Ascending the data usability gap in mountainous regions through scientist-stakeholder co-production

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**Hyperion project**

**Objectives**
- Develop multi-metric dataset evaluation toolkit
- Engage stakeholder community for decision-relevant metrics
- Provide insight into the usability of climate information
- Identify sources of model error
- Evaluate cutting-edge climate model simulations

**Software pipeline under development**

climatemodeling.ucdavis.edu/hyperion
Case studies

Sacramento-San Joaquin Watershed, California (CA)

Susquehanna River (Su)

Colorado Headwaters (CO)

South Florida (FL)
Scientist-Stakeholder co-production

• Stakeholders get:
  • A chance to shape the science in a way that ultimately benefits their work
  • A chance to learn more about the science, what is knowable and unknowable

• Scientists get:
  • A challenge – can we make our models good enough to meet real-world challenges?
  • Can we characterize uncertainties in a way that is accessible and represents limits in knowledge?
  • A chance to be relevant / useful

• Scientist-Stakeholder co-production leads to:
  • New perspectives for scientific research
  • Potentially more usable climate information that is not solely based on “ivory tower” objectives
  • A new way of interrogating datasets and models, aka decision relevant metrics
Scientist-Stakeholder co-production

Goal: Create scientist-stakeholder interactions to discuss the usability of climate information and develop decision relevant metrics.

- **Dec 2016**
  - First Workshop
  - Climate challenges
  - Hydroclimate data use
  - Info gaps
  - Issues & metrics

- **Apr 2017**
  - Regional Stakeholder WG calls
  - Identify key issues and metrics
  - Regional Stakeholder Advisory Group Meeting
  - Stakeholder feedback on progress
  - Updated metrics

- **May 2017**
  - Science Lead Calls
  - Inputs on metrics

- **Aug 2017**
  - Stakeholder Advisory Group Meeting
  - Stakeholder feedback on progress
  - Docs for each hydroclimate phenomena

- **Sept 2017**
  - Regional Scientist Meeting
  - Identify decision-relevant metrics

- **Nov 2017**
  - Scientist-Stakeholder Focus Group Discussions
  - Finalize list of metrics
  - Discuss regional science plans
  - Guiding doc with complete metrics list
  - Consolidated metric summaries

- **Feb 2018**
  - Second Workshop
  - Feedback on science workflow
  - Regional decision-context & priorities
  - Updated metrics
  - Case study narratives

- **2016**
  - **2017**
  - **2018**

*Courtesy of Kripa Jagannathan*

Hyperion scientist-stakeholder co-production at Feb 2018 workshop
What is a decision-relevant metric?

Case Studies
- CA
- CO
- Su
- FL

Issues
- Drought
- Water Supply
- Flood

Hydroclimate Phenomena
- Snowpack
- Snowmelt
- Streamflow
- Dry/Wet Spells
- Flooding
- Extreme Precip

Aspect of Phenomenon
- Peak
- Timing
- Rate
- Variability
- Intensity
- Duration
- Frequency

Metrics
- Mean Snow Accumulation Rate
- Magnitude of 10-year 3-day precipitation event.
What is a decision-relevant metric?

Case Studies
- CA
- CO
- Focus of my talk

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Metrics
- Mean Snow Accumulation Rate
- Magnitude of 10-year 3-day precipitation event.
Creating a set of decision-relevant snowpack metrics

What are the key components of a snow season?

Data: Livneh et al., 2015 (L15)
doi:10.1038/sdata.2015.42
Creating a set of decision-relevant snowpack metrics

The snow water equivalent (SWE) triangle

Data: Livneh et al., 2015 (L15) doi:10.1038/sdata.2015.42

Water Resources Research

Snowpack regimes of the Western United States

Ernesto Trujillo, Noah P. Molotch
First published: 11 June 2014 | https://doi.org/10.1002/2013WR014753 | Cited by: 30

UC-eLinks

SECTIONS
Creating a set of decision-relevant snowpack metrics

How well does the SWE triangle represent the snow season in the headwaters of California’s major reservoirs?

Data: Livneh et al., 2015 (L15)
doi:10.1038/sdata.2015.42

L15 – all years

L15 – 1988

L15 – 1991

20-year daily climate average

Water year with less ephemeral snow

Water year with more ephemeral snow
Four Current Types

1. **Statistical Downscaling**
   Observed trends and/or DEM update global model output

2. **Dynamical Downscaling**
   Regional climate model (RCM) with prescribed data from global climate model (GCM)

3. **Hybrid Approach**

4. **Variable-Resolution Global Climate Models (VRGCM)**
   Provide regional resolution refinement internally within a global climate model

**Issues to Address**

1. Resolution dependence of surface heterogeneity
2. Bias propagation
3. Lack of direct feedback between large and small scales
4. Computational cost
5. Stationarity assumption
6. Uncertainty from incorporation of multiple models, observational datasets and/or climate change projections
Using and evaluating cutting-edge GCMs that can telescope resolution

**Variable-Resolution in the Community Earth System Model (VR-CESM)**

**Benefits:**
- Global simulation (atmosphere-ocean-land teleconnections)
- Globally conserved energy, mass and momentum (climate simulation)
- Increased resolution in specified areas (better topography)
- Decrease in model runtime and data storage ("smaller" server usage)
- Eliminates multi-model dataset needs (bias propagation)
- Merges regional and global modeling communities (scale awareness)
- Glimpse into the future of high-resolution global climate modeling

**Sampling of some of the new and ongoing projects using VR-CESM**

- **Sierra Nevada and western United States:** 7km
- **South American Andes:** 14km
- **Greenland:** 28km
Using and evaluating cutting-edge GCMs that can telescope resolution

Using VR-CESM to project potential snowpack loss in the western US (RCP8.5)

4th National Climate Assessment, Volume 1 – Chapter 8
Using the SWE triangle for multi-metric, multi-dataset evaluation

Observationally constrained snow products

- SNSR
- L15
- NLDAS_2_SAC
- NLDAS_2_VIC

RCMs forced by GCMs

- MPI_ESM_RCM at 50 km
- CanESM2_CanRCM4 at 50 km
- CanESM2_CRCM5 at 50 km
- MPI_ESM_CRCM5 at 50 km
- HadGEM2_WRF at 50 km
- HadGEM2_WRF at 25 km
- EC_EARTH_HIRHAM5 at 50 km
- GFDL_WRF at 50 km
- GFDL_WRF at 25 km
Using the SWE triangle for multi-metric, multi-dataset evaluation

Z-score error in SWE triangle metric - too low (too high)

Observationally constrained snow products

RCM forced by atmospheric reanalysis

RCM forced by GCM

VR-CESM

<table>
<thead>
<tr>
<th>18 California Regions</th>
<th>S01</th>
<th>S02</th>
<th>S03</th>
<th>S04</th>
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<td>0.75</td>
<td>3.18</td>
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</table>

Statistical downscaling (LOCA)
Identifying potential causation of the SWE triangle metric error

| Evaluation Simulations* | Total error | From Accum. | From Precip. | From Mean Precip. | From Precip. Distrib. | From Temp. | From Topo. | From Residual Temp. | From Thresh. Temp. | From Ablation | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
|------------------------|-------------|-------------|-------------|-------------------|------------------------|------------|-----------|---------------------|-----------------|--------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| CRCM5 - 44             | -69%        | -44%        | -31%        | -23%              | -10%                   | -16%       | -31%      | 13%                 | 0%              | -41%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
| CRCM5 - 22             | -47%        | -16%        | -24%        | -8%               | -17%                   | 6%         | -12%      | 17%                 | 0%              | -33%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
| CRCM5 - 11             | -38%        | -9%         | -21%        | -1%               | -20%                   | 9%         | -5%       | 13%                 | 0%              | -30%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
| CanRCM4 - 44           | -87%        | -55%        | -50%        | -42%              | -13%                   | -6%        | -31%      | 25%                 | 0%              | -64%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
| CanRCM4 - 22           | -65%        | -29%        | -43%        | -30%              | -18%                   | 25%        | -12%      | 35%                 | 0%              | -46%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
| RegCM4 - 44            | -56%        | 72%         | -20%        | -1%               | -19%                   | 13%        | -33%      | 40%                 | 55%             | -67%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
| RegCM4 - 22            | 33%         | 153%        | 7%          | 34%               | -20%                   | 39%        | -13%      | 46%                 | 55%             | -43%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
| WRF - 44               | -77%        | -20%        | -18%        | -16%              | -2%                    | -5%        | -17%      | 13%                 | 0%              | -64%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |
| WRF - 22               | -55%        | 12%         | -5%         | -2%               | -3%                    | 16%        | -6%       | 22%                 | 0%              | -54%         | $\varepsilon$ | $\varepsilon_A$ | $\varepsilon_P$ | $\varepsilon_\overline{p}$ | $\varepsilon_T$ | $\varepsilon_\overline{p}$ | $\varepsilon_r$ | $\varepsilon_{Th}$ | $\varepsilon_M$ |

Even when you correct for mean precipitation, spatial distribution produces an underestimated SWE (too much at mid-elevation, not enough at high-elevation).

Unresolved topography leads to warm bias.

cold bias after elevation correction.

All models show large errors in ablation, however do not provide radiation variables to interrogate further.
**Understanding the response of SWE triangle metrics to climate change across models**

**Historical, mid-century, end-century (RCP8.5)**

**RCM forced by GCM**

- **RCM** – symbol, **GCM** - color

### Multi-model mean (p=0.05)

- **Historical**: 8.54±3.39 (MAF)
- **Mid-century**: 1.94±2.23 (MAF)
- **End-century**: 0.76±1.07 (MAF)
Understanding the response of SWE triangle metrics to climate change between downscaling methods

**Historical, mid-century, end-century (RCP8.5)**

**RCM forced by GCM**

$\text{RCM} - \text{symbol, GCM} - \text{color}$

**Multi-model mean ($p=0.05$)**

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<tr>
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**Statistical downscaling**

**Multi-model mean ($p=0.05$)**

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<th>Year</th>
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<tbody>
<tr>
<td>Historical</td>
<td>9.91±0.36</td>
</tr>
<tr>
<td>Mid-century</td>
<td>6.82±0.51</td>
</tr>
<tr>
<td>End-century</td>
<td>4.28±0.48</td>
</tr>
</tbody>
</table>
Summary

- Scientist-stakeholder co-production can...
  1. Lead to new process understanding in climate models
  2. Enhance the usability of climate data in management and planning
  3. Influence future research and model development directions

- Decision-relevant metric development is a means to focus interaction between the two communities

- The SWE triangle multi-metric framework was one such attempt at creating decision relevant metrics and led to several useful insights...
  1. The uncertainty in SWE total water volume is large even between best-available observationally constrained products (2x difference)
  2. Climate model snow ablation rates are too fast even at high-resolution (~12km) or within cutting-edge climate downscaling techniques (e.g., VR-CESM)
  3. Under a high-emissions scenario, multi-model RCM ensemble highlights SWE total water volume will be substantially reduced by end-century (~79%)
  4. Statistical downscaling can better represent historical trends, but important differences at mid-to-end century with dynamical downscaling were seen (e.g., on average, SWE total water volume ~3-4 MAF higher at end-century)
Thanks for listening! Questions or comments?
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(In Review) Xu, Y., A.D. Jones, and A.M. Rhoades "Quantitative decomposition of the snowpack error in regional climate models: the interacting role of temperature, precipitation and ablation biases" Submitted to Scientific Reports.


