Estimating SWE from snow depth data: comparison of different approaches

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Davos Atmosphere and Cryosphere Assembly DACA-13 Davos, 10-07-2013

## Background and objectives

# • Snow Water Equivalent (SWE) has a fundamental role in mountain hydrology

- Many recent papers focused on estimating SWE from snow depth (HS) modelling snow density ( $\rho_s$ ) using historical datasets or field campaigns (e.g. Jonas *et al.* 2009, Sturm *et al.* 2010, Bormann *et al.* 2013, Lopez-Moreno *et al.* 2013, Sexstone *et al.* 2013, ...)
- Monthly or biweekly modelling of SWE spatial distribution at regional scale (Aosta Valley-NW Italian Alps, 3000 Km<sup>2</sup>). End users: water management authorities and hydropower companies
- Objectives: (*i*) test few approaches to estimate SWE at a given point and (*ii*) understand the impact of these approaches on SWE estimation at regional scale



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Estimating single point SWE Current vs. past data



# Estimating single point SWE



Current vs. past data



SWE at regional scae



Dataset Approaches Results

# Estimating single point SWE

# How can we estimate SWE at a given point using snow depth?



# SWE-HS- $\rho_{s}$ dataset

- manual measurements in snow pits from 2005 to 2012
- data elevation range: [880-3900 m asl]
- total number of SWE-HS- $\rho_s$  data: 4154

HS [cm]	$ ho_s \; [kg \cdot m^{-3}]$	SWE [mm]
Min. : 7.0	Min. : 71	Min. : 9.9
Median : 92.0	Median :280	Median : 245.3
Mean :104.8	Mean :287	Mean : 311.0
Max. :530.0	Max. :583	Max. :2798.0



### Dataset Approaches Results

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• Test recently published methods to model snow density ( $\rho_s$ ) from snow depth (HS) data on Aosta Valley dataset (2005-2012)

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② Sturm et al. 2010:  $ho_{smod_i} = (
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ho_0)[1 - e^{(-k_1HS_{obs_i}) - k_2DOY)}] + 
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Dataset Approaches **Results** 

# $\rho_s$ modelling





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# $\rho_s$ modelling





Dataset Approaches **Results** 

# SWE modelling: $SWE_{mod_i} = HS_{obs_i}\rho_{smod_i}$





Dataset Approaches **Results** 

# SWE modelling: $SWE_{mod_i} = HS_{obs_i}\rho_{smod_i}$ or $SWE_{mod_i} = H\overline{S_{obs_i}}\overline{\rho_{sobs}}$





Dataset Approaches **Results** 

# SWE modelling: Nash-Sutcliffe model efficiency (EF) seasonal course



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  - Image: Median of observations:  $\rho_{smod_i} = \overline{\rho_{sobs}}$
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- SWE<sub>mod<sub>i</sub></sub> = HS<sub>obs<sub>i</sub></sub>ρ<sub>smod<sub>i</sub></sub>
- SWE variability is mainly explained by HS  $\rightarrow$  fitting of mixed model:  $SWE_{mod_i} = HS_{obs_i} + elev_i + east_i + north_i + 1|climatic_i$ 
  - $\bullet$  based on restricted maximum likelyhood  $\rightarrow$  more robust against heteroscedasticity
  - random effect (climatic) to account for spatial or temporal autocorrelation



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# SWE modelling: Nash-Sutcliffe model efficiency (EF) seasonal course



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EF ratio: seasonal course EF ratio: hydrological year effect

# Current vs. past data

# Do real time snow density data provide better SWE estimates than past years data?



 Do we get an improvement in point level SWE modelling using real time snow density data (i.e. snow density data of the current year)?

EF<sub>[current]</sub>/EF<sub>[past]</sub>

- *EF*<sub>[current]</sub>: e.g. Jan 2013 SWE modelled using snow density data collected during Jan 2013
- *EF*<sub>[*past*]</sub>: e.g. Jan 2013 SWE modelled using all snow density data collected in Jan in the period 2005-2012
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EF ratio: seasonal course EF ratio: hydrological year effect

### EF ratio: seasonal course



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EF ratio: seasonal course EF ratio: hydrological year effect

### EF ratio: interannual variability



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# SWE at regional scale (3000 km<sup>2</sup>)

# What's the impact on total SWE at regional scale?



# Impact on SWE at regional scale (3000 km<sup>2</sup>)

- SWE at regional scale (Aosta Valley) is modelled, from Nov to May with monthly or biweekly frequency, using *MODIS Maximum Snow Cover Extent* data (MOD10A2 Product–v005) and *SWE regression kriging*
- To roughly evaluate the impact of the different approaches (*median vs. mixed models*) and datasets (*real time vs. past years data*) we compared the seasonal course of the total modelled SWE values



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# e.g. hydrological year 2009-2010 'normal' year



### e.g. hydrological year 2010-2011 early snowmelt



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# e.g. hydrological year 2008-2009 anomalous snowy winter



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# Conclusions



- using the median of observations  $(\overline{\rho_{s_{obs}}})$  is not worse than the other tested methods
- mixed models ( $SWE_{mod} \sim HS_{obs}$ ) are, in most cases, at least as good as  $\overline{\rho_{s_{obs}}}$  or the other tested methods
- real time  $\rho_s$  data are usually better, but not always (e.g. edges of the season, periods with few data, ...)



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# take home messages (2/2): SWE modelling at regional scale

- the four approaches (ρ<sub>sobs</sub> real time, ρ<sub>sobs</sub> past data, mixed model real time data, mixed model past data) usually agree but can provide different results especially in extreme years (e.g. 2008/2009)
- given (*i*) our end users (hydropower companies and water management authorities) and (*ii*) the increase of extreme events frequency, keeping the four approaches could be a way to encompass model uncertainty



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# ... Thanks for your attention

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# 2009/2010: SWE and EFcv





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