i}$, $R_{sh,j}$, and $R_{sh,i,j}$) on a friction pile in varying soils (clay, loam, and sand with varying levels of organic content, as well as peat), ground temperatures (-10°C to 0°C), and ground ice content ($<20\%$ and $>20\%$) are prescribed in Russian standard SP 25.13330.2012²⁸. These are implemented as a series of polynomial equations, each for a specific soil composition and ground ice content, in which stress (given in kgf/cm^2) is calculated based on ground temperature (given in $^\circ\text{C}$). These equations and their outputs, as adopted from Streletskiy et al. (2012)¹⁸ and Streletskiy (2010)²⁹, are given in Supplementary Fig. 12 and 13. The stress values used to calculate bearing capacity thus depend on PT, while $A_{af,i}$ and $A_{sh,j}$ depend on the ALT. The amount of stress on the piles will be highest when PT is low and ALT is low. If PT increases, the soil cohesion decreases, and the ground is less able to keep the pile in place. As ALT increases, the surface area where the pile can bond to the frozen soil decreases, also decreasing F_u .

The U.S. Army and Air Force Technical Manual TM 5-852-4/AFM 88-19, Chap. 4, “Arctic and Subarctic Construction, Foundations for Structures”³⁰ provides experimental values of stress for 5 to 6-meter-long steel pilings in low-organic silt, with conversion factors for sand, as well as other pile types (Supplementary Fig. 14). The Russian standard suggests more conservative values of shear stress compared to the American standard, which in turn likely results in overly conservative bearing capacity estimates when applied to Alaskan construction.

The American standard also emphasizes higher design factors of safety for geotechnical applications than those implemented in Russia, as suggested by Streletskiy et al. (2012)¹⁸, which could justify the more conservative values assigned for cohesion in Russian standards. Ideally, pile bearing capacity for Alaskan buildings should be computed using stress values prescribed for piling foundations of American design. However, the values prescribed in Russian standard SP 25.13330.2012 cover a wider range of ground temperatures, ground ice content, and soil composition. For example, TM-5-852-4/AFM 88-19 only considers temperatures down to 25°F, or -3.9°C, which does not provide enough information to accurately calculate pile bearing capacity for regions such as the North Slope where temperatures can be lower³¹. It also does not consider variation in ground ice content, which varies considerably across Alaska³². ”

Continued on next page...

Supplementary information (page 13):

a)

Table 7.1. Normal stress (R) at the bottom of the pile as a function of soil texture, peat presence, and temperature at pile depth.

Soil texture	Organic matter coef. (Kv)	Normal stress at the base of pile (R, kgf/cm ²)
Sand	0.00-0.03	$R = -0.046T_m^2 - 4.217T_m + 16.18$ (7.3.1)
	0.03-0.10	$R = -0.156T_m^2 - 3.48T_m - 0.37$ (7.3.2)
	0.10-0.30	$R = -0.110T_m^2 - 2.39T_m - 0.08$ (7.3.3)
Loam and clay	0.30-0.50	$R = -0.090T_m^2 - 1.85T_m - 0.12$ (7.3.4)
	0.00-0.05	$R = -0.012T_m^2 - 2.373T_m + 7.44$ (7.3.5)
	0.05-0.10	$R = -0.132T_m^2 - 2.80T_m - 0.23$ (7.3.6)
	0.10-0.30	$R = -0.105T_m^2 - 2.09T_m - 0.17$ (7.3.7)
Peat	0.30-0.50	$R = -0.089T_m^2 - 1.74T_m - 0.31$ (7.3.8)
	>0.50	$R = -0.071T_m^2 - 1.40T_m - 0.39$ (7.3.9)

b)

Table 7.2. Shear stress (R_{af}) at the middle of the pile in permafrost with low ice content as a function of soil texture, peat presence and equivalent temperature.

Soil texture	Organic matter coef. (Kv)	Shear stress at a side contact of pile with frozen ground with low ice content (R_{af} , kgf/cm ²)
Sand	0.00-0.03	$R_{af} = -0.039T_e^2 - 0.828T_e + 0.43$ (7.4.1)
	0.03-0.10	$R_{af} = -0.020T_e^2 - 0.470T_e + 0.43$ (7.4.2)
	0.10-0.30	$R_{af} = -0.019T_e^2 - 0.412T_e + 0.16$ (7.4.3)
Loam and clay	0.30-0.50	$R_{af} = -0.015T_e^2 - 0.326T_e + 0.12$ (7.4.4)
	0.00-0.05	$R_{af} = -0.032T_e^2 - 0.655T_e + 0.32$ (7.4.5)
	0.05-0.10	$R_{af} = -0.020T_e^2 - 0.443T_e + 0.16$ (7.4.6)
	0.10-0.30	$R_{af} = -0.016T_e^2 - 0.334T_e + 0.02$ (7.4.7)
Peat	0.30-0.50	$R_{af} = -0.015T_e^2 - 0.310T_e - 0.06$ (7.4.8)
	>0.50	$R_{af} = -0.015T_e^2 - 0.300T_e - 0.11$ (7.4.9)

c)

Table 7.3. Shear stress (R_{sh}) at the middle of the pile with cement solution in permafrost with high ice content as a function of soil texture, peat presence and equivalent temperature.

Soil texture	Organic matter coef. (Kv)	Shear stress at a side contact of pile with frozen ground with high ice content (R_{sh} , kgf/cm ²)
Sand	0.00-0.03	$R_{sh} = -0.035T_e^2 - 0.793T_e + 0.85$ (7.9.1)
	0.03-0.10	$R_{sh} = -0.048T_e^2 - 0.791T_e + 0.23$ (7.9.2)
	0.10-0.30	$R_{sh} = -0.026T_e^2 - 0.505T_e + 0.05$ (7.9.3)
	0.30-0.50	$R_{sh} = -0.018T_e^2 - 0.377T_e + 0.05$ (7.9.4)
Loam and clay	0.00-0.05	$R_{sh} = -0.028T_e^2 - 0.599T_e + 0.54$ (7.9.5)
	0.05-0.10	$R_{sh} = -0.025T_e^2 - 0.531T_e + 0.14$ (7.9.6)
	0.10-0.30	$R_{sh} = -0.020T_e^2 - 0.404T_e - 0.02$ (7.9.7)
	0.30-0.50	$R_{sh} = -0.018T_e^2 - 0.344T_e - 0.02$ (7.9.8)
Peat	>0.50	$R_{sh} = -0.015T_e^2 - 0.314T_e - 0.08$ (7.9.9)
Ice		$R_{sh} = 0.324\ln(-T_e) + 0.17$ (7.9.10)

Supplementary Figure 12. Polynomial equations used to calculate stress values for bearing capacity estimation. Equations are provided for (a) normal stress (R), (b) shear stress (R_{af}) in permafrost with low ice content (<20%), and (c) shear stress (R_{sh}) in permafrost with high ice content (>20%). Each polynomial equation was fit based on experimental values of normal and shear stress for specific soil textures, organic matter content, and ground ice content prescribed by Russian standard SP 25.13330.2012 referenced in the main manuscript.

a)

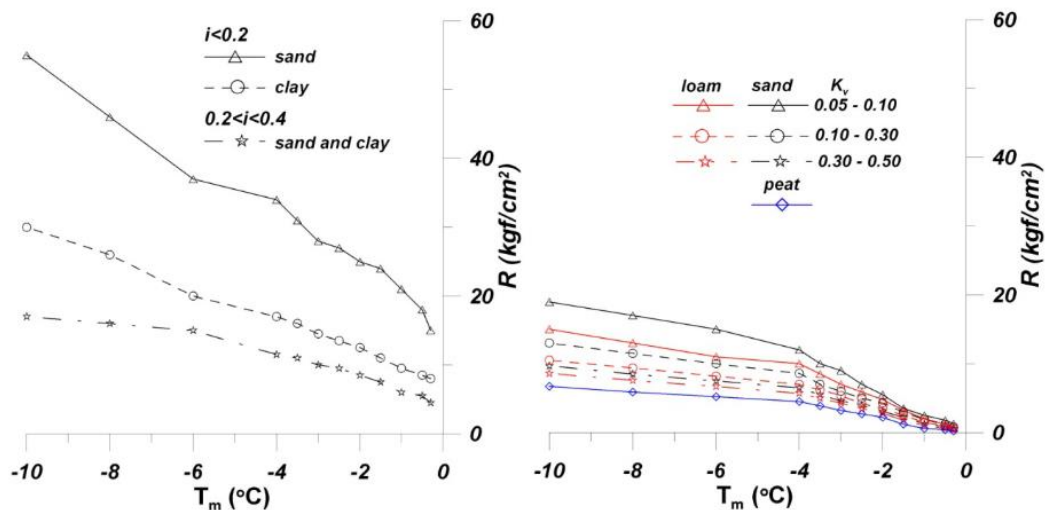


Figure 7.1. Normal stresses R generated at the base of the 10 m pile for different types of soil texture and ice content (left) and for relative value of peat content (right) based on data from CNR (1990).

b)

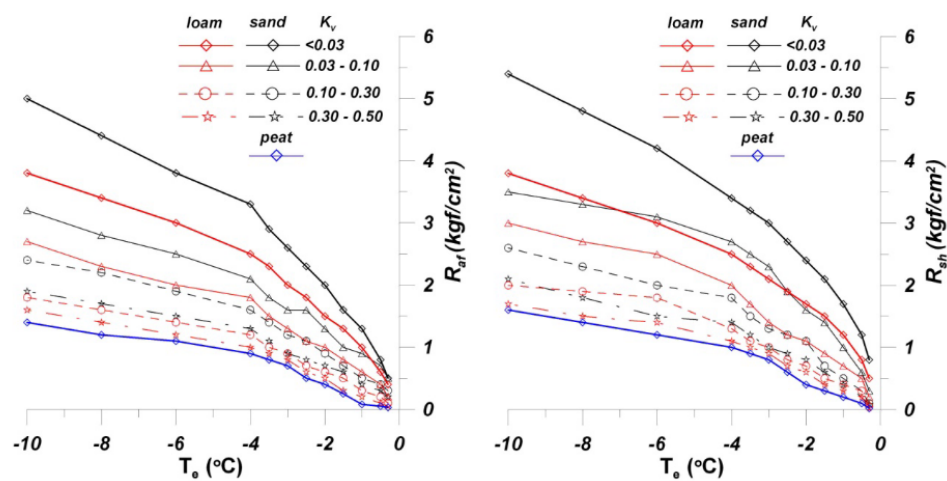
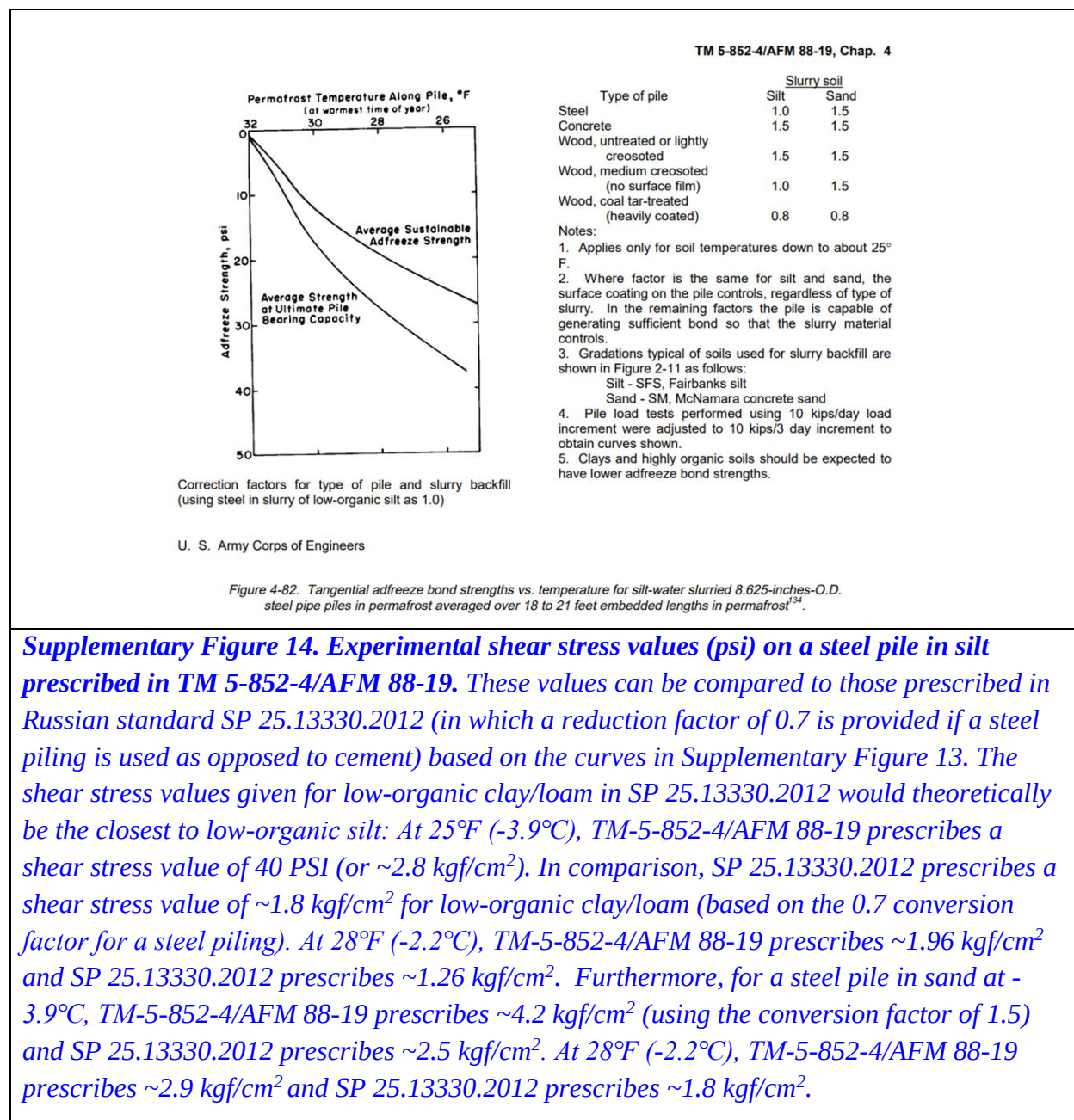


Figure 7.2. Shear stresses generated at the side contact of pile and permafrost (R_{af}) and special ground solution (R_{sh}) depending on equivalent temperature of the ground for different types of soil texture, ice content relative value of peat content (right). Based on data from CNR (1990)

Supplementary Figure 13. Outputs of the polynomial equations in Supplementary Figure 12. Outputs are given for (a) normal stress (R) and (b) shear stress (R_{af} or R_{sh}), based on ground temperatures ranging from -10°C to 0°C.

Supplementary information (page 15):



4. Discrepancies in estimated future cost. The calculations provided in the manuscript do not specify the time period over which these costs are projected. This ambiguity makes it difficult to compare the results with other studies.

We have clarified the time period over which costs are projected throughout the manuscript.

The following revisions were made:

Abstract (page 2, lines 35-38):

“We identified infrastructure at risk of damage from bearing capacity loss and ground subsidence between the decades 2015–2024 and 2055–2064 projected by a permafrost geotechnical model. Estimated damages to buildings and roads could cost Alaska \$37B to \$51B under the SSP245 and SSP585 scenarios, respectively.”

Introduction (page 7, lines 149-152):

“A refined cost estimate of infrastructure damages caused by permafrost hazards between 2015-2024 and 2055-2064 using (a) our new Alaska infrastructure inventory and (b) existing permafrost thaw hazard maps developed from geotechnical engineering methods.”

Introduction (page 8, lines 167-170):

“The two datasets were then used to estimate costs of building and road damages across the discontinuous and continuous permafrost zones of Alaska by mid-century (period 2055-2064) under the SSP245 and SSP585 climate scenarios (Fig. 1).”

Results (page 14, lines 240-242):

“Estimated total cost of permafrost associated damages in Alaska within the discontinuous and continuous permafrost zones range from \$37B (SSP245) to \$51B (SSP585) between the decades 2015-2024 and 2055-2064 (Supplementary Table 3).”

<Reviewer's response: Black font color >

<Author response: Blue font color. *Copied revised text from the manuscript is in italics.* >

Reviewer #2

We thank the reviewer for their constructive comments that have helped us elevate our manuscript. We have provided a point-by-point response with references to the changes made (see below). The reviewer suggested we exclude the cost estimate of infrastructure damages because "... a lot of research work has been carried out in this area". We appreciate previous work (as evident by our references) and we respectfully disagree with Reviewer #2 that our cost estimate of infrastructure damage is "not new". Cost estimates of infrastructure damage requires data on infrastructure and our work includes a new dataset, if not the most detailed so far, of infrastructure across all of Alaska. The equations to estimate infrastructure damage are indeed not new and we chose that approach so that our comparison to existing published work is primarily a reflection of the impact that this new infrastructure dataset has on cost estimates. We sincerely hope that the Reviewer appreciates the reasoning behind our decision.

In this paper, a deep-learning AI method is proposed to identify Alaskan roads, buildings and storage tanks by remote sensing images, and the stability of roads, buildings and storage tanks is simulated using a permafrost geotechnical model, and the cost of infrastructure damage is estimated under the SSP5-8.5 climatic scenario. Based on deep-learning to identify infrastructure by remote sensing images, this provides us with a new method, which is a well reference. However, the cost estimation of simulated infrastructure stability and infrastructure damage based on a permafrost geotechnical model is not a new, and a lot of research work has been carried out in this area. In terms of simulated infrastructure security for a geotechnical engineering models, it is more important to provide risk zoning of infrastructure for future climate change. Therefore, it is recommended that the authors focus on infrastructure identification and geotechnical simulation, and delete the cost estimate of infrastructures damage. This allows for a more detailed discussion of the stability and reliability of Alaska's infrastructure under future climate change.

We appreciate previous work (as evident by our references) and we respectfully disagree with Reviewer #2 that our cost estimate of infrastructure damage is "not new". This as the cost estimate of infrastructure damage requires data on infrastructure and our work includes a new, if not the most detailed, dataset so far of infrastructure across all of Alaska. The equations to estimate infrastructure damage are indeed not new and we chose that approach so that our comparison to existing published work is primarily a reflection of the impact that this new infrastructure dataset has on cost estimates.

There are still some questions:

1. Whether all the buildings in Alaska are pile foundations or whether they are elevated pile foundations, there is a huge difference in the response of permafrost to climate change under

these two types of pile foundations. Please explain whether the article considers pile foundation and elevated pile foundation uniformly. How are damage standards for infrastructures obtained?

Considering the large region (all of Alaska) covered in this study, we had to make assumptions on the foundation designs. We assumed that all buildings are constructed on a standard square cement piling foundation ($0.35 \times 0.35 \times 10$ m) with vertically loaded friction piles. This approach follows methods published by others in estimating infrastructure damage cost caused by permafrost thaw (Streletskiy et al. 2012, 2023, Suter et al., 2019). We recognize that our findings of building damages should be interpreted with caution due to the assumptions and limitations of the approach to pile bearing capacity estimation and are conveying that in our manuscript. Revisions in the manuscript to (1) clarify our approach and (2) and specify the origin of the damage thresholds for infrastructure can be found here:

Discussion (page 20, lines 364-368):

“Findings of building and road damages reported in this study (and previous studies) should be interpreted alongside the assumptions and limitations surrounding the approach to pile bearing capacity estimation and road surface material. First, the approach assumes one type of piling foundation for all buildings, while in reality there is a wide variety of pile materials, lengths, installation methods, and local soil properties.”

Methods (page 24, lines 452-459):

“Between the baseline and future decades, it is assumed that ground subsidence exceeding 10 cm will cause substantial damage to roads^{18,54}. This damage is assumed to be distributed evenly between the baseline and future decades. According to Russian construction standards SP 25.13330.2012 and SP 22.13330.2016, bearing capacity loss exceeding 15% between the two periods will cause substantial damage to buildings^{46,55,56}, requiring them to be replaced. These thresholds were used by Streletskiy et al.¹⁸ and are thus used here in order to allow for a direct comparison between infrastructure loss estimates.”

Supplementary information (page 26, lines 154-166):

“In the approach developed by Streletskiy et al. (2012)¹⁸, the capacity of permafrost-affected ground to bear square cement piling foundations ($0.35 \times 0.35 \times 10$ m) with vertically loaded friction piles is calculated as the sum of normal stresses at the base of the pile and shear stress at the pile sides in contact with permafrost. This calculation is a function of PT and ALT. The model was previously used to calculate pile bearing capacity changes on the North Slope of Alaska and was shown to be effective at facilitating the general depiction of locations where changes in bearing capacity can create hazardous conditions¹⁸. To spatially assess the impact of pile bearing capacity changes across Alaskan permafrost, we have assumed that all buildings are constructed with this piling foundation (such was also assumed in various similar studies^{3,4,24,25}). Most buildings on the North Slope and northwest coast of Alaska, and many in southwestern Alaska and interior rural communities, are indeed constructed on pilings²⁶. This

‘passive principle of permafrost construction’ aims to maintain thermal stability of the underlying ground across the lifespan of the building by disconnecting the building from the ground²⁷. ”

2. Road in towns is basically covered with asphalt pavement, and road is gravel pavement in other permafrost regions. There is a big difference in permafrost changes under these two types for the response to climate change. In this paper, whether gravel pavement or asphalt pavement is used, how to obtain the standard of road damage in permafrost regions, annual settlement deformation or cumulative deformation?

The stressor-response model does not differentiate between road type (gravel or paved). Instead, all roads that are subject to >10 cm of ground subsidence are considered damaged beyond repair. An average construction for all types of roads is implemented in this study. This threshold and cost was implemented by Streletskiy et al. (2023) and are therefore used here to allow for a direct comparison between our findings. This damage is assumed to be distributed evenly between the decades 2015–2024 and 2055–2064 (i.e., cumulative deformation).

Accordingly, the following revisions were made (page 21, lines 384-386):

“Finally, while paved and unpaved roads can have different responses in terms of permafrost thaw, we do not distinguish between roads of different surface materials in this study.”

Methods (page 23, lines 434-438):

" To estimate the potential cost of damages to infrastructure caused by permafrost thaw hazards, the median construction cost of one square meter of a building and one kilometer of road in Alaska were derived from publicly available sources. These were compiled by Streletskiy et al.¹⁸. The cost for one kilometer of road does not differentiate between paved or unpaved roads.”

Methods (page 24, lines 452-459):

“Between the baseline and future decades, it is assumed that ground subsidence exceeding 10 cm will cause substantial damage to roads^{18,54}. This damage is assumed to be distributed evenly between the baseline and future decades. According to Russian construction standards SP 25.13330.2012 and SP 22.13330.2016, bearing capacity loss exceeding 15% between the two periods will cause substantial damage to buildings^{46,55,56}, requiring them to be replaced. These thresholds were used by Streletskiy et al.¹⁸ and are thus used here in order to allow for a direct comparison between infrastructure loss estimates.”

3. In this paper, the results of three GCM models are used. Whether the SSP5-8.5 climate scenario employ the ensemble average of three GCM or the SSP5-8.5 output of each model? Please explaining. Why does the author only use the SSP585 high-emission scenario? At least one low-emission scenario should be considered. Suggesting that the authors add a low-emission SSP2-4.5 scenario.

We have updated the study to additionally include building (including storage tanks) and road damage costs estimated using pile bearing capacity loss and ground subsidence maps based on the SSP2-4.5 scenario. Also, we clarify that the estimated damage costs of both structures are averages of the damages estimated separately from each GCM-specific bearing capacity and subsidence map.

Accordingly, revisions to the manuscript include:

Abstract (page 2, lines 37-38):

“Estimated damages to buildings and roads could cost Alaska \$37B to \$51B under the SSP245 and SSP585 scenarios, respectively.”

Introduction (page 8, lines 167-170):

“The two datasets were then used to estimate costs of building and road damages across the discontinuous and continuous permafrost zones of Alaska by mid-century (period 2055-2064) under the SSP245 and SSP585 climate scenarios (Fig. 1).”

Results (page 14, lines 240-246):

“Estimated total cost of permafrost associated damages in Alaska within the discontinuous and continuous permafrost zones range from \$37B (SSP245) to \$51B (SSP585) between the decades 2015-2024 and 2055-2064 (Supplementary Table 3). These findings are based on infrastructure represented by the merged HABITAT-OSM building and road map. Under SSP245 scenario, the overall footprint of buildings at risk of damage is 10.4M m², which would cost an estimated \$13B. Here, the length of roads at risk of damage is 18,397 km, which would cost an estimated \$24B.”

Results (page 14-15, lines 257-265):

“Under the SSP245 scenario, the estimated per capita costs of infrastructure damage among communities range from \$2,400 to \$9.3M (Supplementary Fig. 3a, Supplementary Fig. 5a, Supplementary Data 2). Here, the highest per capita cost of a community is associated with relatively larger costs attributed to road damages (89%), whereas road damage is only representing 8% in the community with the lowest per capita cost. When organizing the costs according to borough or census areas, the cost per capita ranges from \$6,100 to \$1.3M (Supplementary Fig. 5b, Supplementary Data 3). The borough/census area representation shows a similar cost-distribution attributed to road damage no matter the total cost (92 and 93% for highest and lowest total cost, respectively).”

Results (page 15, 271-277):

“If assessing the total costs (i.e., not normalized by population number), projected infrastructure damages among the 178 communities located on continuous or discontinuous permafrost range from \$0.15M to \$3.2B (SSP245) (Supplementary Fig. 4a, Supplementary Fig. 7a) and to \$1.6M

to \$3.4B (SSP585) (Supplementary Fig. 4b, Supp Fig. 6b). Here, the lowest values represent communities where all costs were attributed to building damage. If represented by borough or census area, the total costs ranged from \$0.5B to \$11B (SSP245) (Supplementary Fig. 7b) and \$0.8B to \$13.4B (SSP585) (Fig 4b). ”

Methods (page 24, lines 445-447):

“Using permafrost thaw hazard maps and the stressor-response modeling approach presented by Streletskiy et al.¹⁸ under the SSP245 and SSP585 scenarios, we estimated the costs of building and road damage caused by permafrost hazards in Alaska.”

Methods (page 25, lines 478-483):

“For each GCM-specific hazard map, damages are computed by summing the cost of buildings that are located in areas with >15% bearing capacity reduction and roads that are located in areas with >10 cm ground subsidence. For one climate scenario, this results in three GCM-specific estimates of building and road costs that are averaged to obtain the cost of building and road damages under that particular scenario. These averaged costs are then spatially joined to individual town boundaries and to borough/census area boundaries.”

Supplementary information (pages 25-26, lines 145-148):

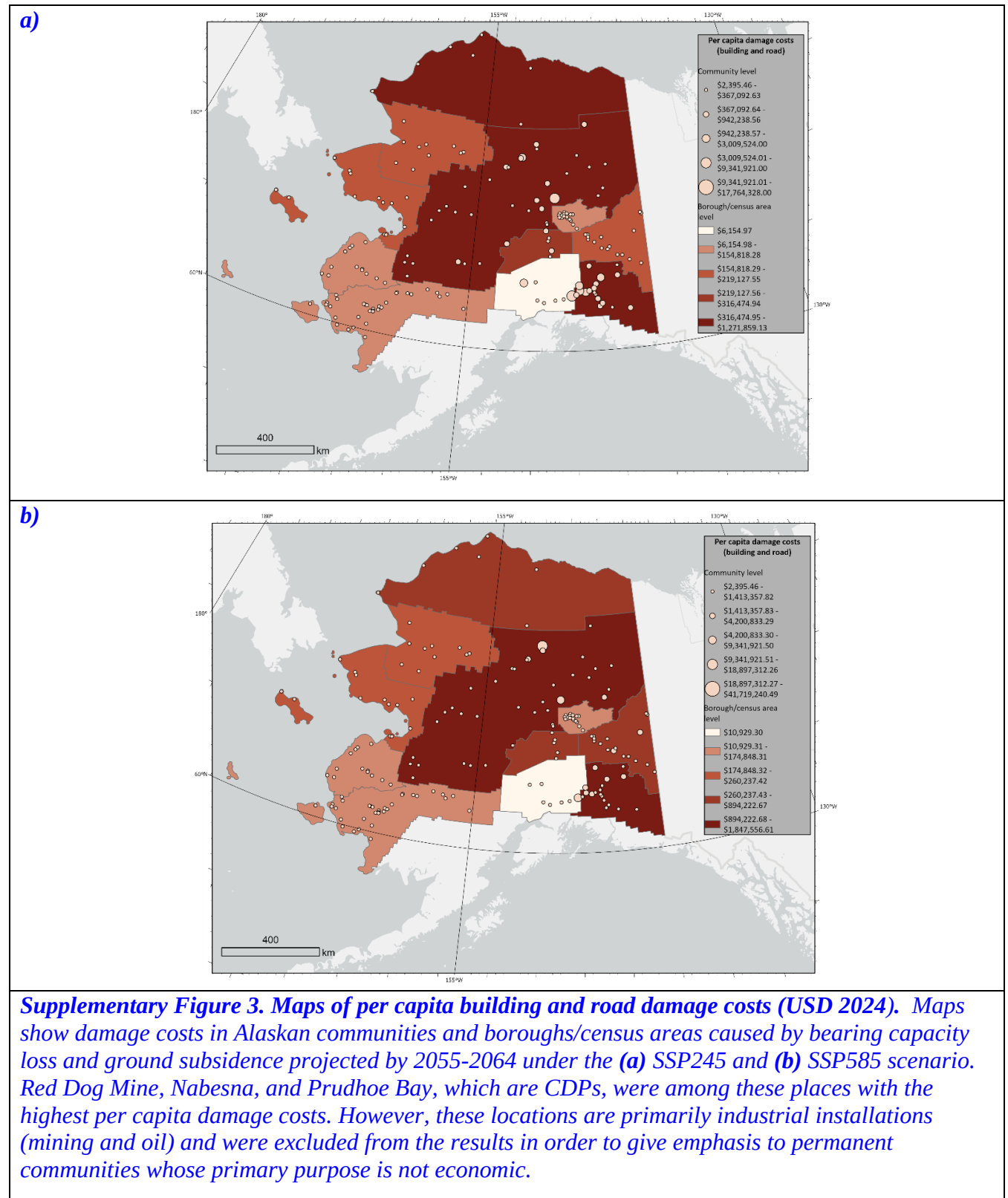
“Each GCM was analyzed via the shared socioeconomic pathway (SSP) 245 and 585 scenarios^{21,22}. SSP245 is a ‘middle-of-the-road’ pathway that represents the lower limit of climate change that can be realistically attained by mid-century. This includes moderate challenges to mitigation and adaptation.”

Supplementary information (page 29, lines 221-224):

“For each of the two SSP scenarios, three GCM-specific estimates of bearing capacity loss and ground subsidence between the baseline and future periods were produced using PT and ALT estimated from the permafrost model using each GCM. Therefore, there are a total of twelve bearing capacity loss and ground subsidence maps.”

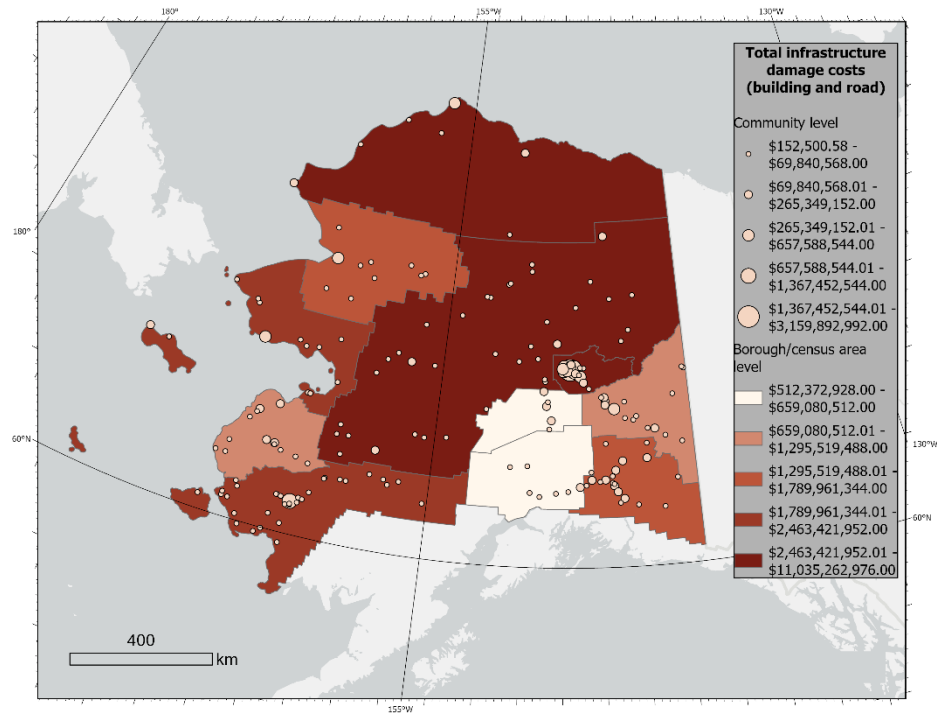
Continued on next page...

Supplementary information (page 4):

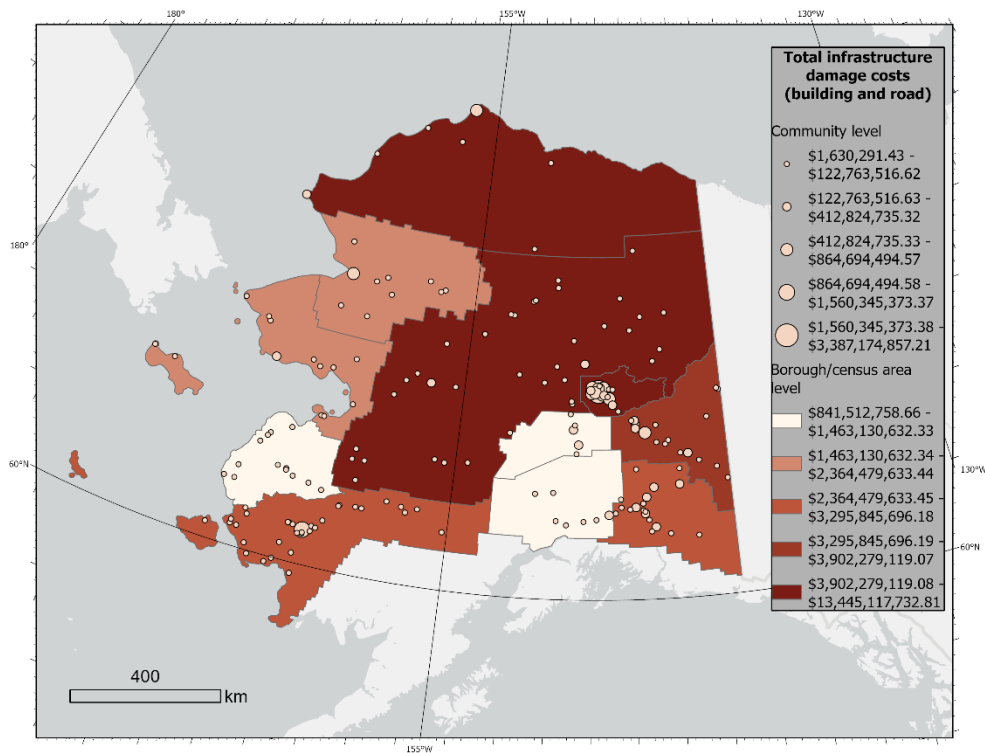


Supplementary information (page 5):

a)

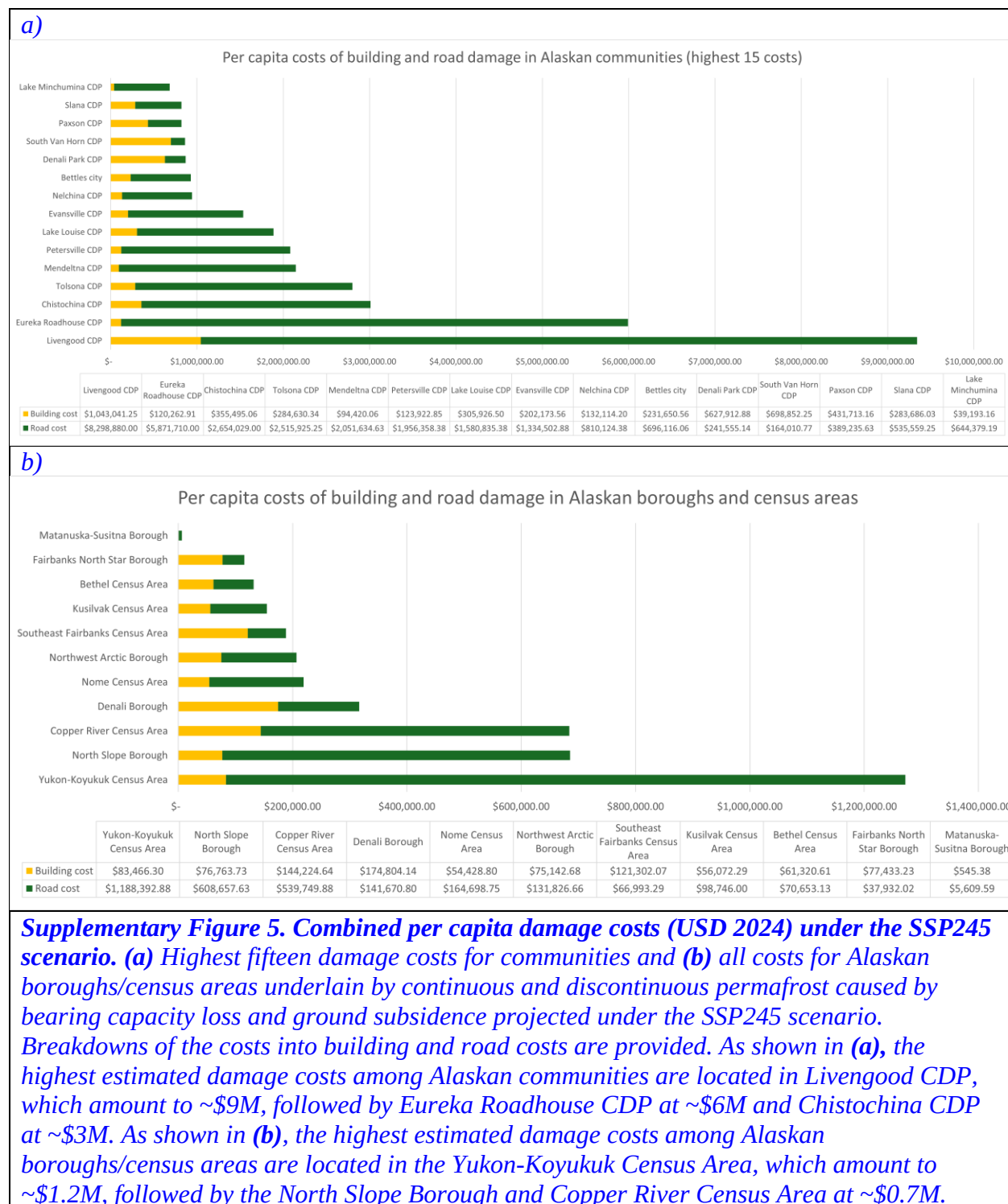


b)



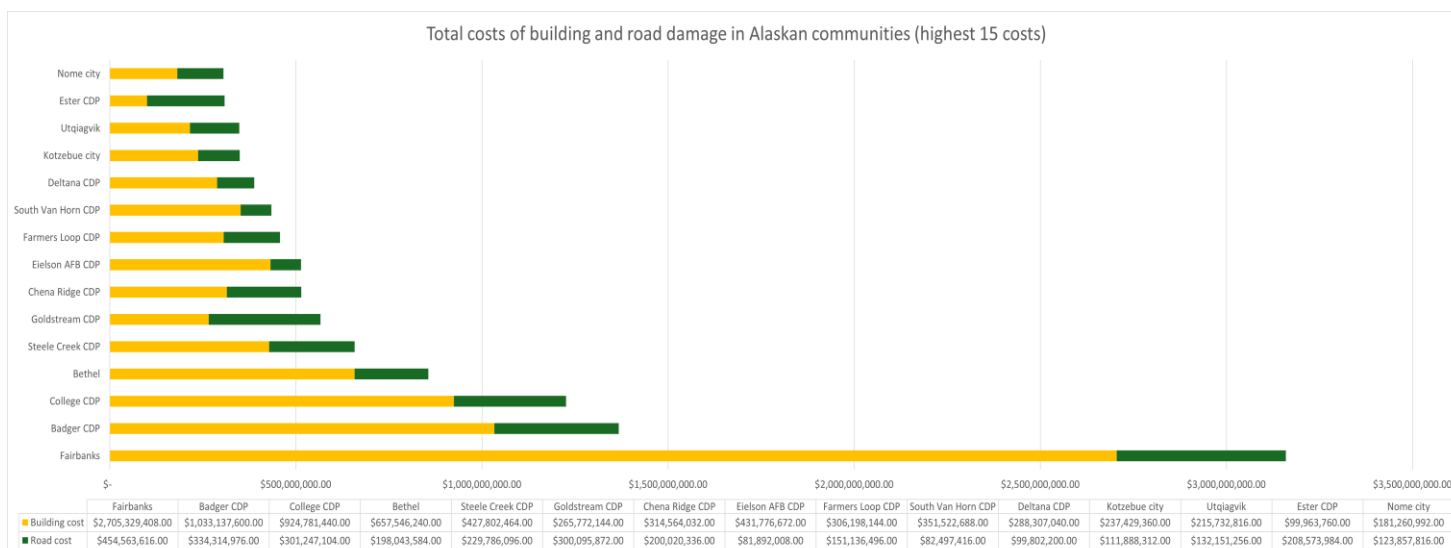
Supplementary Figure 4. Total (not normalized by population) building and road damage costs (USD 2024). Maps show costs in both Alaskan communities and boroughs/census areas caused by bearing capacity loss and ground subsidence projected by 2055-2064 under the (a) SSP245 and (b) SSP585 scenario.

Supplementary information (page 6):

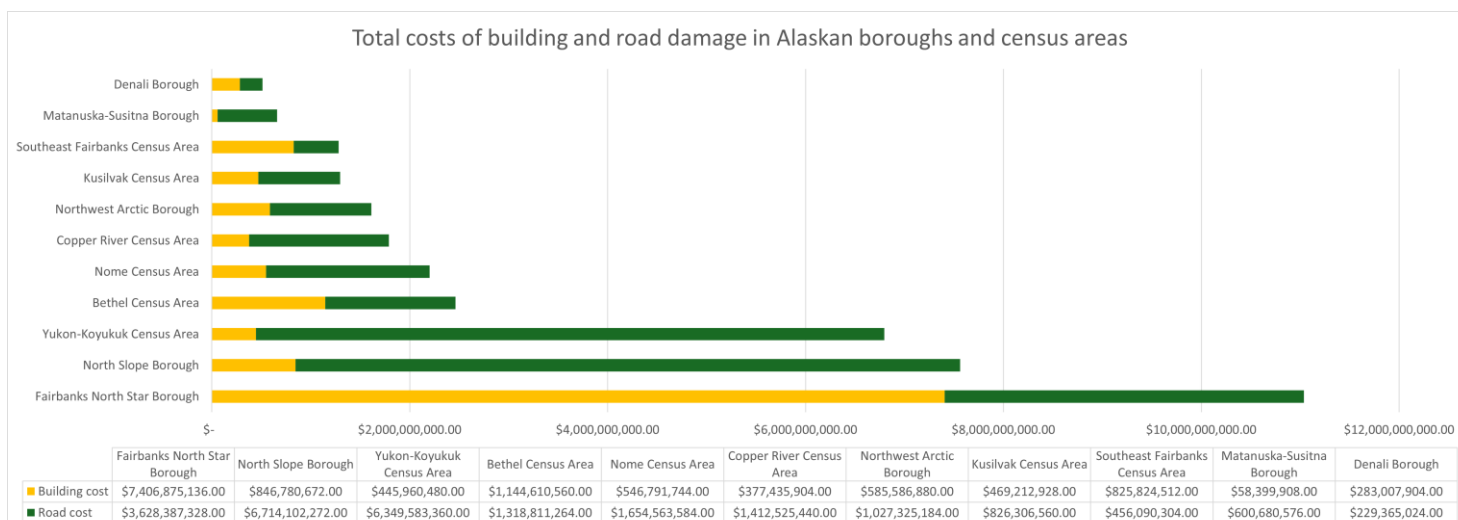


Supplementary information (page 8):

a)

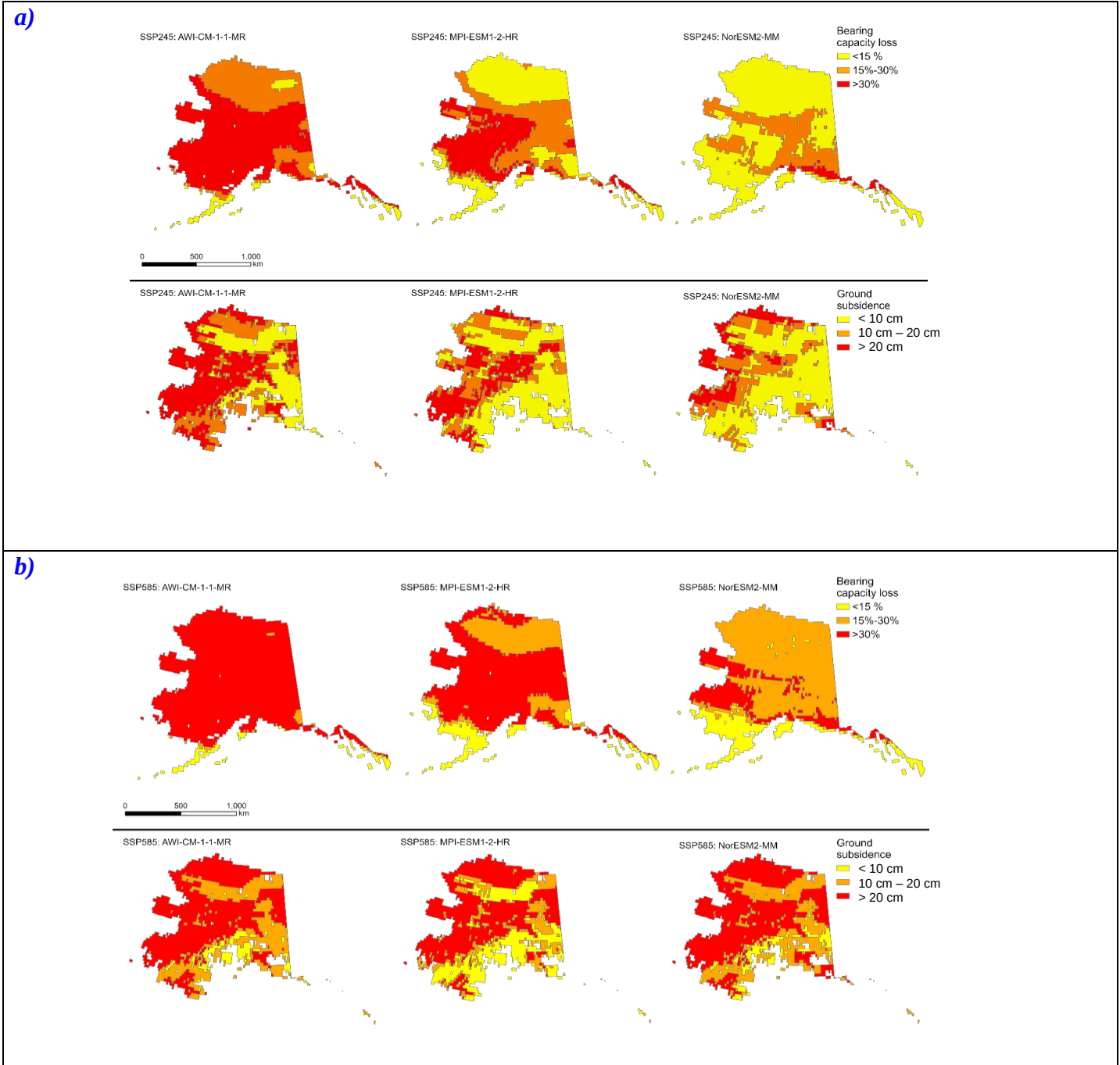


b)



Supplementary Figure 7. Total damage costs (USD 2024) under the SSP245 scenario. (a) Highest fifteen damage costs for communities and (b) all costs for Alaskan boroughs/census areas caused by bearing capacity loss and ground subsidence projected by 2055-2064 under the SSP245 scenario. Breakdowns of the costs into building and road costs are provided. As shown in (a), the highest total estimated damage costs among Alaskan communities are located in Fairbanks, which amount to ~\$3.2B, followed by Badger CDP at ~\$1.4B and College CDP at ~\$1.2B. As shown in (b), the highest total estimated damage costs among Alaskan boroughs/census areas are located in the Fairbanks North Star Borough, which amount to ~\$11B, followed by North Slope Borough at ~\$7.6B and Yukon-Koyukuk Census Area at ~\$6.8B.

Supplementary information (page 11):



Supplementary Figure 10. Bearing capacity loss and ground subsidence mapped by the permafrost geotechnical model. Maps show bearing capacity loss and ground subsidence grouped in low (yellow), moderate (orange), and high risk (red) classes based on the **(a)** SSP245 and **(b)** SSP585 scenarios. If buildings and roads fall within moderate-high risk zones, they are considered to be damaged beyond repair and require replacement.

Supplementary information (page 20):

Supplementary Table 3. Projected average, minimum, and maximum area/length and damage costs of buildings and roads in Alaskan discontinuous and continuous permafrost regions at risk of bearing capacity loss and ground subsidence between the decades 2015-2024 and 2055-2064. Calculations are based on the AWI-CM-1-1-MR, MPI-ESM1-2-HR, and NorESM2-MM global climate models analyzed under the SSP245 and SSP585 scenarios.

	Total infrastructure			Area/length at risk			Cost of replacement (billion USD 2024)		
	Statewide	Within discontinuous/ continuous permafrost		Mean	Min	Max	Mean	Min	Max
<i>Buildings</i>	53M m ²	13M m ²							
			SSP 245	10.36M m ²	8.08M m ²	12.31M m ²	12.99	9.23	16.37
			SSP 585	12.15M m ²	12.05M m ²	12.31M m ²	16.06	15.88	16.37
<i>Roads</i>	50,477 km	32,628 km							
			SSP 245	18,397 km	13,244 km	23,981 km	24.22	22.96	30.34
			SSP 585	28,499 km	25,666 km	30,083 km	35.30	32.15	36.99
					Total costs	SSP245	37.21	32.19	46.71
						SSP585	51.36	48.03	53.36

Here is some specific suggesting:

1. Ref 1 seems too old. The climate is changing dramatically, and the permafrost is shrinking. Therefore, new literature is recommended.

We have removed the first reference from Table 1. See the next point for changes made to Table 1.

2. Table 1 does not seem to be needed and is recommended as additional information if it must be listed.

Table 1 was indeed too large. We have moved it to the supplementary information and condensed it to only focus on studies that estimated monetary losses of infrastructure damages in Alaska. It is important to keep this table because the cost estimates of infrastructure damages from previous studies, as well as the data that was used to make them, provide a justification of our study's novel findings.

Accordingly, the following revisions were made:

Supplementary information (pages 16-17):

Supplementary Table 1. Peer-reviewed studies that have estimated monetary losses of infrastructure damage caused by projected permafrost thaw hazards in Alaska.				
<i>Reference</i>	<i>Study area</i>	<i>Infrastructure focus</i>	<i>Geospatial infrastructure inventory</i>	<i>Findings (costs adjusted for inflation to USD 2024)</i>
<i>Larsen et al.¹⁴</i>	<i>Alaska</i>	<i>Public infrastructure (e.g., airports, bridges, defense facilities, emergency services, energy, healthcare, railroads, roads)</i>	<i>Publicly owned structures and their costs (USD 2006) were compiled from public sources (e.g., the Alaska State Office of Risk Management, Denali Commission).</i>	<i>Climate change (including other hazards besides permafrost thaw) could add \$5.6–\$9.5B (+10% to +20% above normal wear and tear) to future costs for public infrastructure from now to 2030 and \$8.7–\$11.8B (+10% to +12%) from now to 2080.</i>
<i>Melvin et al.¹⁵</i>	<i>Alaska</i>	<i>Publicly owned roads, airports, buildings, railroads, and pipelines</i>	<i>Publicly owned structures and their costs (USD 2015) were compiled from numerous public sources including State</i>	<i>Cost of permafrost thaw damage to infrastructure without adaptation measures from 2015 to 2099 will total \$2.1B for RCP4.5 and \$2.8B for RCP8.5.</i>

			<i>of Alaska and national geospatial datasets</i>	
<i>Suter et al.¹⁶</i>	<i>Pan-Arctic</i>	<i>Roads, railroads, pipelines, airports/ports, buildings</i>	<i>Public sources of governmental geodata were used to compile a pan-Arctic infrastructure inventory. Costs were based on (Larsen et al., 2008) and adjusted to USD 2017. Only publicly owned Alaskan infrastructure is considered.</i>	<i>Cost of damaged infrastructure across the entire Arctic is \$27.7B by 2059 under RCP8.5. An estimated 22% of total assets will be affected in Alaska. Damages in Alaska amount to \$4.5B.</i>
<i>Streletskiy et al.¹⁷</i>	<i>Pan-Arctic</i>	<i>Roads, railroads, runways, buildings</i>	<i>OpenStreetMap data was used to compile a pan-Arctic inventory. Country-specific costs (USD 2020) for each infrastructure type were calculated by averaging several sources.</i>	<i>Under SSP245, 29% of roads, 23% of railroads, and 11% of buildings will be affected, costing \$221B by 2055-2064. Under SSP585, 44% of roads, 34% of railroads, and 17% of buildings will be affected with estimated cost of \$335B. Damages in Alaska amount to \$17.2B under SSP245 and \$29.7B under SSP585 by 2055-2064.</i>

Continued on next page....

3. Lines 133-134, this sentence is not well understood. It is suggested to modify it more clearly.

The sentence from lines 133-134 has been revised and is underlined in the below passages. We have clarified this sentence by providing percentages that describe how much each dataset uniquely contributes to our infrastructure map, or how much overlap exists between the datasets. Hopefully, this is more digestible for the audience.

The following revisions were made:

Results (pages 9-10, lines 183-201):

“In total, the combined HABITAT-OSM map consists of a total building footprint of 53M m² and a road network of 50,477 km (Fig. 3) across the state of Alaska. Of the 53M m² building footprint, 47% (25M m²) is shared by both OSM and HABITAT, while 32% (17M m²) and 21% (11M m²) is solely represented by HABITAT or OSM, respectively. Areas that were only mapped by OSM is because cloud-free satellite image scenes were not available. A majority of the road network is solely represented by OSM (72%, 36,359 km), while 28% (14,118 km) are shared between both OSM and HABITAT. HABITAT did not contribute any new roads to those already represented in OSM. Accordingly, HABITAT identified an additional 47% of building footprints overall to those already available in the OSM dataset. In 204 of the 285 communities, HABITAT produced a 500% larger building footprint on average compared to OSM (Supplementary Fig. 1).

On discontinuous and continuous permafrost, the combined HABITAT-OSM dataset include a 13M m² building footprint and 32,628 km of road network. HABITAT accounts for 6M m² (46%) that is not included in OSM, while 4M m² (31%) are shared between the two datasets, while OSM contributes another 3M m² (23%) in areas that prevented mapping by HABITAT due to lack of cloud-free satellite imagery. Accordingly, HABITAT identified an additional 86% of building footprints to those already available in the OSM dataset. Regarding the total length of the road network, 84% (27,561 km) is solely represented by OSM, while 16% (5,067 km) are shared by both OSM and HABITAT.”

Discussion (page 17, lines 298-300):

“Our method did not add to the length of mapped roads across Alaska, most likely due to the completeness of roads in the OSM dataset. Nine years ago, the global OSM road network was ~83% complete⁴³ and additions have likely been made since then.”

4. Lines 1365-143, whether the difference in the amount of infrastructure identified is related to time. Because there may be new roads, houses, etc., different times may make a difference.

Correct, differences in the acquisition times of source imagery used to map buildings in our HABITAT dataset versus in OSM may influence the discrepancy between resulting building areas. We now mention this in the discussion. However, the main difference in mapped

infrastructure between our product and OSM is that OSM is a volunteer-based mapping effort that relies on manual digitization of all features, while ours is an automated solution that requires only a small subset of features to be manually digitized.

Clarifications to the differences in the datasets are now provided:

Discussion (page 17, lines 283-300):

“Automated image analysis can efficiently map infrastructure across a large region from high-resolution satellite imagery. The mapping can also be easily repeated upon the acquisition of new imagery. In comparison, due to the volunteer-based manual digitization approach to OSM data creation, it would take a considerable amount of time to update OSM with digitization using new imagery. The Arctic landscape and communities are already experiencing the impacts of permafrost thaw, which highlights the need for expanded infrastructure map products that can be efficiently produced based on automated image analysis approaches (e.g., machine learning or deep learning). We added a significant coverage of mapped buildings (+17M m²) over the state of Alaska, including the portion of the state that is underlain by continuous and discontinuous permafrost (+6 M m²).

Our results confirmed the incompleteness of buildings mapped over Alaska. Several studies have demonstrated or reported concerns about the completeness of OSM in the Arctic^{13,29,30}. This discrepancy is largely due to a lack of focus given to the Arctic region by volunteer OSM mappers. Differences in the acquisition years of source imagery used to map buildings may also be a factor between results from the OSM manual volunteer effort and our automated mapping via HABITAT over Alaska. Our method did not add to the length of mapped roads across Alaska, most likely due to the completeness of roads in the OSM dataset. Nine years ago, the global OSM road network was ~83% complete⁴³ and additions have likely been made since then.”

5. How to obtain the accuracy evaluation and what factors are used as the basis for accuracy evaluation.

We have expanded the description of the validation process. This was achieved by expanding the analysis to include an increased sampling area in order to include a more representative range of the built environments (e.g., rural village, medium-sized city, large city) found in Alaska. Accuracy assessment across a range of built environments, each with unique challenges to building and road detection, gave us the proper basis upon which to discuss possible false positives and negatives and to recognize the strengths and weaknesses of the map.

The edits to the manuscript include:

Results (pages 10-12, lines 203-237):

“The HABITAT map was found to have an overall accuracy of 82% by visually validating the ground truth of 1,373 randomly selected building, storage tank, road, and background

predictions. Data used in accuracy assessment included the communities of Bethel, Fairbanks, Hooper Bay, and Noorvik (Table 1). The user's accuracy of 0.58 for the background class is due to the compounded effect of false negatives (i.e., missed detections) of buildings and roads, reflected by their respective producer's accuracies of 0.83 and 0.77. These false negatives of buildings and roads mostly occur due to how satellite image scenes are split into tiles for model training and subsequent mapping. Firstly, large buildings oftentimes cannot fit within the dimensions of 256×256 pixels (approximately 128 by 128 m at 0.5 m resolution), which is the input image size that we chose for the deep learning model. In these cases, the model must detect a single building that has been split across multiple tiles, resulting in partially completed, fragmented building footprints (Supplementary Fig. 2). Within the accuracy assessment, this particular cause of false negatives is almost exclusively found in Fairbanks, which is the largest city in Alaska located on continuous or discontinuous permafrost. Fairbanks has large buildings whose areas extend well beyond the dimensions of the images input to our deep learning model. Conversely, the small buildings in the rural villages do not lead to this type of misclassification. Secondly, satellite image scenes are split into non-overlapping tiles, which can be problematic in the detection of roads as they are spatially continuous features that interconnect with each other. Splitting satellite image scenes into tiles with some degree of overlap ultimately forces a deep learning segmentation model to repeat predictions of the same road at the same location. This not only increases the chances that the road will be predicted to begin with, but also that roads will be connected across space.

The user's accuracies of the building, road, and storage tank classes reflect false positives (i.e., detected instance of an object that does not exist in reality) that are mostly due to the deep learning model being confused by miscellaneous impervious cover or anthropogenic features in urban communities (e.g., Fairbanks and Bethel) with visual properties that may appear similar to the classes of interest (Supplementary Fig. 2). However, based on the user's accuracy values, these false positives were limited. For example, part of a paved parking lot may be confused for a paved road. Built anthropogenic features with distinct edges that are not buildings, such as an ice-skating rink, may be confused for buildings. Circular patterns marked in the ground may be confused for storage tanks, which are themselves circular structures. On the other hand, false positives due to natural land cover features were minimized (see Methods section Postprocessing of detected buildings and roads). The model displays minimal confusion between different types of infrastructure (Methods sections Deep-learning-based building and road detection and Thematic map accuracy assessment for details on how this map was created and validated)."

Results (page 12):

Table 1. Thematic map accuracy assessment of HABITAT (see Methods section Thematic map accuracy assessment for details on the applied metrics).

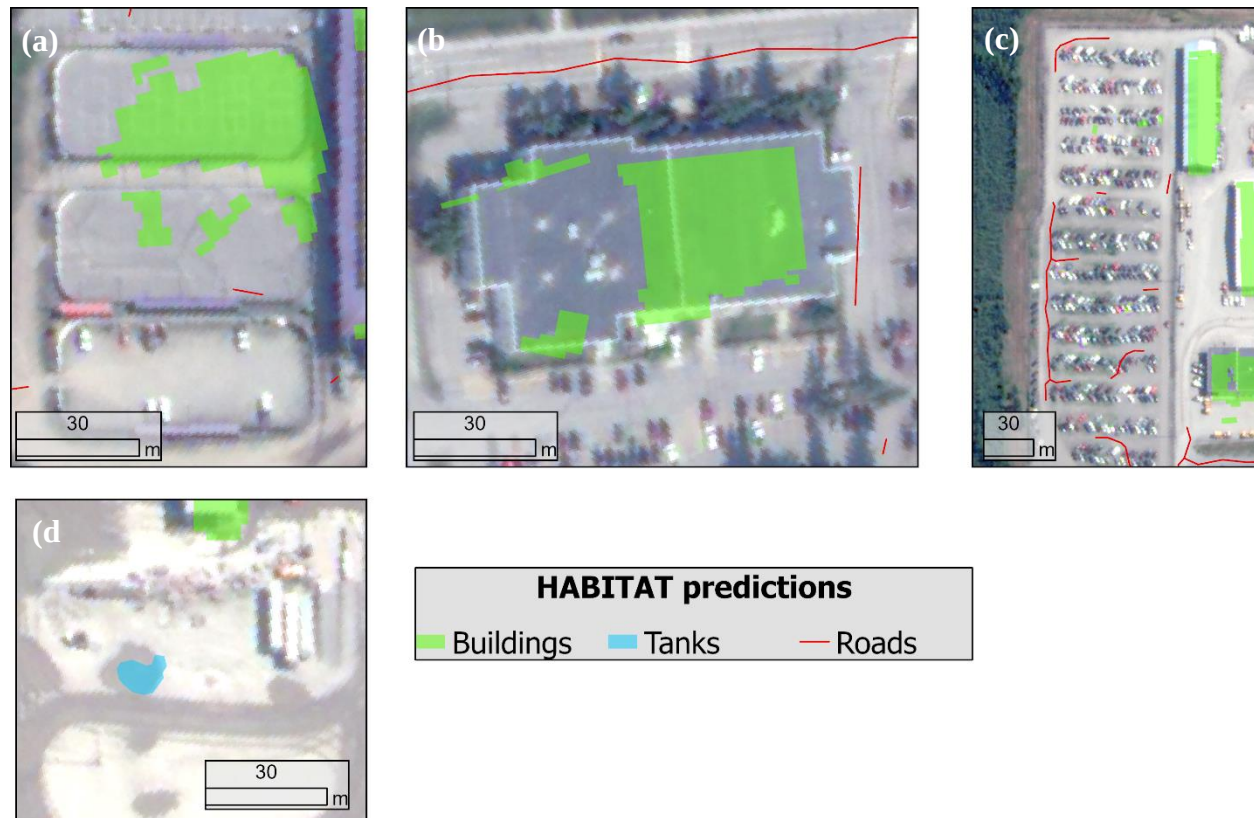
	Background	Building	Road	Storage tank	Total	User's accuracy
Background	213	81	72	0	366	0.58
Building	40	438	6	0	484	0.90
Road	24	7	262	0	293	0.89
Storage tank	19	0	0	211	230	0.92
Total	296	526	340	211	1373	
Producer's accuracy	0.72	0.83	0.77	1		
					Overall accuracy	0.82

Methods (pages 27-28, lines 518-548):

“Following best practices outlined by Olofsson et al.⁶² and Congalton and Green⁶³, we conducted thematic accuracy assessment of the HABITAT map. We selected four Alaskan communities that represent the various built environment settings relative to Alaska. Noorvik and Hooper Bay were selected to represent rural villages, Bethel was selected to represent medium-sized cities, and Fairbanks was selected to represent the largest of Alaskan cities. Each of these settings are characterized by buildings and roads of various geometries, spatial distributions, construction materials, and topologies that are evident from satellite imagery. Fairbanks, for example, is a highly developed urban environment notably characterized by larger buildings that can often take on irregular geometries, which is typical of non-residential development associated with a larger economy (office buildings, industrial buildings, retail centers, etc.) Urban road networks are generally dense, with many interconnected roads that are long compared to those of rural communities. Additionally, urban roads are mostly paved. Conversely, rural villages, such as Hooper Bay and Noorvik, that rely on mixed cash-subsistence economies⁴¹ have little non-residential development. Therefore, rural villages are mostly composed of small, detached houses and sparse networks of unpaved roads.

For each of the four communities, we randomly sampled 300-350 predicted polygons from the HABITAT map representing buildings, storage tanks, and roads, as well as locations with no prediction (i.e., background) using stratified random sampling. This sampling scheme randomly distributes points across polygons of each class, in which each class has a number of points proportional to its relative area. This was done using the Create Accuracy Assessment Points tool in the ArcGIS Pro software. Because roads are represented as line features in the HABITAT map, a 10 m buffer was applied in order to convert them to polygon features that cover the footprint of the road. For each community, we constrained the random sampling to the footprint of the Maxar satellite image scene used to map it. In total, there were 1,373 random selections. For each sampled location, we visually interpreted the underlying Maxar satellite imagery at that location to identify the true class label. If infrastructure is present, we identified the specific infrastructure class; if there is no infrastructure, the ground truth label is considered to be “background”. Then, we computed the error matrix using the ArcGIS Compute Confusion Matrix tool, which is a cross-tabulation of the class labels allocated in the remote sensing-derived map against the true data collected from sampled validation sites. From the error matrix with q classes, we computed the following accuracy metrics:”

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Supplementary Figure 2. Examples of false positive and negative detections in the HABITAT map in Fairbanks, Alaska. (a) A building was falsely detected over an ice-skating rink. (b) A large building was not fully detected. (c) Roads were falsely detected in a parking lot. (d) A storage tank was falsely detected due to a circular pattern in the ground.

6. Whether the permafrost geotechnical model can simultaneously simulate the stability of road, building, and storage tank?

Within the implemented approach from Streletskiy et al. (2012), (2023), buildings (including storage tanks) and roads are treated separately because of their relationship with permafrost. For buildings, changes in the capacity of permafrost-affected ground to bear the piles of building foundations are considered. For roads, differential ground subsidence is considered. We have not made any revisions regarding this point.

Black text: reviewer 1

Blue text: authors

The authors provided thorough responses and made significant revisions. They have satisfactorily addressed my previous four major comments. I agree with their explanations and the revisions. The results are now well supported and their limitations are clearly identified. I believe the revised manuscript has scientific merit and contributes to the permafrost community in both science and engineering fields.

We thank the reviewer for their constructive criticism that elevated our manuscript to a higher quality. We also appreciate the encouraging words.

Black text: reviewer 2

Blue text: authors

Although authors does not agree my suggestion about excluding the assessment of the cost estimation of infrastructures damage, I agree with their ideas. Authors clearly clarified my doubts and made changes. I have no further comments or suggestions. I agree to publish this article in Communication Earth & Environment.

We thank the reviewer for their constructive criticism that elevated our manuscript to a higher quality.