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Estimation of the spatiotemporal dynamics of snow covered area by using cellular automata models

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ABSTRACT

Given the need to consider the cryosphere in water resources management for mountainous regions, the purpose of this paper is to model the daily spatially distributed dynamics of snow covered area (SCA) by using calibrated cellular automata models. For the operational use of the calibrated model, the only data requirements are the altitude of each cell of the spatial discretization of the area of interest and precipitation and temperature indexes for the area of interest. For the calibration step, experimental snow covered area data are needed. Potential uses of the model are to estimate the snow covered area when satellite data are absent, or when they provide a temporal resolution different from the operational resolution, or when the satellite images are useless because they are covered by clouds or because there has been a sensor failure. Another interesting application is the simulation of SCA dynamics for the snow covered area under future climatic scenarios. The model is applied to the Sierra Nevada mountain range, in southern Spain, which is home to significant biodiversity, contains important water resources in its snowpack, and contains the most meridional ski resort in Europe.

1. Introduction

Water resources management and operational river forecasts in river basins that enclose high mountainous regions must take into account the cryosphere (i.e. the snowpack). The amount of snow and its spatial and temporal distribution as well as the outflow of water from the snowpack must be estimated from available information. The problem is three-fold: (i) estimation of the snow covered area (SCA); (ii) estimation of the snowpack thickness and (iii) estimation of the snow density. The three variables (covered area, thickness and density) are needed to estimate the snow water equivalent, however estimating each variable is a problem in and of itself. Each variable can be approached by applying different modelling techniques: interpolation methods (e.g. Richer et al., 2013; Mir et al., 2015 to estimate SCA; Collados-Lara et al., 2017 to estimate snow pack thickness; Bormann et al., 2013 and Lopez-Moreno et al., 2013 to estimate snow density; Sexstone and Fassnacht, 2014 and Elder et al., 1998 to estimate snow water equivalent), conceptual methods (e.g. HBV (Lindström et al., 1997); Snowmelt Runoff Model (SRM) (Martinec et al., 2008; Sensoy and Uysal, 2012) or physically-based models (e.g. CROCUS (Bruland et al., 2001); ECHAM (Foster et al., 1996)). Under standard circumstances, SCA can be estimated using satellite data, such as from the Moderate Resolution Imaging Spectroradiometer (MODIS) (Hall et al., 2006; Hall and Riggs, 2007). The question we aim to answer in this work is how to estimate the snow covered area when satellite data are unavailable. Satellite data may be unavailable for different reasons. For instance it could be because the satellite was not launched yet or because the temporal resolution of the satellite data is larger than the temporal resolution of interest. Also satellite data may be useless because the area of interest was covered by clouds or because there was a failure in the sensor. Furthermore, future scenarios of precipitation and temperature could be defined from the simulation performed with different Regional Climatic Models (RCM) for the emission scenarios defined by IPCC (Jacob et al., 2013). These future scenarios of climate in an area, defined by applying a downscaling technique from the RCM simulations, could be used to feed the SCA model in order to assess future SCA scenarios. This is a method commonly applied to assess future scenarios of other hydrological variables from hydrological balance models (Pulido-Velazquez et al., 2011; Pulido-Velázquez et al., 2015). These hydrological model predictions could also be

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improved by incorporating SCA using the data assimilation technique (Thirel et al., 2013; Alvarado Montero et al., 2016).

In addition to the physically-based or conceptual approaches (Molotch et al., 2004), we can also find examples of regression techniques (Richer et al., 2013; Mir et al., 2015) and learning algorithms (artificial neural networks) to estimate Snow Cover Fraction Mapping (Hou and Huang, 2014; Mishra et al., 2014). In this study we propose a novel approach to the problem: the application of an evolutionary algorithm, as the cellular automaton, to estimate SCA. The estimation of SCA fits perfectly in the kind of problems that can be analysed with cellular automata techniques, as they are complex, dynamic systems that can be approached in a discrete way. Cellular automata models are good for simulating complex discrete dynamics by using simple rules that define the interaction between neighbour cells that discretize the study area. They have been applied to different problems in geosciences like urban growth dynamics (Kumar et al., 2014), snow crystal growth (Reiter, 2005) or simulation of snow avalanches (Barpi et al., 2007), among others. Cellular automata have also been used to simulate snow cover dynamics (Leguizamón, 2006). However the latter reference offers only a preliminary study that had significant limitations: (i) it only uses a small synthetic area rather than a real study area, (ii) it simulates a simple dynamic situation of reduction of the snowpack from a starting condition with an existing snowpack, (iii) the simulation is for a short time interval, (iv) the simulation does not introduce driving climatological indexes (precipitation and temperature) in order to guide the dynamics, (v) the procedure cannot start a snowpack in an image where all the cells are without snow. In this paper we extend the idea of using cellular automata to estimate the snow covered area. The extension deals with overcoming each of the aforementioned limitations. We used a real case study so that the cellular automata could be calibrated and validated but the methodology is completely general and can be applied to any area of interest because the data requirements are minimal. The methodology is described in the next section.

2. Methodology

Cellular automata are discrete dynamic models introduced by Wolfram (1984) in order to simulate complex dynamics using simple rules of interaction. The two-dimensional area of interest (i.e. a geographical region projected on a plane) is divided into a finite number of cells or pixels. Time is also discretized in time steps. The shape and size of the study area can be arbitrary, but for the sake of presentation one can think of a rectangular grid of cells: $\{(i,j); i = 1, \ldots, N_x; j = 1, \ldots, N_y\}$. The size of the cell can be any of interest; for example in the case study we will use square cells measuring approximately 460 m × 460 m, which is the spatial resolution of a MODIS image for the latitude of the study area. As was already mentioned, there is also a discretization of time; for example in the case study the time step is one day. Next, each cell (i,j) can be, at each time, t, in one of two possible states (1 or 0):

$$S(i,j,t) = \begin{cases} 1 & \text{if cell}(i,j)\text{is covered by snow at time } t \\ 0 & \text{ifcell}(i,j)\text{is free of snow at time } t \end{cases} \tag{1}$$

The state $S(i,j,t)$ depends, in general, on:

- The state of the cell (i,j) at the previous time step: $S(i,j,t-1)$.
- The states, at the previous time step, of the cells of a given configuration of neighbour cells. For example for an 8-neighbourhood, the states of the cells $(i-1,j-1)$, $(i,j-1)$, $(i+1,j-1)$, $(i+1,j)$, $(i+1,j+1)$, $(i,j+1)$, $(i-1,j+1)$ and $(i-1,j)$ at time $t-1$ are involved.
- A given set of transition rules. In classic cellular automaton models, the transition rules depend on the state of the cell at the previous step and the states of the neighbour cells at the previous step. However, in order to simulate realistic snow dynamics, we must introduce transition rules defined by some driving variables. This can be defined as a mixed cellular automaton. We have chosen a couple climatological indexes as driving variables: precipitation and temperature, $P(t)$ and $T(t)$, respectively, and a terrain variable: the altitude $H(i,j)$ of each cell (i,j). This allows the cellular automaton to evolve even if all the cells of the study area are at state zero. The altitude index in the calculation cells has been obtained as the mean altitude from a digital elevation model which has a spatial resolution of 5 meters (the highest DEM resolution available from the National Geographic Institute of Spain). Temperature and precipitation indices are used in the form of two time series: a time series of daily temperature and a time series of daily precipitation. These time series could be measured at a weather station or obtained from a given estimation product. The absolute values of these indices are not important in this problem because they are calibrated for a specific problem. The truly important feature of these indices is that they capture the temporal climatological variability of the case study.

The cellular automata model is calibrated with experimental snow covered area data for a particular period of time. For example, in our case study the experimental data are daily binary images of snow/no snow cells obtained from MODIS images (Hall et al., 2006) and the calibration period lasts three years. Furthermore, in our case study (next section), the estimation time starts on 1 July of the first year of the calibration period when the state of every cell in the study area is equal to zero (there is no snow in the study area). Hence, a pure cellular automaton cannot work because all the cells have the same state of zero, or equivalently the snowline is at an arbitrarily high altitude, which is larger than the largest altitude in the study area. Thus by introducing the driving variables, the discrete system can follow the realistic dynamics of the snowpack by changing the snowline, which is defined as the altitude above which the terrain can have snow. Thus new transition rules are introduced by using the climatological indexes and the digital elevation model is:

- If the precipitation is larger than or equal to a given threshold, $P(t) \geqslant P_0$, and the altitude of the cell (i,j) is above the snowline $H(i,j) > H_k(t)$, the state of the cell will be 1 (that is, by remaining at state 1 if it was already 1 or by changing from state 0 to state 1). The snow line H_k is defined, discretized in K values, by the temperature index $T(t)$:

  If $T(t) < T_1$ then $H_k(t) = H_1$
  If $T(t) < T_2$ then $H_k(t) = H_2$
  ...
  If $T(t) < T_K$ then $H_k(t) = H_K$
  With $T_1 > T_2 > \ldots > T_K$ and $H_1 > H_2 > \ldots > H_K$.

- If precipitation at day t is below the threshold $P(t) < P_0$ and the temperature has decreased or has increased by an amount smaller than a given threshold:

$$T(t) - T(t-1) \leqslant T_c > 0 \tag{2}$$

then the state of each cell remains at the state of the previous time step.

- Otherwise, if precipitation at day t is below the threshold $P(t) < P_0$ and the temperature has increased by an amount larger than a given threshold