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# First Insights into INTUIT: An Interactive Tactile Physicalization for User Interpretation of RADAR Technology

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*Abstract—The changing climate and increasingly unpredictable sea ice conditions have created life-threatening risks for Inuit, the residents of the Arctic, who depend on the ice for transportation and livelihood. In response, they are turning to technology (e.g., RADAR imagery from the Canadian RADARSAT satellite) to augment their traditional knowledge of the ice and to map potential hazards. The difficulty lies in the actual RADAR interpretation process. In order to support understanding of the RADAR image content, we introduce a work-in-progress, INTUIT, a physicalization that represents the RADAR reflection strength, which is highly influenced by surface roughness, as a tactile texture. Such tactile texture is made by resampling the RADAR imagery to a number of UV cells and mapping the average brightness value of each cell to a physical variable. A proof of concept was designed for a region in Baffin Island (Nunavut) and sent to the Arctic for initial feedback. Preliminary study results are promising: it is expected that INTUIT will facilitate the interpretation learning process for RADAR imagery.*

Residents in the Arctic depend on stable sea ice for their transportation and livelihoods. There is an inherent danger with sea ice travel, however, and hazards can be difficult to detect in the north's constant winter darkness. Inuit have relied on traditional knowledge of ice characteristics and movements to travel safely on the ice, informed by generations of observations and experience. Climate change is also affecting the environmental conditions upon which the traditional knowledge is based, making travel based only on that knowledge increasingly dangerous. In 2009 - 2010, nearly one in twelve residents of Nain, Newfoundland and Labrador, Canada, fell through the sea ice, 68% were afraid to use the ice, and 75% were unable to predict ice conditions [1]. It has been necessary for Inuit to look elsewhere for additional data sources to inform them of ice status and conditions.

One of those data sources is satellite earth observation data, particularly Synthetic Aperture RADAR (SAR) sourced from the [Canadian RADARSAT satellite](#), or the European Space Agency's Sentinel system.

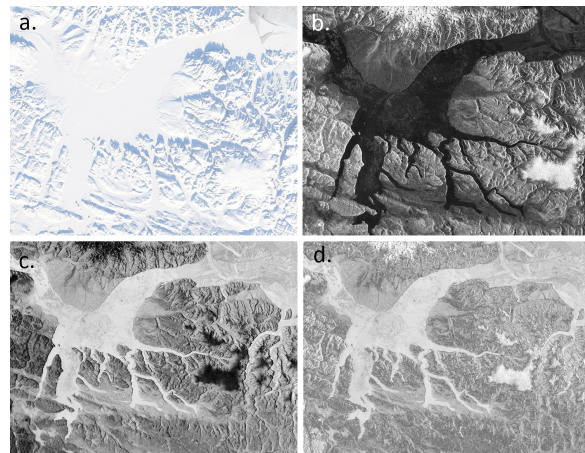
In northern Canada, a multi-year educational program, Sikumit Qaujimajjuti, managed by a social enterprise [SmartICE](#), is underway to train Inuit in remote sensing and digital mapping technologies so that they may augment their own knowledge of the ice with information from the satellite sensors (see [2] for more details). An important component is developing competency in understanding RADAR image content to read the ice conditions and features. RADAR imagery utilizes microwave wavelengths of energy to measure the reflectivity of the Earth's surface. During this process, "rough ice" appears highly reflective, while "smooth" ice exhibits less reflectivity. The resulting grayscale images display varying levels of brightness to represent reflectivity rather than the color of a feature. Consequently, smooth ice, which appears pure white in satellite photos, looks darker in these images, making

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interpretation challenging despite its value for sea-ice observation (see **Figure 1**). Within the framework of the SmartICE program, individuals known as Inuit Mappers are trained to “interpret” RADAR data into practical information. They are employed to achieve the ultimate objective of producing ice safety maps for the community, derived from the information they decipher from the imagery. Nevertheless, interpreters face a challenge when linking image tone to surface roughness. It can be difficult for them to recall that image brightness does not equate to “visual” brightness. To mitigate the associated confusion, merely inverting the image is not an effective solution, as it presents additional complexities in comprehending the data and its correlation with visual brightness. For example, the image’s roughest parts will appear as black areas in the inversion, which could be misinterpreted as shadows, as demonstrated in **Figure 1c**. Furthermore, this inversion process could cause confusion for interpreters when viewing a RADAR image, as they would have to determine whether they’re viewing a “standard” or inverted image. Alternatively, employing custom algorithms to convert RADAR imagery into an image that resembles optical images may reduce ambiguity but could result in data loss during the conversion process (refer to **Figure 1d**). Most crucially, this approach would create a new challenge: interpreters would need to convert the data each time prior to usage, which could undermine the educational value of developing competency in understanding such images. To tackle this issue, tactile physical representations have the potential to help novice interpreters build a cognitive bridge between image tone and surface roughness and would complement the visual representation. Tactile and physical models can be more effective than on-screen visualizations for information retrieval by providing physical touch as a cognitive aid [3]. Such characteristics make physical models effective tools for geography education. Physical models can facilitate deeper learning through kinesthetic and active learning, as well as engagement through interest and novelty [4]. Physical models can also be used as a mode of inquiry to promote constructivist learning [5].

As part of the Sikumit Qaujimajjuti program, innovative learning resources are being co-developed with the Inuit participants. Acknowledging the challenges in learning RADAR concepts, there was a desire to develop a physical model of RADAR imagery. This model would enable learners to feel the surface roughness while simultaneously comparing the brightness on the imagery. By doing so, learners could generate a tactile memory of the relationship between image brightness and the Earth’s surface roughness. This idea aligns



**FIGURE 1:** (a) A satellite photo showing the ice surface, (b) RADAR imagery of the same location, (c) Inverted RADAR image, (d) Inverted RADAR image using a custom algorithm.

with the tactile consciousness created when using “both vision and manipulation of objects” [6].

Here we introduce a work-in-progress, INTUIT, a novel idea of tactile physicalizations of RADAR images to be used by Inuit Mappers. A *physicalization* is an artifact that represents data through its geometry or physical properties [7] and can provide an analytical reading of the data or an artistic representation of it [8]. Focusing on the former goal, INTUIT transforms purely visual radar images into tactile maps where the surface roughness of ice can be experienced through touch. Towards this goal, our algorithm resamples the original RADAR imagery to a number of *UV* cells, extracts the average brightness of each cell as roughness values, and maps the values to physical variables, such as height or size. To facilitate image interpretation, the interpreter views the image while feeling the texture with their hands, with the goal of keeping the idea of surface “roughness” at the forefront of the interpreter’s mind and securing the connection of grey levels to the texture.

The remainder of this paper is structured as follows. In the **Background** Section, we briefly review the literature related to this research. The **Methodology** Section introduces our applied methodology to design tactile surfaces from RADAR imagery. The **Results** Section is dedicated to the introduction of our preliminary results and end-user feedback from the interpreters in Baffin Island. In **Discussion**, we discuss the technical issues we faced during the design of INTUIT and introduce our proposed solutions. Finally, **Conclusion** focuses on the conclusion and future work.

## BACKGROUND

In this section, we first describe RADAR imagery and its importance in sea-ice interpretation and then outline physicalization as a tool for improving the understanding of data.

### RADAR Imagery

Spaceborne synthetic aperture RADAR (SAR) is a valuable source of Earth observation data and has three important distinctions from optical imagery (e.g., Google Earth imagery, air photos) that make it valuable for Arctic ice sensing – active sensing, reliability, and sensitivity to roughness [10]. RADAR is an active sensor, providing its own illumination of the Earth's surface, so ice can be imaged in the darkness of winter. The long microwave wavelengths emitted means that clouds do not provide a barrier to the energy, thereby providing reliable data. When the RADAR pulse meets the Earth's surface, the energy interacts with the features and their structure on the surface, causing scattering and backscattering, with some of the energy being reflected back to the sensor, where its strength is measured. RADAR is also sensitive to terrain and surface roughness, helping to tell the difference between blocky older ice, smooth new ice, and hazards (ridges, water). The roughness information afforded by RADAR imagery is important in sea-ice interpretation and recognizing potential safe zones and hazards [11]. The challenge lies in the actual interpretation process. An optical image that we are more familiar with is generated when a sensor measures the strength of sunlight (visible wavelengths) reflected from the Earth's surface. The reflectance strength is represented by a grey scale on the image; features with a high reflectance value will appear bright or white, and low reflectance features will appear dark. Since this brightness corresponds to the same reflectance sensed by our vision, the image is intuitive to read. RADAR sensors transmit and receive longer wavelength microwave energy that the human eye cannot detect. Microwave energy acts differently than visible light, responding to surface roughness, salinity, and internal geometry of an object, not the “color” [10]. Reflected energy values are still shown in a grey scale with high values appearing bright; however, what those values represent is not what we see, so the image can appear quite different than an optical scene. For example, smooth ice appears white in optical imagery but dark in RADAR imagery, primarily due to its surface roughness properties (Figure 1a,b).

### Data Physicalization

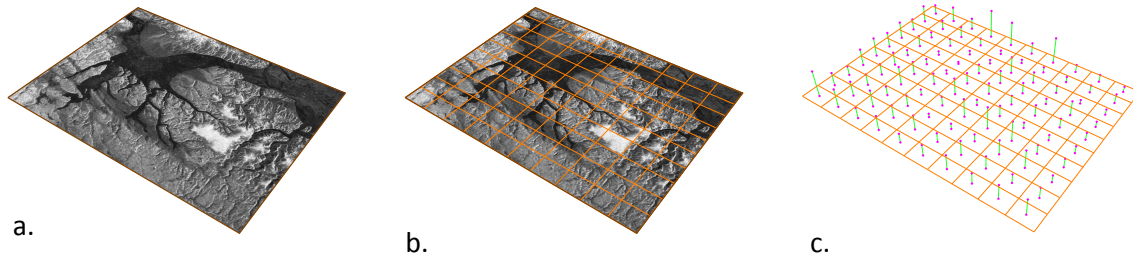
Information has been transformed into physical objects for thousands of years. Dragicevic and Jansen curated a list that contains hundreds of physicalization examples, including clay tokens dating back to 5500 BC, models made by biologists and physicists in the 19th and 20th century, and many examples of physically representing geospatial datasets. The term *data physicalization* is coined to how “computer-supported physical representations of data (i.e., physicalizations) can support cognition, communication, learning, problem-solving, and decision making” [7]. A study done by Stusak et al. [12] showed that physicality can increase the memorability of visualizations. The fact that physicalizations are able to provide physical touch makes them effective tools for conveying messages that are otherwise difficult or even impossible to represent. In [8], Djavaherpour et al. introduce a variety of physicalization types and present and evaluate several methods for their design and fabrication. While many conventional examples of data physicalization involve spatial data, a significant portion of the published research does not. Among the examples that utilize spatial data for physicalization, *Boxcars on Potatoes* [9] presents a technique for creating physicalizations of glyph-based representations of a scalar field on 3D surfaces. Similarly, our research introduces a method for physicalizing a scalar field defined over a regular grid.

## METHODS

This paper introduces a computational design approach to generate design variations for tactile models that can be digitally fabricated and used as image interpreter tools. A model is defined in principle by a tactile surface that physically encodes the roughness values of the RADAR imagery (i.e., our input data source). Such a physical model helps to interpret the roughness data (in a controlled, warm environment) by feeling the texture that is visually depicted only by the grayscale tone of the image. Thus, hypothetically, viewing the image and physically interacting with the surface simultaneously helps the interpreters to learn what grayscale tones relate to what types of surface roughness on the ground. Such interaction has the potential to make the reading of the data a multi-sensory experience rather than a visual-only one.

### Processing the RADAR Data

To make the tactile surface, we first set an arbitrary initial surface with a rectangular domain and map



**FIGURE 2:** Methodology diagram of generating the tactile surface from the RADAR imagery. (a) The input RADAR image representing roughness, (b) UV segmentation and reading the brightness values, (c) moving the centroid of UV cells along the z axis proportional to their brightness values.

the RADAR imagery on it (**Figure 2a**). As described earlier, RADAR imagery is an image different than an optical scene (see **Figure 1**). The typical spatial resolution of RADARSAT imagery is usually 8-100m (See **RADARSAT**), where the intensity value is 0 for the pixels representing a smooth surface and 255 for the pixels showing the roughest parts.

In the next step, our algorithm resamples the image by dividing the original domain into a number of  $U$  and  $V$  divisions, respectively, along the row and the column of the input image, making  $U \times V$  rectangular cells (**Figure 2b**). This resampling has a critical role in assigning the roughness to the surface. The number of the  $UV$  cells should be decided by considering the fabrication technique employed and its limitations in handling complex models. A higher  $UV$  value provides a higher resolution and results in a surface that more accurately reflects the original RADAR texture and tone.

Having the resampling set, our algorithm then processes the original RADAR imagery at each  $UV$  cell to extract the average brightness values ( $\gamma$ ) of the sub-domains. A brightness value is a number ranging from 0 to 1, with 0 being pure black, a smooth surface, and 1 being pure white, the roughest surface. We linearly map  $\gamma \in [0, 1]$  to  $[0, H]$ , where  $H$  is the maximum height for the resulting tactile model. Next, the algorithm moves the centroids along the z axis proportional to their brightness values (**Figure 2c**). These displaced points and their height values can be later used to generate different design options for the tactile surface.

### Generating Tactile Models

Using the method discussed above, we generated three different design variations by setting the resampling resolution at  $100 \times 100$  (i.e.,  $U=100$  and  $V=100$ ) (**Figure 3**).

In the first approach for making the tactile model,

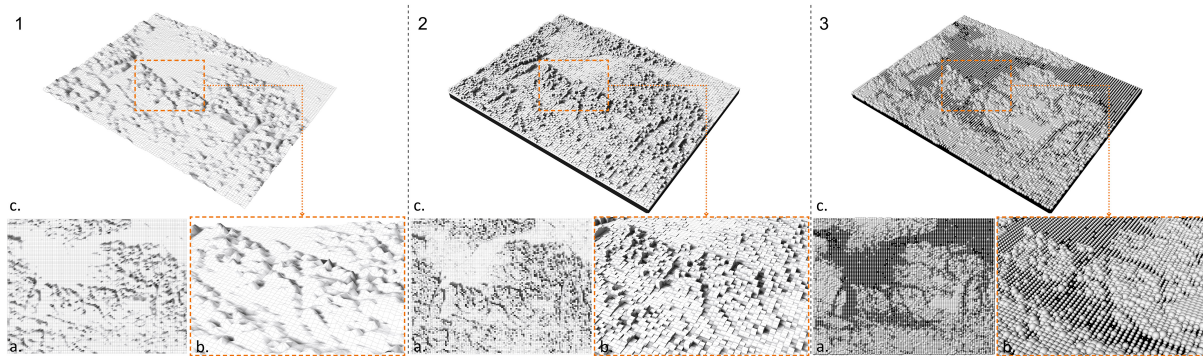
we used the displaced points as vertices to generate a mesh representing the roughness of the ice (**Figure 3-1**). However, the results of a previous study on geospatial physicalizations show that such representations are misinterpreted by users to be peaks and valleys of a terrain [4]. Thus, any approach that resembles terrain or elevation data should not be incorporated into the design of the final model.

In order to avoid a design that resembles elevation, we used the information provided by the tactile surface to generate a prism map, using the rectangle made by each  $UV$  cell and the brightness values ( $\gamma$ ) as an extrusion factor (**Figure 3-2**). Here, we linearly map  $\gamma \in [0, 1]$  to  $[0 + \varepsilon, H]$ , where  $\varepsilon$  is a small number to avoid failure in extrusion. However, since the cubes making the prism map fill the entire surface of the model, the tactile model will be inevitably single-colored, which will reduce visual correlation to the RADAR imagery. Such a representation risks making the interpretation process a challenging task for the Inuit.

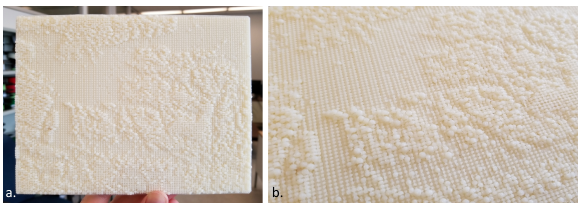
To be able to better preserve the appearance of the RADAR imagery and match it to the tactile model, we took another design approach by employing a bump map texture using spheres. For this design variation, we placed the centroid of spheres at centroids of  $UV$  cells and mapped the corresponding brightness values to their radii (**Figure 3-3**). Based on the initial discussions, we believed that this roughness model was capable of providing the required tangible tactile experience while keeping a high visual correspondence to the original RADAR imagery.

## RESULTS AND PRELIMINARY FEEDBACK

The RADAR imagery used for this exploration was a region of rough and smooth ice areas near Baffin Island, Nunavut, Canada. We built this surface in one piece with an FDM 3D printer using ABS filament.



**FIGURE 3:** Three different variations of the tactile model generated from the RADAR imagery at the resampling resolution of  $100 \times 100$ . (1) The mesh variation ((a) Top, (b) Close-up, (c) Perspective). (2) The prism map variation. (3) The final design approach for the tactile model, generated by spheres.

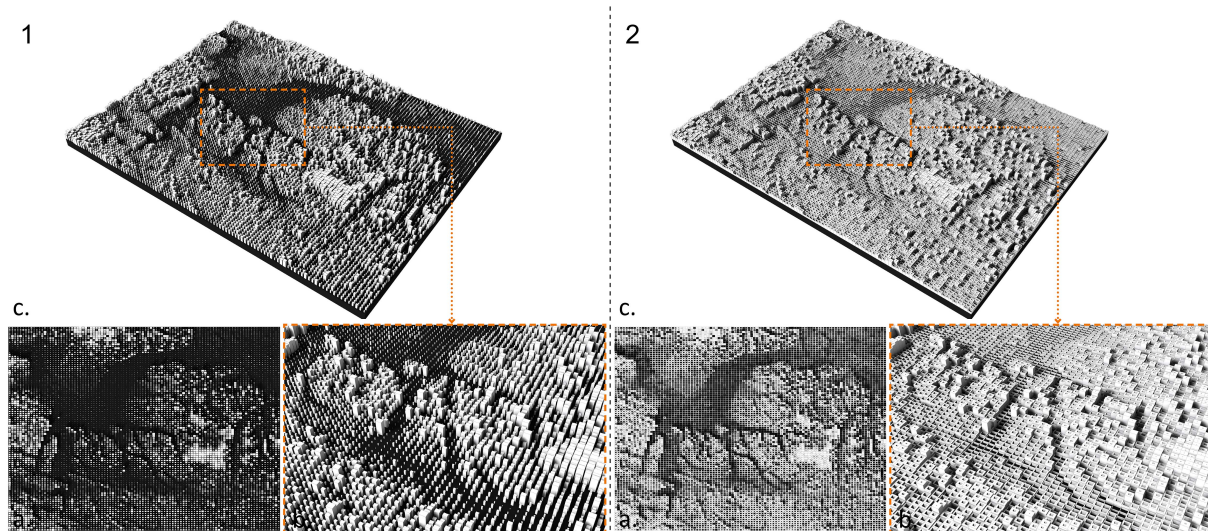


**FIGURE 4:** The 3D printed model: (a) The version 3D printed with white ABS, (b) A close-up view.

We chose ABS over PLA to provide higher strength and durability for INTUIT. Although the goal was to fabricate the model with dual colors to better mimic the original RADAR imagery, we ended up building two single-colored prototypes. This happened due to the technical difficulties we faced during the fabrication process as a result of the 3D printer's limitations in handling the required resolution (see [Discussion](#) for more details). We made two prototypes using light (white) and dark (grey) filaments to give interpreters the option to choose the model that they are more comfortable working with. **Figure 4** shows the version of the model 3D printed with white ABS filament, as well as a close-up view of its details.

The models were brought to an ongoing RADAR training session in Pond Inlet, Baffin Island, to get initial feedback (See [\[2\]](#) for more details about co-development with Inuit and training approaches in the context of Sikumik Qaujimagjuti). The participants knew how a RADAR image was generated but were struggling to secure the connection of image tone to surface roughness when they started interpreting images. To get an initial sense of whether such a model would be useful in helping learners understand RADAR, the models were introduced with the corresponding imagery, and the participants were asked to interpret

the image while feeling the model. There were five participants who tried both color variations of the 3D printed models, feeling the texture on the model as they looked at a corresponding area on the image. The reactions were monitored by an observation team, and all reactions were immediate and consistent. The models generated interest and sparked a conversation about how the texture related to the tone. Each participant spent more time examining the imagery than they had in the past, thinking about the texture. During this study session, we observed an enhancement in both the self-efficacy of the group and the accuracy of their image interpretations. Here, “self-efficacy” refers to an individual's confidence in their ability to complete a task successfully (Please see [Wang \(2019\)](#) for the use of this concept in Human-Computer Interaction Design). In our context, the improvement in self-efficacy was measured through qualitative statements from individuals or their self-assessments, reflecting their growing confidence in interpreting images. The sphere-based model was felt to portray the roughness in a way that best helped feel the texture. One participant, despite knowing what the models represented, temporarily confused the roughness for elevation, thinking of the model as a relief model, aligning with the findings of [\[4\]](#). This generated an opportunity to review the idea of surface roughness and how the model was generated from the tone of the image. Another mentioned having a bit more visual contrast in the textures of the 3D printed models would be helpful to even better distinguish areas of different roughness. The preliminary feedback from the interpreters affirmed the models helped in developing RADAR interpretation competency and interest in learning. Although the concept of this type of RADAR imagery was familiar to them, we were told by the interpreters that it was only after using the tactile model and touching its texture that



**FIGURE 5:** (1) Variation 2 of the tactile model to better preserve the visual appearance of the RADAR imagery, (2) Variation 3 of the model.

they were able to fully connect the surface roughness with the tone on the image. This is an important step in applying the knowledge to ice conditions and ultimately generating a [sea ice safety map](#) to be consulted before deciding on the sea ice travel routes by Inuit.

## DISCUSSION

As discussed in the [Methodology](#) Section, one core step to generate the tactile surface is setting the number of  $UV$  values, which is partially impacted by the limitations of the employed fabrication technique. In FDM 3D printing, the designed geometry should be tessellated for the fabrication process, for which the dominant format is STL (an unstructured collection of triangles used to represent structured meshes). In STL files, the coordinates of any vertex are encoded once for each of the triangle incidents at that vertex, which leads to a highly redundant representation. While there is no recommended file size for STLs, anecdotally, the slicing software fails to write the G-Code for 3D printing when the number of vertices making the model gets close to 100k. Sometimes in such cases, the file gets sliced, but the 3D printing process fails. In our case, we had the number of  $U$  and  $V$  set to 100 to achieve the desired resolution for our surface, but it made the “sphere” model too complicated for FDM 3D printing.

In order to avoid such failures, we need to either slice the model into several pieces, fabricate each piece separately, and assemble them to have the final prototype or apply another roughness pattern to make the tactile surface. The initial feedback that we got

from the interpreters supports our hypothesis that having a dual color representation that visually matches the physical model to the RADAR imagery would be preferable. As a result, one design solution to make the tactile model while preserving the appearance of the RADAR imagery could be applying a scaling factor to each cell of the prism map shown in Figure 3-2. Such scaling factor should be in reverse order, i.e., the cell with the least brightness (shortest height) shrinks the most (**Figure 5-1**). Although the resulting roughness model from this approach seems promising in terms of representing the roughness values and visually matching the RADAR imagery, it has high potential for breakage having too many tiny and narrow details. One possible solution to overcome this issue is to carve the scaled cells in Figure 5-1 out of the original cells to make varying apertures (Figure 5-2). Such an approach helps in preserving the appearance of the RADAR imagery and can provide a dual-color appearance without the necessity to be printed in dual colors.

## CONCLUSION AND FUTURE WORK

In this WIP paper, we presented a novel approach for representing RADAR imagery showing the ice roughness in a tangible method. Our approach uses the core concept of physicalizations to convey the message of such important and critical data in an interactive tactile method by using an accessible 3D printer. It is expected that INTUIT will facilitate the learning of RADAR content and interpretation, ultimately reducing

the life-threatening risks for these Arctic residents. In the future, we plan to formally compare different design variations to show roughness. A formative study will be conducted to identify the ideal resolution for the designs, considering both the limitations of fabrication and human tactile perception. This study will also aim to decrease the number of design options for the final evaluation involving interpreters in the North. The forthcoming versions will undergo formal testing as part of the Sikumik Qaujimajuti training with new participants. This testing will aim to determine user design preferences, efficacy, and performance impacts. Co-development of the design will be critical, as well as incorporating measures and assessment of experience, learning impact, and self-efficacy from an Inuit perspective and with Inuit values.

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