RECENT DEVELOPMENTS WITH THE COMMUNITY SNOW OBSERVATIONS PROJECT - FROM CONCEPT TO OPERATIONAL MODELING

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ABSTRACT: The Community Snow Observations (CSO) project crowd-sources snow depth information from backcountry recreationists and professionals in mountain environments. These individuals frequently traverse steep areas of complex terrain that are under-sampled by existing snow data networks such as the SNOTEL network in the USA. The CSO project then assimilates these data into high-resolution models of snowpack distribution and evolution in these areas, and returns model results to project participants in near-real time. Our modeling work has shown that assimilating crowd-sourced snow depth information improves our models beyond what can be achieved assimilating SNOTEL data alone. Here, we review aspects of model performance and review recent project developments, which include the use of forecast weather data and the production of new mobile apps for the visualization and exploration of the model results.

Keywords: modeling, data assimilation, community science, snow distribution

1. INTRODUCTION

Storage of water as seasonal snowpack is a substantial and important component of the hydrologic cycle. The peak snow-water-equivalent (SWE) of the western United States (Mote et al., 2018) has been estimated at 150 km^3 and that of North America (Wrzesien et al., 2018) at nearly 1700 km^3. An understanding of the distribution and evolution of this snowpack is important for many reasons, including water resources planning, hazard mitigation, ecosystem services and function, economic benefit, and hydrosphere and cryosphere modeling, among others.

We can measure or estimate the distribution of snow properties using several different techniques. In the United States, in-situ measurements come from Snow Telemetry (Schaefer and Johnson, 1992) (SNOTEL), Soil Climate and Analysis (SCAN), and Snow Course Data (SCD) networks operated by the Natural Resources Conservation Service (NRCS), state snow-survey programs, state Departments of Transportation, and other sources. In-situ observations are typically at low spatial-resolution and they under-sample high-elevation regions of complex terrain due to the need for vehicular access for installation and maintenance of equipment.

Snow information is also sourced from remote-sensing campaigns, and can come from airborne LIDAR (light detection and ranging) (Painter et al., 2016), UAV (Unpiloted Aerial Vehicle) LIDAR (Jacobs et al., 2020), satellite LIDAR (Abdalati et al., 2010), visible-range imagery (Painter et al., 2009), and radar (Gusmeroli et al., 2014), among other methods. The spatial resolution of these data projects can be very high, on the order of 1 m for airborne LIDAR. The spatial coverage depends upon the platform. Airborne measurements are local-to-regional, while satellite platforms can offer near global coverage. A disadvantage of remotely sensed measurements is their high cost and comparatively low temporal resolution. For example, the Ice, Cloud, and Elevation Satellite (ICESat-2) (Neumann et al., 2019) mission repeats ground tracks every 91 days.

Modeling (Essery et al., 2013) of snowpack processes is an important third source of snow information that is able to 'fill the gaps' in space and time that exist in remotely-sensed and in-situ datasets. They also have considerable operational (real-time predictions) (Franz et al., 2008) value to a wide range of stakeholders, including avalanche forecasters and water managers. Models can be run at a wide range of spatial and temporal resolutions and can be statistically or physically based. An exam-

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ple of the latter, energy balance models use either weather station data or gridded reanalysis or modeled fields to drive estimations of energy fluxes and surface hydrology.

Community involvement in designing and carrying out science campaigns is a powerful additional tool, largely due to the issues of scale and capacity. Fixed-station networks are often limited and cannot sample everywhere all of the time (Crall et al., 2015; Roy et al., 2012). Volunteer community scientists can add to these datasets by collecting data at times and places not covered by fixed-station networks. The idea of crowdsourcing environmental data from community scientists is far from new. The Cooperative Observer Program (COOP) (Leeper et al., 2015) of the National Weather Service (USA) was started in 1891 and presently has in excess of 11,000 observers contributing measurements. In the narrower context of seasonal snow and ice, there have been previous efforts (Dickerson-Lange et al., 2016) to document snow cover with smart phones and studies (Carey et al., 2016) of how high-elevation mountaineers and alpinists can inform science based on their observations from the field.

Community science brings with it a unique set of opportunities and challenges. One advantage is that there is evidence (Garbarino and Mason, 2016; Bonney et al., 2016; Mitchell et al., 2017) that community science democratizes access to science and encourages scientific literacy in the greater public. Additionally, the measurements can be comparatively low cost and potentially increase spatial coverage. They come from volunteers who possess the resources and skills (or obtain them with minimal training) to travel to the field, collect the data, and transmit it to the project team. Regarding challenges, by its very nature, community science can be decentralized and unstructured. A project team can offer suggestions about sampling strategy, but ultimately must rely on decisions made by the participants. Another challenge has to do with data quality control. Protocols can be developed and tutorials provided but, in the end, measurements are coming from a diverse body of contributors with differing levels of experience.

In 2017, the Community Snow Observations (CSO; communitysnowobs.org) (Hill et al., 2018) project was launched, with the goal of developing a global network of citizen scientists who would collect and submit measurements of snow depth. While anyone can participate, the project has prioritized participation by backcountry recreationists (skiers, snowmobilers, snowshoers, etc.) and snow professionals (ski patrollers, avalanche forecasters, etc.) since these users visit high-elevation regions of complex terrain. The primary goal of the CSO project has been to demonstrate that *citizen* scientist participation in the collection of snow information can improve models of snowpack evolution and distribution in these complex locations (Crumley et al., 2020). Largeron et al. (2020) provide a recent and comprehensive look at data assimilation in snowpack modeling which focuses on measurements by research scientists. In 2021, the CSO project launched the website `mountainsnow.org` (Section 4) in order publicly share model results and other snow information with project participants and the general public. This website is part of the two-way communication and collaboration between participants and team scientists.

In this paper we first review the structure of and participation in the CSO project. We look at where, when, and how frequently users contribute data. We next demonstrate the utility of the data, in terms of improving snowpack model performance, and we give examples of model products that can be returned to participants, to further engage participation and provide a wider understanding of snowpack distribution. Finally, we compare CSO data to a wide variety of NASA and NOAA snow products to show how citizen science data can be used to validate national and global snow datasets.

2. MATERIALS AND METHODS

The CSO project requires five primary components to function. These include (1) a program to recruit and retain community scientists, (2) instrumentation for measuring snow depth in the field, (3) instrumentation for logging and submitting measurements, (4) web services for gathering and displaying participant data online, for public exploration and download, and (5) a modeling environment for assimilating community scientist measurements into snowpack estimates and comparing measurements and model results to other model products and remote sensing measurements.

2.1. Partipant Recruitment

We recruit three general categories of participants. First, the majority of CSO participants are winter recreationists, including backcountry skiers, snowboarders, snowshoers, and snowmobilers. These participants participate in CSO as part of their recreational day out in the backcountry. We reach these participants through a broad mix of outreach efforts. Our second major category of project participants includes snow professionals such as avalanche forecasters and ski patrollers. These users end up logging snow depth information as part of their own work. We reach these participants partly through publishing articles about the project in trade magazines (Hill, 2019; Hill and Redpath, 2020). Finally, our project receives many submissions from outdoor education programs that run winter classes. To retain participants, our project team creates and disseminates snow products (images, animations, etc.) that are related to the snow conditions at the locations where participants collect and submit data. We also provide educational materials about snow science and snow data sources, with the goal of educating participants and building their interest in how snow is distributed and evolves.

2.2. Field Snow Measurements

To minimize cost and complexity, the CSO project focuses only on snow depth (Hs), rather than more complex and time-consuming variables such as snow-water-equivalent (SWE) or albedo. The primary tool for CSO participants is an avalanche probe. An avalanche probe is a key piece of safety equipment carried by backcountry snow enthusiasts and professionals. While they vary from manufacturer to manufacturer, most probes are 3 m long and have 1 cm markings. They are compact, easy to deploy, and easy to use. Participants who live in areas where avalanche hazards do not exist (gentle terrain) can easily use a meterstick, or a tape measure affixed to a basket-less ski or trekking pole. Key elements to a good measurement include finding an area of undisturbed snow and making multiple measurements over an area of a few square meters in order to obtain a reliable average depth for that area.

2.3. Logging and Submitting Measurements

CSO requires geo-located and time-stamped snow depth measurements. In order to maximize participation from the broadest possible audience, CSO has both mobile and desktop platforms for submitting these measurements. Mobile apps are the best choice for most users since only a smart phone is required. Other users, such as avalanche forecasters, go out into the field to collect much more complicated datasets, including vertical profiles of the snowpack structure. These users commonly log data in a field notebook, so a desktop application is best for allowing them to submit data later from their home or office.

Currently, CSO sources most of its data from two platforms. The mobile app (Android and iOS) is the Snow Scope App from Propagation Labs (https://www.propagationlabs.com/). This app was customized, with input from the CSO team, to allow a 'one tap' entry of Hs from the landing page of the app. Even if a user is out of cell service, use of the app at the location of a measurement records the time and location, and this information (along with Hs) will be uploaded once back in cell service. The desktop application is Snow Pilot (https://snowpilot.org/) which is a widely used program used primarily by avalanche forecasters and other snow-safety professionals. While Snow Pilot allows (as does Snow Scope) the logging of complete pit profiles, only Hs values are used by the CSO program at this time.

2.4. Project Data Infrastructure

The CSO project has developed a data infrastructure for ingesting, managing, and serving Hs measurements submitted by community scientists using either of the supported platforms. This infrastructure is hosted on a commercial cloud provider (Amazon Web Services; AWS) and leverages specific cloud services, including AWS Relational Database Service (RDS) and AWS Lambda serverless compute. CSO data harvesters query Hs data from platform-provider APIs (Application Programming Interface), filter them for first-order quality thresholds, and integrate them in a common form in a relational database. A CSO API provides public access to CSO data to third parties and also to the CSO web map application. This web map application allows the user to filter, visualize, and download the data.

2.5. Snowpack Modeling Framework

The CSO project uses an unstructured, rapidly-deployable approach that is data-driven based on where participants travel and measure snow; we welcome an 'anytime, anyplace' approach to data collection by participants. The full details are provided by Crumley et al. (2020) and only summarized here. We use Micromet (Liston and Elder, 2006b) and SnowModel (Liston and Elder, 2006a), to distribute weather forcing to a high-resolution model grid and evolve the snowpack, respectively. To rapidly launch new model domains, we have developed freely available scripts and digital notebooks (e.g., Jupyter) that (1) fully automate the acquisition of weather, terrain, and land cover data for a prescribed area and time period, (2) obtain SNOTEL and SCAN weather and snowpack data for the purposes of calibration, (3) automatically calibrate the model, and (4) run the model operationally to provide estimates of today's snowpack.

As an initial step in the operational modeling, all Hs measurements are converted (Hill et al., 2019) to SWE estimates using regression methods. The next step in the modeling process is to assimilate in the data collected from community scientists using SnowAssim (Liston and Hiemstra, 2008). The community scientist SWE estimate is compared to the model SWE estimate and a correction 'surface' is created that adjusts precipitation inputs and / or melt rates in order to guide the model simulations back to the citizen scientist measurements. Where available, direct SWE measurements from SNOTEL stations are also assimilated. With our data-driven approach, the CSO project can rapidly implement model simulations in areas where project participation is high and where calibration data exist (usually SNOTEL). Typical spatial resolutions are 30 - 100 m and snow properties are saved at a daily time step.

3. RESULTS

Here we look back at the history of the project to quantify participation, and to briefly look at how participation affects our ability to accurately model snow distribution. We additionally look at how the data from our participants compare with other sources of snow information.

3.1. Participation Statistics

The growth in the cumulative number of submissions and unique participants is shown in Fig. 1. While CSO is a global program, the majority of our submissions come from the Northern Hemisphere. This explains the seasonal nature of the rate of observations. The rate of submissions during the 2019-2020 snow season was less due to the Covid-19 restrictions that curtailed access to many public lands used by winter recreationists (national forest, national park, etc.). Since the project inception, the mean number of submissions per user is 8, and there are 665 users who have made more than 10 measurements, 150 who have made more than 50 measurements, and 61 who have made more than 100.

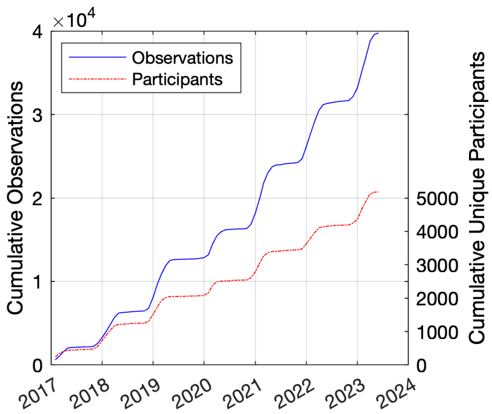

Figure 1: Cumulative observations and participants for the CSO project.

3.2. Inclusion of CSO Data in Snowpack Modeling

The CSO concept was initially tested in a pilot study at Thompson Pass, southcentral Alaska (USA). Following model calibration (using the Upper Tsaina River SNOTEL station), assimilation runs were conducted with a variety of 'subsetting' methods for the community scientist submissions. A sample result is shown in Fig. 2. In this figure the 'No Assim' result is the calibrated model run, with no community input. It is clear that the model significantly overestimates the snowpack, with a bias of 7 cm and a root-mean-square-error (RMSE) of 10 cm. Biases like these are commen when using gridded reanalysis (CFSv2 in this case) data for model forcing. The 'Best Assim' result shows the assimilation run with the combination of CSO observations that was found to yield the lowest errors. In this case, the bias is 0 cm and the RMSE is 1 cm. This demonstrates the exciting potential that community participation has, in terms of overcoming model forcing deficiencies and improving knowledge of snow distribution and evolution.

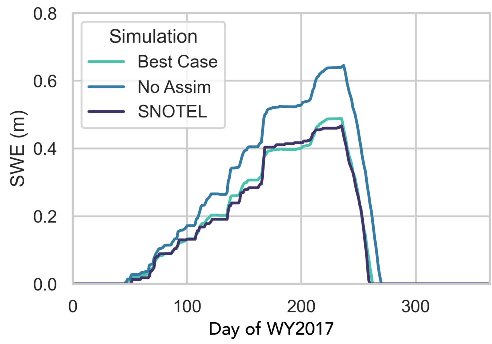

Figure 2: Comparison of observed and modeled snow water equivalent (SWE) at the Upper Tsaina River SNOTEL site for water year 2017.

3.3. Comparison to SNODAS

The Snow Data Assimilation System (SNODAS) (Carroll et al., 2001) provides daily gridded (1 km) information on snow variables over the conterminous United States (CONUS) beginning in 2003. The SNODAS modeling system assimilates in a wide variety of information including SNOTEL, snow course data, CoCoRaHS data, and others. Figure 3 (top) shows heat maps of SNODAS Hs estimates compared to CSO data. In each case, a 'nearest neighbor' approach was used to extract the SNODAS value corresponding to the measurement location.

The density functions of the errors between the SNODAS estimates and the measurements of Hs are also shown in Fig. 3 (bottom). Error is defined as SNODAS estimate minus the measurement. There is a significant negative bias, indicating that the SNODAS model is under-predicting the snow in the high mountain areas visited by CSO participants. This tendency for SNODAS to underestimate the snow in high elevations has been noted before (Sirén et al., 2018). The large CSO dataset may therefore be of value to regional-to-national scale assimilative modeling efforts.

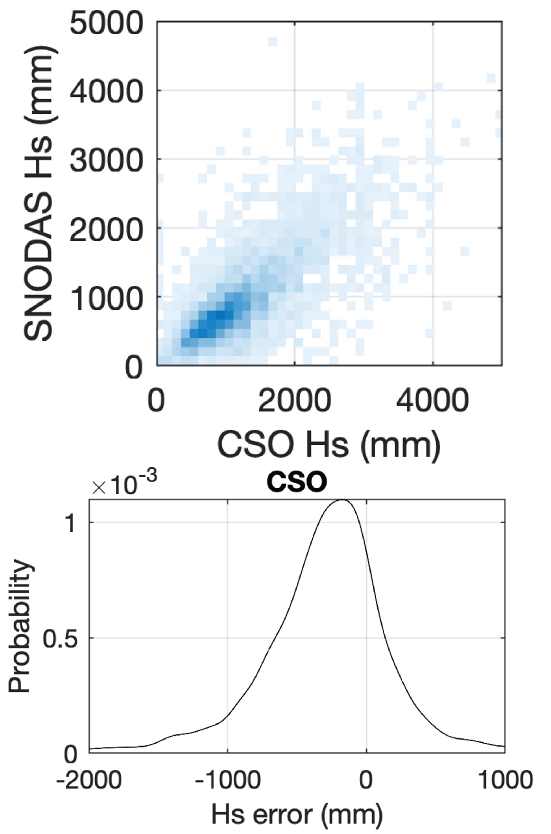

Figure 3: Heat map (top) of SNODAS Hs estimate compared to CSO Hs measurement. Errors (bottom) between SNODAS estimates and CSO Hs measurements.

3.4. Comparison to MODIS

A variety of snow products are provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) (Hall et al., 1995) and VIIRS (Key et al., 2013) missions. As one example, the MOD10A1 product (Version 6) is a 500 m, daily product. One of the variables provided by the MOD10A1 product is the Normalized Difference Snow Index (NDSI). While there is regional variability, an NDSI value of 40 (%) is an accepted global standard (Riggs et al., 2015) for indicating snow-covered-area (SCA).

CSO data points are typically from high-elevation, complex-terrain environments and provide a unique comparison with the MOD10A1 product. CSO observers are typically only out in the field when there is snow. Additionally, CSO observers tend to be in regions of considerable snow depth. The mean depth of the CSO database is 135 cm. The location and time of CSO submissions should therefore be reliable indicators of snow-covered areas. As a check of this, the NDSI values were extracted at CSO submission locations (CONUS only) for two seasons (4000 measurements) using a nearest neighbor approach. Of the 4000 measurements, 1298 returned valid NDSI values and over 2600 were flagged as cloud-covered. A histogram of the valid values (Fig. 4 top) is very consistent with the idea of NDSI > 40 indicating SCA. Only 79 (6%) of the valid measurements have an NDSI less than this threshold value. There are 24 (2%) valid measurements that have NDSI $= 0$.

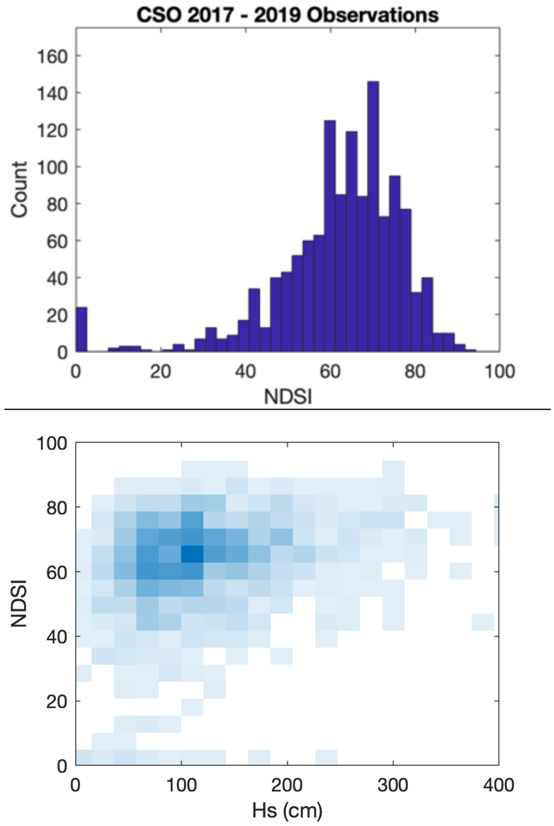

Figure 4: Histogram (top) of NDSI values at CSO observation locations / times. Heatmap (bottom) of MODIS NDSI value compared to CSO Hs value.

A heatmap between NDSI and Hs (Fig. **??** bottom) provides a deeper look into the data and we see that most of the points with low NDSI have non-zero Hs. One possibility could be that a user was entering a no-depth measurement (which is valid, if infrequently reported, data) but mis-typed and entered a non-zero depth. In this case, MODIS correctly reports NDSI $= 0$ and the CSO point is in error and could be flagged as an outlier. A second possibility could be a geolocation error. In this case, the CSO user is correctly reporting non-zero Hs, but it gets incorrectly reported in a location with no Hs (and NDSI $= 0$ from MODIS) and the point could be flagged as an outlier. A third possibility is related to sub-grid scale variability. A pixel with an NDSI value of 0 is supposed to indicate a snow-free land surface over the 500 m grid cell. There are several processes, including wind redistribution and differential melting that can lead to 'mixed pixel' conditions where both snow and bare ground exist. If a pixel is mostly bare (say near the snow line), then it seems possible to have a valid non-zero Hs measurement accompany a NSDI $= 0$ value.

When we examined the 24 data points with NDSI $= 0$, we found that they were all in high mountain locations during snow season. These facts reduce the likelihood that the first two explanations above are responsible for the low NDSI. To better understand the low NDSI values, future CSO measurements spanning whole MODIS pixels should be made. An organized effort like this will help determine the degree to which MODIS data could be used to identify outlier CSO points, or the degree to which CSO data might help refine the MODIS results.

4. OPERATIONAL SNOW PRODUCTS

A key feature of the CSO program is that it is a 'two-way' collaboration between program participants and the program scientists. Participants share their data with us, but also their ideas on what sorts of snow information most interests them. And, the CSO project team, in turn, provides this snow information, in real time. To make this happen, we launched the Mountain Snow website (`https://mountainsnow.org`) a few years into the project. At this site, users can explore and interact with Hs and SWE data from the CSO project, Hs and SWE data from SNODAS, satellite imagery, and MODIS snow-cover data. Together, these products provide a holistic view of snow, how it is distributed, and how it is changing. To give just one example, viewers can access snow information for any given day of the water year, but they can also choose to view a 72-hour 'delta' or change in the snowpack. This layer provides valuable information about recent large snowfall events, which may lead to increased avalanche hazards. Figure 5 provides both an overview of all of our modeling efforts and also a zoomed in view of one of our domains on a typical day. In addition to providing results visually, all of our data are freely available (as cloud-optimized geoTIFF files) on Google Cloud Storage for download and use by any interested party. To access the data simply go to `https://console.cloud.google.com/storage/browser/cso_test_upload`.

One recent development has to do with the timing of the model runs. The operational modeling uses reanalysis data (CFSv2) from the Climate Forecast System, on a six-hour time step. Within the Google Earth Engine framework, there is a two day latency. What this means (Fig. 6) is that on a given day (day n) you can access data up to and including the day before yesterday (n-2). But, running the model also takes a day. So, on day n, the 'latest' results that can be viewed at Mountain Snow are the results from

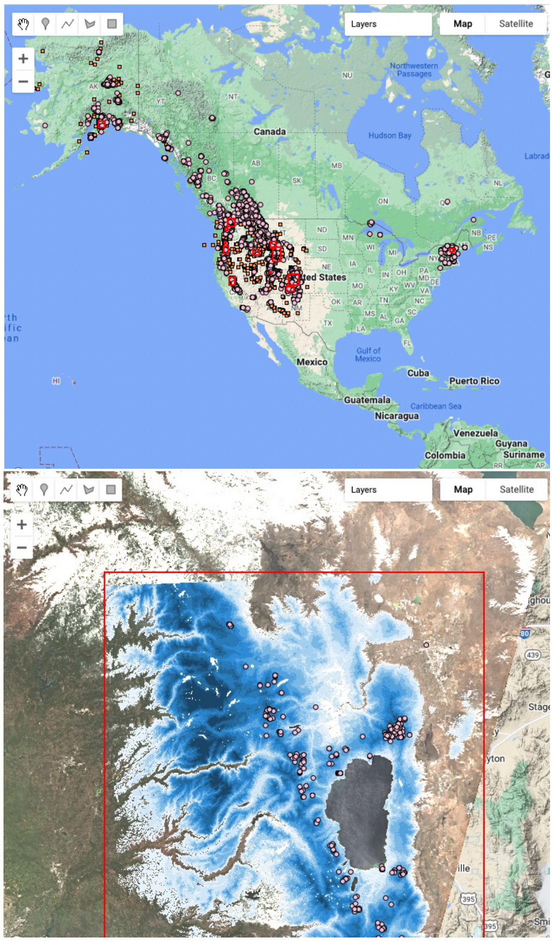

Figure 5: Overview map (top) of current operational modeling domains in the USA. Red boxes show domains and pink dots show locations of CSO observations. Zoomed in view (bottom) of Tahoe modeling domain showing 50 m modeled snowpack, and underlying Sentinel imagery on April 15, 2023.

day n-3. This left a three day gap at Mountain Snow. Starting in spring 2023, however, we closed this gap by blending reanalysis data with forecast data. This is illusted by the blue and pink symbols in Fig. 6. On hour 18 of day n-2, we acquire 72 hours of forecast data to allow for computations through 'tomorrow' (day n+1). The net result of this is that when you visit Mountain Snow, you will see gridded snow distribution results that run up to and including 'today,' thereby providing a truly real-time source of snow information.

5. CONCLUDING REMARKS

The Community Snow Observations project has successfully demonstrated that opportunistic, crowd-sourced snow depth data can significantly improve models of snow distribution and evolution in data-sparse mountainous terrain. The project receives data from a very wide range of users that include recreational users such as skiers, snowboarders and snowshoers; snow professionals

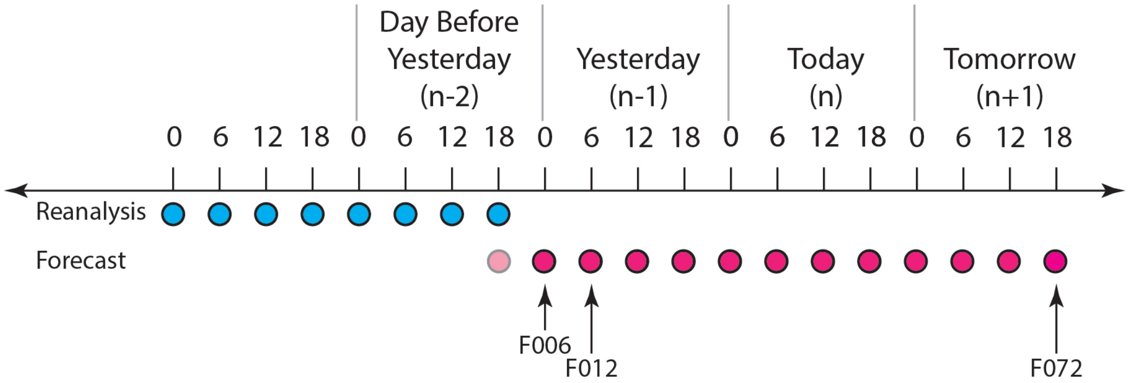

Figure 6: Conceptual figure of model timing for operational runs.

such as avalanche forecasters and ski patrollers; and individuals involved in educational and environmental programs. We continually grow our pool of participants through numerous outreach efforts and we train our participants through easy-to-follow and intuitive video and written tutorials. Finally, we have developed our project to be geographically responsive to participation. Through fully automated setup and calibration procedures, we are able to deploy new model implementations quickly and efficiently.

The project benefits in that it receives high-value data that are not available by other means, and participants benefit through learning more about their local snowpack and through seeing visual and video products that are the direct result of their measurements. Having the word ‘community’ in the name of the project is intentional. Beyond the scientific goals of the CSO project, we hope to realize two additional goals. First we hope to inspire individuals to learn more about their local snow and water resources. Second, we hope to inspire the recognition that a community of community scientists can advance scientific understanding in ways that disconnected individuals cannot.

ACKNOWLEDGEMENT

Funding for this project has been provided by NASA (CSESP16-0015), the CUAHSI Pathfinder Fellowship (R. Crumley and C. Aragon), the DeVaan Fellowship (C. Aragon), and National Geographic (D. Hill).

References

Abdalati, W., Zwally, H. J., Bindschadler, R., Csatho, B., Farrell, S. L., Fricker, H. A., Harding, D., Kwok, R., Lefsky, M., Markus, T., Marshak, A., Neumann, T., Palm, S., Schutz, B., Smith, B., Spinhirne, J., and Webb, C.: The ICESat-2 Laser Altimetry Mission, Proceedings of the IEEE, 98, 735–751, doi:10.1109/JPROC.2009.2034765, conference Name: Proceedings of the IEEE, 2010.

Bonney, R., Phillips, T. B., Ballard, H. L., and Enck, J. W.: Can citizen science enhance public understanding of science?, Public Understanding of Science, 25, 2–16, doi:10.1177/0963662515607406, URL https://doi.org/10.1177/0963662515607406, publisher: SAGE Publications Ltd, 2016.

Carey, M., Garrard, R. W., Cecale, C., Buytaert, W., Huggel, C., and Vuille, M.: Climbing for science and ice: From Hans Kinzl and mountaineering-glaciology to citizen science in the Cordillera Blanca, Revista de Glaciares y Ecosistemas de Montaña, 1, 59–72, URL https://issuu.com/inaigem/docs/revista_inaigem_final_y_car__t.__1_, num Pages: 14 Number: 1 Publisher: Instituto Nacional de Investigación en Glaciares y Ecosistemas de Montaña, 2016.

Carroll, T., Cline, D., Nilsson, A., Li, L., and Rost, A.: NOHRSC operations and the simulation of snow cover properties for the conterminous U.S., in: Proc. 69th Annual Meeting of the Western Snow Conf., p. 14pp, Sun Valley, ID, 2001.

Crall, A. W., Jarnevich, C. S., Young, N. E., Panke, B. J., Renz, M., and Stohlgren, T. J.: Citizen science contributes to our knowledge of invasive plant species distributions, Biological Invasions, 17, 2415–2427, doi:10.1007/s10530-015-0885-4, URL https://doi.org/10.1007/s10530-015-0885-4, 2015.

Crumley, R., Hill, D., Wikstrom-Jones, K., Wolken, G., Arendt, A., Aragon, C., and Cosgrove, C.: Assimilation of citizen science data in snowpack modeling using a new snow dataset: Community Snow Observations, Hydrology and Earth System Sciences, in review, 2020.

Dickerson-Lange, S., Eitel, K., Dorsey, L., Link, T., and Lundquist, J.: Challenges and successes in engaging citizen scientists to observe snow cover: from public engagement to an educational collaboration, Journal of Science Communication, pp. 1–14, doi:https://doi.org/10.22323/2.15010201, URL https://jcom.sissa.it/author/susan-dickerson-lange, last Modified: 2016-01-21T12:10+01:00 Publisher: SISSA Medialab, 2016.

Essery, R., Morin, S., Lejeune, Y., and B Ménard, C.: A comparison of 1701 snow models using observations from an alpine site, Advances in Water Resources, 55, 131–148, doi:10.1016/j.advwatres.2012.07.013, URL http://www.sciencedirect.com/science/article/pii/S0309170812002011, 2013.

Franz, K. J., Hogue, T. S., and Sorooshian, S.: Operational snow modeling: Addressing the challenges of an energy balance model for National Weather Service forecasts, Journal of Hydrology, 360, 48–66, doi:10.1016/j.jhydrol.2008.07.013, URL http://www.sciencedirect.com/science/article/pii/S0022169408003508, 2008.

Garbarino, J. and Mason, C. E.: The Power of Engaging Citizen Scientists for Scientific Progress, Journal of Microbiology & Biology Education, 17, 7–12, doi:10.1128/jmbe.v17i1.1052, 2016.

Gusmeroli, A., Wolken, G. J., and Arendt, A. A.: Helicopter-borne radar imaging of snow cover on and around glaciers in Alaska, Annals of Glaciology, 55, 78–88, doi:10.3189/2014AoG67A029, URL https://www.cambridge.org/core/journals/annals-of-glaciology/article/helicopterborne-r adar-imaging-of-snow-cover-on-and-around-glaciers-in-alaska/73316806597608C606DAFC6AD1DF54A2, publisher: Cambridge University Press, 2014.

Hall, D. K., Riggs, G. A., and Salomonson, V. V.: Development of methods for mapping global snow cover using moderate resolution imaging spectroradiometer data, Remote Sensing of Environment, 54, 127–140, doi:10.1016/0034-4257(95)00137-P, URL http://www.sciencedirect.com/science/article/pii/003442579500137P, 1995.

Hill, D.: Community Snow Observations: Using Citizen Scientist Data to Build Better Snow Models, The Avalanche Review, 37, 16–17, 2019.

Hill, D. and Redpath, T.: Snow Data or No Data; it's up to You, New Zealand Avalanche Dispatch, 1, 70–73, 2020.

Hill, D., Wolken, G., Wikstrom-Jones, K., Crumley, R., and Arendt, A.: Crowdsourcing Snow Depth Data with Citizen Scientists, Eos, doi:https://doi.org/10.1029/2018EO108991, URL https://eos.org/science-updates/crowdsourcing-snow-depth-data-with-citizen-scientists, library Catalog: eos.org, 2018.

Hill, D. F., Burakowski, E. A., Crumley, R. L., Keon, J., Hu, J. M., Arendt, A. A., Wikstrom Jones, K., and Wolken, G. J.: Converting snow depth to snow water equivalent using climatological variables, The Cryosphere, 13, 1767–1784, doi: https://doi.org/10.5194/tc-13-1767-2019, URL https://tc.copernicus.org/articles/13/1767/2019/, publisher: Copernicus GmbH, 2019.

Jacobs, J. M., Hunsaker, A. G., Sullivan, F. B., Palace, M., Burakowski, E. A., Herrick, C., and Cho, E.: Shallow snow depth mapping with unmanned aerial systems lidar observations: A case study in Durham, New Hampshire, United States, The Cryosphere Discussions, pp. 1–20, doi:https://doi.org/10.5194/tc-2020-37, URL https://tc.copernicus.org/preprints/tc-2020-37/, publisher: Copernicus GmbH, 2020.

Key, J. R., Mahoney, R., Liu, Y., Romanov, P., Tschudi, M., Appel, I., Maslanik, J., Baldwin, D., Wang, X., and Meade, P.: Snow and ice products from Suomi NPP VIIRS, Journal of Geophysical Research: Atmospheres, 118, 12,816–12,830, doi:10.1002/2013JD020459, URL https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2013JD020459, _eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2013JD020459, 2013.

Largeron, C., Dumont, M., Morin, S., Boone, A., Lafaysse, M., Metref, S., Cosme, E., Jonas, T., Winstral, A., and Margulis, S. A.: Toward Snow Cover Estimation in Mountainous Areas Using Modern Data Assimilation Methods: A Review, Frontiers in Earth Science, 8, doi:10.3389/feart.2020.00325, URL https://www.frontiersin.org/articles/10.3389/feart.2020.00325/full, publisher: Frontiers, 2020.

Leeper, R. D., Rennie, J., and Palecki, M. A.: Observational Perspectives from U.S. Climate Reference Network (USCRN) and Cooperative Observer Program (COOP) Network: Temperature and Precipitation Comparison, Journal of Atmospheric and Oceanic Technology, 32, 703–721, doi:10.1175/JTECH-D-14-00172.1, URL https://journals.ametsoc.org/jtech/article/32/4/703/4722/Observational-Perspectives-from-U-S-Climate, publisher: American Meteorological Society, 2015.

Liston, G. E. and Elder, K.: A Distributed Snow-Evolution Modeling System (SnowModel), Journal of Hydrometeorology, 7, 1259–1276, doi:10.1175/JHM548.1, URL http://journals.ametsoc.org/doi/abs/10.1175/JHM548.1, 2006a.

Liston, G. E. and Elder, K.: A Meteorological Distribution System for High-Resolution Terrestrial Modeling (MicroMet), Journal of Hydrometeorology, 7, 217–234, doi:10.1175/JHM486.1, URL http://journals.ametsoc.org/doi/abs/10.1175/JHM486.1, 2006b.

Liston, G. E. and Hiemstra, C. A.: A Simple Data Assimilation System for Complex Snow Distributions (SnowAssim), Journal of Hydrometeorology, 9, 989–1004, doi:10.1175/2008JHM871.1, URL https://journals.ametsoc.org/jhm/article/9/5/989/5869/A-Simple-Data-Assimilation-System-for-Complex-Snow, publisher: American Meteorological Society, 2008.

Mitchell, N., Triska, M., Liberatore, A., Ashcroft, L., Weatherill, R., and Longnecker, N.: Benefits and challenges of incorporating citizen science into university education, PLOS ONE, 12, e0186 285, doi:10.1371/journal.pone.0186285, URL https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0186285, publisher: Public Library of Science, 2017.

Mote, P. W., Li, S., Lettenmaier, D. P., Xiao, M., and Engel, R.: Dramatic declines in snowpack in the western US, npj Climate and Atmospheric Science, 1, 1–6, doi:10.1038/s41612-018-0012-1, URL https://www.nature.com/articles/s41612-018-0012-1, number: 1 Publisher: Nature Publishing Group, 2018.

Neumann, T. A., Martino, A. J., Markus, T., Bae, S., Bock, M. R., Brenner, A. C., Brunt, K. M., Cavanaugh, J., Fernandes, S. T., Hancock, D. W., Harbeck, K., Lee, J., Kurtz, N. T., Luers, P. J., Luthcke, S. B., Magruder, L., Pennington, T. A., Ramos-Izquierdo, L., Rebold, T., Skoog, J., and Thomas, T. C.: The Ice, Cloud, and Land Elevation Satellite – 2 mission: A global geolocated photon product derived from the Advanced Topographic Laser Altimeter System, Remote Sensing of Environment, 233, 111 325, doi:10.1016/j.rse.2019.111325, URL http://www.sciencedirect.com/science/article/pii/S003442571930344X, 2019.

Painter, T. H., Rittger, K., McKenzie, C., Slaughter, P., Davis, R. E., and Dozier, J.: Retrieval of subpixel snow covered area, grain size, and albedo from MODIS, Remote Sensing of Environment, 113, 868–879, doi:10.1016/j.rse.2009.01.001, URL http://www.sciencedirect.com/science/article/pii/S0034425709000029, 2009.

Painter, T. H., Berisford, D. F., Boardman, J. W., Bormann, K. J., Deems, J. S., Gehrke, F., Hedrick, A., Joyce, M., Laidlaw, R., Marks, D., Mattmann, C., McGurk, B., Ramirez, P., Richardson, M., Skiles, S. M., Seidel, F. C., and Winstral, A.: The Airborne Snow Observatory: Fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo, Remote Sensing of Environment, 184, 139–152, doi:10.1016/j.rse.2016.06.018, URL http://www.sciencedirect.com/science/article/pii/S0034425716302577, 2016.

Riggs, G., Hall, D., and Roman, M.: VIIRS Snow Cover Algorithm Theoretical Basis Document (ATBD), Tech. rep., NASA Goddard Space Flight Center, Greenbelt, MD, 2015.

Roy, H. E., Pocock, M. J. O., Preston, C. D., Roy, D. B., Savage, J., Tweddle, J. C., and Robinson, L. D.: Understanding citizen science and environmental monitoring: final report on behalf of UK Environmental Observation Framework, URL http://www.ukeof.org.uk/documents/understanding-citizen-science.pdf, num Pages: 173 Place: Wallingford Publisher: NERC/Centre for Ecology & Hydrology, 2012.

Schaefer, G. and Johnson, D.: Development and operation of the SNOTEL system in the western United States, in: Proc. United States/People's Republic of China Flood Forecasting Symp., vol. 1, pp. 29–48, Office of Hydrology, National Weather Service, Portland, OR, 1992.

Sirén, A. P. K., Somos-Valenzuela, M., Callahan, C., Kilborn, J. R., Duclos, T., Tragert, C., and Morelli, T. L.: Looking beyond wildlife: using remote cameras to evaluate accuracy of gridded snow data, Remote Sensing in Ecology and Conservation, 4, 375–386, doi:https://doi.org/10.1002/rse2.85, URL https://zslpublications.onlinelibrary.wiley.com/doi/abs/10.1002/rse2.85, _eprint: https://zslpublications.onlinelibrary.wiley.com/doi/pdf/10.1002/rse2.85, 2018.

Wrzesien, M. L., Durand, M. T., Pavelsky, T. M., Kapnick, S. B., Zhang, Y., Guo, J., and Shum, C. K.: A New Estimate of North American Mountain Snow Accumulation From Regional Climate Model Simulations, Geophysical Research Letters, 45, 1423–1432, doi:10.1002/2017GL076664, URL https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017GL076664, _eprint: