Recent advances in data-driven modeling of remote sensing applications in hydrology

Noël D. Evora and Paulin Coulibaly

ABSTRACT

Artificial neural networks (ANNs) are very effective statistical models for (1) extracting significant features or characteristics from complex data structures and/or for (2) learning nonlinear relationships involved in any input–output mapping. Another interesting aspect of ANN modeling is the fact that overall performance of these models is not greatly hampered by the presence of error-corrupted values in some input nodes. ANNs have gained interest in remote sensing applications as valuable inverse models that can retrieve physical characteristics of interest, such as precipitation, from remote sensing measurements collected from radars or satellites. The spatial coverage and high resolution of remote sensing measurements relative to ground-based measurements can improve the hydrological modeling of the water cycle at both local and global scales. This review paper intends to present recent advances in artificial neural network modeling of remote sensing applications in hydrology. This paper focuses on precipitation and snow water equivalent (SWE) retrievals from remote sensing data.

Key words | artificial neural network, hydrology, inverse model, rainfall, remote sensing, snow water equivalent

Noël D. Evora (corresponding author)
Water Resources Engineering Department,
Manitoba Hydro Place,
360 Portage Avenue 15th Floor,
Winnipeg MB,
Canada R3C 0G8
E-mail: *nevora@hydro.mb.ca*

Paulin Coulibaly
Department of Civil Engineering/School of Geography and Earth Sciences,
McMaster University,
Hamilton Ontario,
Canada L8S 4L7

INTRODUCTION

Data-driven models, and more specifically ANNs, are very attractive tools that are used in hydrology and remote sensing applications. Indeed, ANNs are very powerful models that can learn the nonlinear relationships characterizing many processes of hydrological, climatological or weather prediction models. Herein, the focus is on remote sensing applications that could improve the hydrological modeling at different scales (local, regional and global scales). A huge number of hydrological models are applied all over the world. Even if they can be assigned to deterministic, stochastic or event-based types of models, they all need input data to forecast the flows at the outlet of a basin through the modeling of specific processes providing the state variables at each modeling step. One of the key input components of hydrologic models is precipitation. The key state variables that could benefit from the advances in ANN modeling in remote sensing are soil moisture and SWE.

The physical characteristics of a basin are crucial and necessary information for distributed hydrological models. Remote sensing can provide valuable information on soil classification and land cover. Overall, remote sensing can supply valuable information relative to a basin at time and spatial scales that match the requirements of distributed hydrological models. Reliable information on SWE, for instance obtained from neural network-based retrieval algorithms, can be used to update the state variables of numerical forecasting models (hydrological, climate and weather prediction models) through a data assimilation procedure.

This review paper focuses on recent advances in artificial neural network modeling of remote sensing

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applications involving precipitation and SWE retrievals that could be used in hydrologic modeling for operational water management or runoff and stream flow forecasting purposes. Papers published since 2000 are particularly of great interest.

FORWARD AND INVERSE MODELS

Remote sensing measurements, especially those from space, have been increasing throughout recent years. Since the 1970s, sophisticated satellites have been launched. Compared to remote-sensing-based data acquisition systems, the ground-based measurement networks have their own weaknesses such as their limited spatial coverage and their low resolution scale. Retrieval algorithms have then been developed to retrieve the physical characteristics of interest from remote sensing measurements. These algorithms are inversion techniques and include, among others, regression, lookup table searching and iteration methods (Vann & Hu 2002). The functional relation f between a vector $\boldsymbol{X}$ of satellite measurements or observations and the physical characteristic to be retrieved, $\boldsymbol{Y}$, is called a forward model and is obtained by solving a radiative transfer equation (Vann & Hu 2002; Krasnopolsky & Schiller 2003):

$$\boldsymbol{X} = f(\boldsymbol{Y}) \tag{1}$$

Conventional inversion techniques involve deriving $\boldsymbol{Y}$ from $\boldsymbol{X}$ by solving the inverse problem

$$\boldsymbol{Y} = f^{-1}(\boldsymbol{X}) \tag{2}$$

The functional relation f^{-1} is called a transfer function or retrieval algorithm. If the forward model is a linear function, the transfer function can be a simple linear regression model. However, usually a nonlinear relationship exists between $\boldsymbol{Y}$ and $\boldsymbol{X}$. ANNs can be used as retrieval algorithms because of their ability to approximate nonlinear relationships (Loyola 2006). Indeed, the transfer function can be viewed as a continuous or almost continuous mapping between $\boldsymbol{Y}$ and $\boldsymbol{X}$. Mathematically, the forward problem is a well-posed problem. In contrast, the inverse problem is often an ill-posed problem (Krasnopolsky & Schiller 2003).

REMOTE SENSING RAINFALL ESTIMATION

Precipitation is a crucial component of the Earth's (global scale) or basin (local scale) hydrological cycle. It provides freshwater and is responsible for the hydrologic model dynamics. Major concerns about precipitation are related to its distribution, rates and amount. Many applications in hydrology, such as the drainage of urban rainfalls, need accurate rainfall estimation at small spatial and time scales.

Neural network retrieval algorithms have been used to retrieve rainfall rate (usually in mm per hour) or rainfall amount (usually in mm) on a daily, hourly or half-hourly timescale. These neural network inverse models use remote measurements provided by radars or by satellites as inputs and, as output, rainfall gauge data or radar observations of rainfall rate or radar precipitation estimates.

Radar-based studies

One of the most used techniques of radar-based rainfall retrieval is a two-parameter power-law function between the reflectivity factor (radar echo), Z, and rainfall intensity, R (Chiang *et al.* 2007):

$$Z = aR^b \tag{3}$$

where a and b are empirical parameters.

Even though the above Z–R equation is rather simple, the relationship between reflectivity and rainfall rate is indeed more complex and has been restricted within specific cases. Trafalis *et al.* (2002) successfully used reflectivity and spectrum width as inputs to a feedforward neural network for improving radar rainfall estimation. Radar data were obtained from a US network of advanced radars (Weather Surveillance Radar–1988 Doppler, WSR-88D). Chiang *et al.* (2007) used a recurrent neural network to learn the complex nonlinear relationships involved in the Z–R function and derived instantaneous quantitative precipitation estimations and one-hour-ahead quantitative precipitation forecasts. Radar data were taken from a C-band Doppler radar.

Previous work by Liu *et al.* (2001) demonstrated that an adaptive radial basis function neural network was able to provide rainfall estimation fairly accurately. This study was intended for real-time implementation of ANN-based rainfall retrieval algorithm on WSR-88D radars.

Satellite-based studies

Conventional methods for rainfall monitoring have used geostationary satellites that provide thermal infrared (TIR) data that are continuous and that have high-spatial and temporal resolutions. The basic idea around these algorithms is that rainfall can be inferred from the temperature of cloud tops. The Cold Cloud Duration (CCD), which is the number of hours for which the cloud-top temperature in a pixel is colder than a specified temperature threshold, is used as a predictor to estimate the rainfall amount R_a assumed to be linearly related to the CCD (Arkin 1979):

$$R_a = a_0 + a_1 \, \mathrm{CCD} \tag{4}$$

where a_0 and a_1 are empirical parameters.

The Geostationary Operational Environmental Satellite (GOES) Precipitation Index (GPI) is the most widely used algorithm of the form of Equation (4). GPI overestimates rainfall amounts over land as reported by Arkin *et al.* (1994). Indeed, a weakness of this method is due to the fact that cloud top temperatures are imperfectly correlated with rainfall reaching the surface.

Other usual algorithms have used, since the late 1970s, passive microwave data measured by sensors like the Special Sensor Microwave Imager (SSM/I) installed on polar-orbiting satellites. The main problems related to the use of passive microwave data for rainfall monitoring are (1) the high variability of the emissivity captured by the sensor depending on the vegetation and the soil moisture, (2) the signal scattering for frequencies greater than 60 GHz due to the presence of ice particles within the clouds and which is not related to raindrop intensity and (3) the fact that polar-orbiting satellites have poor temporal resolution with one or two overpasses per day (Grimes *et al.* 2003).

Since the launching, in 1997, of the Tropical Rainfall Measuring Mission (TRMM) satellite, retrieval algorithms using precipitation radar data for rainfall estimation have been developed and are considered as promising precipitation monitoring methods (Grimes *et al.* 2003). The radar transmits a beam of microwave energy downward inside clouds. Then the raindrops scatter back the energy to the radar, providing information on rainfall intensity and vertical distribution.

To account for the weaknesses of these different measurement techniques, researchers around the world have combined satellite and radar measurements to minimize the limitations and take advantage of the strengths of the various techniques.

Many studies involving the above types of satellite data and the use of ANN-based models have been reported in the scientific literature since 2000. Bellerby *et al.* (2000) developed a satellite precipitation algorithm to generate high spatial and temporal resolution rainfall estimates. A multilayer feedforward neural network (MFFN) uses as inputs coincident brightness temperatures and their spatial derivatives for three infrared (IR) and one visible sensor on the GOES-8 satellite. The MFFN had a consistent performance over the optimized GPI in terms of correlations with the validation data.

Staelin & Chen (2000) used two simple MFFNs to capture the nonlinear functional relation between microwave radiances and precipitation at 15 km and 50 km resolution, respectively. Major inputs of the neural networks were from passive observations at 50–191 GHz from the Advanced Microwave Sounding Unit (AMSU) on the NOAA-15 meteorological satellite. Neural net estimates were compared to the NEXt generation RADar (NEXRAD) 3 GHz observations of precipitation rate. The morphology of NEXRAD hurricane and frontal precipitation data smoothed to 15 km resolution over the United States was well reproduced by the neural network. However, at 50 km resolution some root mean square discrepancies between observed and estimated data for two frontal systems and two passes over Hurricane Georges were noticed. This work was further improved by Chen & Staelin (2003) to supplement existing global precipitation datasets over both land and sea at rates approaching 100 mm/h by providing precipitations rates with 15 km and 50 km horizontal resolution as initial products of Atmospheric Infrared Sounder/Advanced Microwave Sounding Unit/Humidity Sounder for Brazil (AIRS/AMSU/HSB) precipitation estimates. The method's potential global applicability was confirmed by the analysis of representative images of precipitation for tropical, mid-latitude and snow conditions.

Very well-known rainfall rate estimation systems based on the use of neural network models were developed since the late 1990s. The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks system (PERSIANN) was designed at the University of Arizona by Hsu *et al.* (1997). It is a geostationary IR-based algorithm. An adaptive Modified Counter Propagation Network (MCPN) estimates rainfall rates using IR satellite imagery and ground-surface information. The original counterpropagation neural network was developed by Hecht-Nielsen (1987). The MCPN is composed of a Self-Organizing Feature Map (SOFM) hidden layer and the output layer is a modified version of the Grossberg linear layer.

The PERSIANN system was further improved by Hong *et al.* (2004) who developed the PERSIANN Cloud Classification System. The PERSIANN CCS is a cloud-patch-based algorithm and provides rainfall rate estimates (every 30 min) and distribution at a fine scale ($0.04° \times 0.04°$). A cloud-top brightness temperature and rainfall rate relationship is calibrated for each classified cloud group obtained by a SOFM network. Infrared brightness temperature images were used by PERSIANN and GOES infrared (10.7 μm) imagery for PERSIANN CCS. Hong *et al.* (2005) improved the diurnal variability of retrieved rainfall by the PERSIANN system. The model parameters of PERSIANN are adjusted using coincident rainfall derived from the TRMM Microwave Imager (TMI). Moradkhani *et al.* (2006) built a framework for analysing the effect of various sources of uncertainties in hydrologic response. PERSIANN CCS satellite precipitation data were used as forcing data to a hydrologic model. PERSIANN CCS error was characterized through a power law function. Four uncertainty scenarios were set up. Satellite precipitation error resulted in a wide uncertainty range of the streamflow forecasts. At the opposite scale, this range was narrow to account for parameter uncertainty.

The TAMANN2 (Tropical Applications of Meteorology using satellite data Artificial Neural Network 2) system was developed by Grimes *et al.* (2003) to provide real-time rainfall estimation at a daily time step in Zambia (central Africa). The core of this system is a feedforward multilayer perceptron (FMLP) that uses 30 inputs. Because this system was designed for real-time operational rainfall monitoring in Africa, a combination of satellite imagery (Meteosat thermal infrared) and data from a numerical weather prediction (NWP) model analysis was preferred. The FMLP has 30 inputs, corresponding to the first five principal components of five meteorological fields of the NWP model, the CCD at four threshold temperatures and the pixel latitude. Small but consistent improvement over the standard CCD approach was obtained. The improvement was greatest for higher rainfalls, which is of great interest for hydrological applications such as large floods' monitoring.

TAMANN3, proposed by Coppola *et al.* (2006), is an improvement relative to TAMANN2. The most important enhancement is in the normalizing procedure for the gauge-pixel rainfall used for the network training. Daily rainfall in Africa exhibits a highly skewed statistical distribution. So, two adjustments were performed: (1) a proportion of the zero rainfall events (90%) were removed and (2) nonzero rainfall amounts were transformed to their empirical probability. TAMANN3 was validated against area-based rain gauge daily data and compared with a multiple linear regression using the same data and a satellite-only model (TAMCCD). TAMANN3 rainfall estimates were less biased compared to the multiple linear regression and TAMCCD estimates.

An operational procedure producing half-hourly rainfall estimates at 0.1° spatial resolution was developed by Tapiador *et al.* (2004) and validated with rain gauge data over Andalusia in Spain. Satellite data sources were composed of passive microwave data based on the Electronically Scanning Microwave Radiometer (ESMR) aboard Nimbus-5 and Nimbus-6, and of infrared data formed from the ~11 μm IR channels aboard the Geostationary Meteorological Satellite-5 (GMS-5), GOES-8, GOES-10, Meteosat-5 and Meteosat-7 geostationary satellites. A FMLP with two hidden layers is the chosen architecture. Previously, several neural nets were evaluated: Adaptive Resonance Theory (ART) nets, ART1, ART2, ARTMAP, distributed ARTMAP and fuzzy ARTMAP. Compared with GPI and the histogram-matching technique, the FMLP had comparable performance in terms of rain delimitation scores and revealed an increase in the temporal and spatial resolutions.

To end this section devoted to remote sensing rainfall estimation, it is worthwhile to mention the Global

Precipitation Measurement program proposed by the National Aeronautics and Space Administration (NASA). The GPM mission is a collaboration between NASA, the Japanese Aerospace Exploration Agency (JAXA) and other US and international partners (Bundas 2006). The GPM mission is intended to begin in 2010 and will study global precipitation (rain, snow and ice). Its main objectives are (1) improve ongoing efforts to predict climate, (2) improve the accuracy of weather and precipitation forecasts and (3) provide more frequent and complete sampling of the Earth's precipitation. Among others, GPM will provide improvements in hydrology and water resources. Hossain & Katiyar (2006) have already identified possible improvements in flood forecasting in international river basins arising from the anticipated NASA's GPM mission.

REMOTE SENSING ESTIMATION OF SNOW PARAMETERS

Snow depth, snow density, snow cover and snow water equivalent are the main snow parameters that have been estimated by remote sensing retrieval algorithms. Snow parameters are very useful indicators of basin-scale water storage and flooding risk thereafter during the melting period in snow-dominated areas, as well as regional or global climate change indicators. SWE is not used as a forcing input data such as precipitation but rather is a state variable whose temporal and spatial (in the case of a distributed model) evolution is obtained from the snowmelt model component of the hydrological model.

Many retrieval algorithms used for snow parameter estimation have been proposed over the last 20 years. These algorithms are mainly multiple linear regression models estimating SWE by directly inverting passive microwave data (Goodison *et al.* 1986; Chang *et al.* 1987, 1996; Aschbacher 1989; Hallikainen 1989; Gan 1996; Foster *et al.* 1997; De Sève *et al.* 1997; Tait 1998; Singh & Gan 2000). Brightness temperatures from the SSM/I sensor have been most frequently used since 1987. Passive microwave data from the Scanning Multispectral Microwave Radiometer (SMMR) were used before 1987. The SSM/I radiometer operates at four frequencies (19 GHz, 22 GHz, 37 GHz and 85 GHz) both at horizontal and vertical polarizations, except at 22 GHz which only operates at vertical polarization. The footprint ranges from 69 km × 43 km at 19 GHz to 15 km × 13 km at 85 GHz.

The common retrieval algorithms make use of channels 19 GHz and 37 GHz. Difficulties restricting the use of passive microwave data for SWE retrieval are: (1) the presence of liquid water inside the snow pack, (2) precipitating clouds in the atmosphere, (3) snow grain size variation, (4) existence of depth hoar and vegetation cover such as forests and (5) the saturation effect by which SWE can increase with no resulting change in brightness temperature (see Carroll *et al.* (1999) for an interesting discussion on some important factors restricting the use of SSM/I data for operational SWE mapping).

Tait's empirical equation for SWE retrieval for a nonforested, noncomplex (flat terrain), with no melting snow and no depth hoar has the following expression (Tait 1998):

$$\mathrm{SWE} = a_0 + a_1(19\mathrm{H} - 37\mathrm{H}) \tag{5}$$

where a_0 and a_1 are empirical parameters, and 19H and 37H are the brightness temperatures at channels 19 GHz and 37 GHz, respectively, in horizontal polarization.

Compared to precipitation, very few studies have used neural network models for SWE retrieval from passive microwave data. Chen *et al.* (2001) developed a snow parameter retrieval algorithm from passive microwave remote sensing measurements. This algorithm consists of three components: a dense media radiative transfer (DMRT) model, a physically based snow hydrology model (SHM) and a neural network model. The DMRT generates the neural network training data. The four input neurons consist of snow parameters including snow depth, grain size, fractional volume and snow physical temperature. The corresponding four brightness temperatures (19V, 19H, 37V and 37H) are the outputs of the neural network. The neural network is used to speed up the snow parameter retrievals from SSM/I measurements. This algorithm is used at each time step, the SHM providing the snow parameters (initial guesses) that are used by the neural network through an iterative snow parameter inversion until the computed SSM/I values converge upon SSM/I observations. The differences between neural-based and measured SSM/I brightness temperatures are utilized to adjust snow parameters. Two cases were investigated. First, when ground truth precipitation data are available, SWE estimates from the SHM gave good results. For the second case, when precipitation inputs for the SHM are provided by a weather forecast model, the performance of the SHM declines. Prior knowledge of snow grain size and density used as additional constraints during the inversion improved the SWE estimates.

Guo *et al.* (2003) improved the work performed by Chen *et al.* (2001). Their algorithm has the same three components as the previous one. However, not only the temporal evolution but also the spatial distribution of SWE and snow depth at a pixel resolution of 5 arcmin (about 10 km grid cell resolution) is estimated based on passive remote sensing measurements. The mapping and retrieval algorithm was improved by (1) using a spatially distributed snow accumulation and melt model, (2) constraining grain size evolution based on the surface air temperature and (3) building a snow grain size evolution library based on *in situ* data. Ground-observed data from four Snowpack Telemetry (SNOTEL) sites in the Upper Rio Grande River basin in Colorado were used. The conclusion from this study was that the new algorithm was able to improve the estimation of snow parameters.

Tedesco *et al.* (2004) developed and tested an inversion technique for the retrieval of SWE and dry snow depth based on ANN. The four input neurons of an FMLP with one hidden layer were made up of 19 GHz and 37 GHz vertical and horizontal brightness temperatures. They compared the ANN-based technique with the spectral polarization difference (SPD) algorithm and the Helsinki University Technology (HUT) model-based iterative inversion algorithm for SWE retrieval. Their results showed that ANNs are able to retrieve the spatial and temporal variations of SWE and snow depth from SSM/I data. Previous to this work, Tedesco *et al.* (2003) developed successfully a neural-network-based algorithm to retrieve snow parameters such as SWE, dry snow temperature and depth. The neural net was a multilayer perceptron. The detection of dry snow and classification of different types of snow were performed with good accuracy by a competitive neural network. The 19 GHz and 37 GHz SSM/I brightness temperatures were employed to constitute the input vector of the two neural networks.

Evora *et al.* (2008) developed a new modeling framework combining neural-network-based models, passive microwave data and geostatistics for SWE retrieval and mapping. The point-based SWE observations were interpolated by a kriging with an external drift (KED) algorithm to produce area-based SWE data at the same resolution as the SSM/I data. They used an FMLP neural network with 8 input neurons: the seven SSM/I channels and the interpolated minimum temperature as predictors. The training of the neural network was performed with the best pixels that were selected using a kind of noise-to-signal ratio denoted r_{KED} determined for each pixel as the ratio between the variance of estimation and the interpolated values of SWE by KED. Optimal division of the sample of available pixels is achieved by performing a clustering of the input and output data by means of a self-organizing feature map (SOFM). The prediction error of the neural network was assessed by bootstrap.

Areal extent of snow cover is an interesting indicator that is very useful in validating the areal extent of snow cover simulated by distributed hydrological models or by land-surface schemes coupled to numerical weather prediction models. Since 2000, only two relevant papers were published. Simpson & McIntire (2001) developed two neural-based approaches to detect clear land, cloud and snow in satellite images of mid-latitude regions. Satellite data were from the Advanced Very High Resolution Radiometer (AVHRR) and from GOES-8, -9 and -10. For single images, a feedforward neural network was designed both for AVHRR and GOES images. The output of these networks is a three-component vector corresponding to a class of data ($X =$ clear land, $Y =$ cloud, $Z =$ snow, values of X, Y and Z between 0 and 1). For the classification of a sequence of images, a recurrent neural network was developed and uses information from the current image in the time series as input as well as data from the previous texture input and the previous network output. Both spectral (satellite data) and texture (homogeneity and entropy) measures are used as inputs to the feedforward and recurrent neural networks. Validation of these classifiers was performed over the US using satellite and SNOTEL data and confirmed the accuracy of the classification in areas far from cover transitions (94% for AVHRR using a feedforward neural network and 97% for GOES using a recurrent neural network).

Ghedira *et al.* (2005) designed an adaptive multilayer neural network system to identify snow pixels from SSM/I data in the northern Midwest of the United States. The architecture of this network is composed of an input layer with five neurons corresponding to five SSM/I channels (19H, 19V, 22V, 37V and 85V), two hidden layers with 10 neurons each and an output layer with one neuron producing the neural network decision (snow and non-snow). Preliminary results from this system provided a significant improvement in snow mapping accuracy over the filtering algorithm developed by Grody & Basist (1996) and used by NOAA-NESDIS. The filtering algorithm uses the same five SSM/I channels and then ease the classification accuracy comparison between the two techniques.

Before ending this section, it is worth mentioning the availability of a new source of passive microwave data provided by the Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E) which is a mission instrument launched aboard NASA's Aqua Satellite on 4 May 2002. This satellite travels in a polar, Sun-synchronous orbit. The main improvements of AMSR-E over past microwave radiometers, such as SMMR and SSM/I, resides in its doubled spatial resolution and the fact that all the individual SMMR and SSM/I channels are combined into one sensor for AMSR-E.

CONCLUSION

This paper reviews recent advances in artificial neural network modeling of remote sensing applications that could be beneficial to hydrology. A rather large number of applications involving both precipitation and SWE retrieval from remote sensing data have been developed since 2000. The need for precipitation estimation at high resolution over basins of different scales is of major concern in distributed hydrological modeling or in urban drainage studies in the case of extreme rainfall events. Reliable snow water equivalent retrievals are needed for operational streamflow forecasting in snow-dominated areas as well as in meteorological and climatological modeling. The launching of sophisticated and high resolution satellites and radars (NASA's Global Precipitation Measurement mission, for instance) will provide remote sensing measurements that are very useful information used as inputs to neural-network-based retrieval models. There are some interesting research perspectives concerning the development of satellite-based precipitation and snow monitoring techniques that will provide high spatial and temporal resolutions products that could benefit hydrological applications such as flood monitoring.

REFERENCES

Arkin, P. A. 1979 The relationship between the fractional coverage of high cloud and rainfall accumulations during GATE over the B-scale array. *Mon. Weather Rev.* **107**, 1382–1387.

Arkin, P. A., Joyce, R. & Janowiak, J. E. 1994 The estimation of global monthly mean rainfall using infrared satellite data: the GOES precipitation index. *Remote Sens. Rev.* **11**, 107–124.

Aschbacher, J. 1989 *Land Surface Studies and Atmospheric Effects by Satellite Microwave Radiometry*. PhD Dissertation, University of Innsbruck, Innsbruck, Austria.

Bellerby, T., Todd, M., Kniveton, D. & Kidd, C. 2000 Rainfall estimation from a combination of TRMM precipitation radar and GOES multispectral satellite imagery through the use of an artificial neural network. *J. Appl. Meteorol.* **39**, 2115–2128.

Bundas, D. 2006 Global precipitation measurement mission–architecture and mission concept. In: *Proceedings of the 2006 IEEE Aerospace Conference, Big Sky, MT*. IEEE, New York.

Carroll, S. S., Carroll, T. R. & Poston, R. W. 1999 Spatial modeling and prediction of snow-water equivalent using ground-based, airborne, and satellite snow data. *J. Geophys. Res.* **104** (D16), 19623–19629.

Chang, A. T. C., Foster, J. L. & Hall, D. K. 1987 Nimbus-7 SMMR derived global snow cover parameters. *Ann. Glaciol.* **9**, 39–44.

Chang, A. T. C., Foster, J. L. & Hall, D. K. 1996 Effects of forest on the snow parameters derived from microwave measurements during the BOREAS winter field campaign. *Hydrol. Process.* **10**, 1565–1574.

Chen, C. -T., Nijssen, B., Guo, J., Tsang, L., Wood, A. W., Hwang, J. -N. & Lettenmaier, D. P. 2001 Passive microwave remote sensing of snow constrained by hydrological simulations. *IEEE Trans. Geosci. Remote Sens.* **39**, 1744–1756.

Chen, F. W. & Staelin, D. H. 2003 AIRS/AMSU/HSB precipitation estimates. *IEEE Trans. Geosci. Remote Sens.* **41**, 410–417.

Chiang, Y. M., Chang, F. -J., Jou, B. J. -D. & Lin, P. -F. 2007 Dynamic ANN for precipitation estimation and forecasting from radar observations. *J. Hydrol.* **334**, 250–261.

Coppola, E., Grimes, D. I. F., Verdecchia, M. & Visconti, G. 2006 Validation of improved TAMANN neural network for operational satellite-derived rainfall estimation in Africa. *J. Appl. Meteorol. Climatol.* **45**, 1557–1572.

De Sève, D., Bernier, M., Fortin, J. -P. & Walker, A. 1997 Preliminary analysis of snow microwave radiometry using the SSM/I passive-microwave data: the case of La Grande River watershed (Quebec). *Ann. Glaciol.* **25**, 353–361.

Evora, N. D., Tapsoba, D. & De Sève, D. 2008 Combining artificial neural network models, geostatistics and passive microwave data for snow water equivalent retrieval and mapping. *IEEE Trans. Geosci. Remote Sens.* **46**, 1925–1939.

Foster, J. L., Chang, A. T. C. & Hall, D. K. 1997 Comparison of snow mass estimates from a prototype passive microwave snow algorithm, a revised algorithm and snow depth climatology. *Remote Sens. Environ.* **62**, 132–142.

Gan, T. Y. 1996 Passive microwave snow research at the Canadian High Arctic. *Can. J. Remote Sens.* **22**, 36–44.

Ghedira, H., Arevalo, J. C., Lakhankar, T. & Khanbilvardi, R. 2005 An adaptive neural network system for improving the filtration of non-snow pixels from SSM/I images. In: *Proceedings of the 2005 IEEE International Geoscience and Remote Sensing Symposium, Seoul, Korea*. IEEE, New York, Vol. 8, pp. 5459–5462.

Goodison, B. E., Rubinstein, I., Thirkettle, F. W. & Langham, E. J. 1986 *Determination of snow water equivalent on the Canadian prairies using microwave radiometry*. IAHS Publ. 155, pp. 163–173.

Grimes, D. I. F., Coppola, E., Verdecchia, M. & Visconti, G. 2003 A neural network approach to real-time rainfall estimation for Africa using satellite data. *J. Hydrometeorol.* **4**, 1119–1133.

Grody, N. & Basist, A. 1996 Global identification of snow cover using SSM/I measurements. *IEEE Trans. Geosci. Remote Sens.* **34**, 237–249.

Guo, J., Tsang, L., Josberger, E. G., Wood, A. W., Hwang, J. -N. & Lettenmaier, D. P. 2003 Mapping the spatial distribution and time evolution of snow water equivalent with passive microwave measurements. *IEEE Trans. Geosci. Remote Sens.* **41**, 612–621.

Hallikainen, M. T. 1989 Microwave radiometry of snow. *Adv. Space Res.* **9**, 267–275.

Hecht-Nielsen, R. 1987 Counterpropagation networks. *Appl. Opt.* **26**, 4979–4984.

Hong, Y., Hsu, K. -L., Sorooshian, S. & Gao, X. 2004 Precipitation estimation from remotely sensed imagery using an artificial neural network cloud classification system. *J. Appl. Meteorol.* **43**, 1834–1852.

Hong, Y., Hsu, K. -L., Sorooshian, S. & Gao, X. 2005 Improved representation of diurnal variability of rainfall retrieved from the Tropical Rainfall Measurement Mission Microwave Imager adjusted precipitation estimation from remotely sensed information using artificial neural networks (PERSIANN) system. *J. Geophys. Res.* **110**, D06102 (doi:10.1029/2004JD005301).

Hossain, F. & Katiyar, N. 2006 Improving flood forecasting in international river basins. *EOS Trans. Am. Geophys. Union* **87**, 49 (see also 54).

Hsu, K. -L., Gao, X., Sorooshian, S. & Gupta, H. V. 1997 Precipitation estimation from remotely sensed information using artificial neural networks. *J. Appl. Meteorol.* **36**, 1176–1190.

Krasnopolsky, V. M. & Schiller, H. 2003 Some neural network applications in environmental sciences. Part I: forward and inverse problems in geophysical remote measurements. *Neural Netw.* **16**, 321–334.

Liu, H., Chandrasekar, V. & Xu, G. 2001 An adaptive neural network scheme for radar rainfall estimation from WSR-88D observations. *J. Appl. Meteorol.* **40**, 2038–2050.

Loyola, R. D. G. 2006 Applications of neural network methods to the processing of earth observation satellite data. *Neural Netw.* **19**, 168–177.

Moradkhani, H., Hsu, K., Hong, Y. & Sorooshian, S. 2006 Investigating the impact of remotely sensed precipitation and hydrologic model uncertainties on the ensemble streamflow forecasting. *Geophys. Res. Lett.* **33**, L12 401.

Simpson, J. J. & McIntire, T. J. 2001 A recurrent neural network classifier for improved retrievals of areal extent of snow cover. *IEEE Trans. Geosci. Remote Sens.* **39**, 2135–2147.

Singh, P. R. & Gan, T. Y. 2000 Retrieval of snow water equivalent using passive microwave brightness temperature data. *Remote Sens. Environ.* **74**, 275–286.

Staelin, D. H. & Chen, F. W. 2000 Precipitation observations near 54 and 183 GHz using the NOAA-15 satellite. *IEEE Trans. Geosci. Remote Sens.* **38**, 2322–2332.

Tait, A. B. 1998 Estimation of snow water equivalent using passive microwave radiation data. *Remote Sens. Environ.* **64**, 286–291.

Tapiador, F. J., Kidd, C., Levizzani, V. & Marzano, F. S. 2004 A neural networks-based fusion technique to estimate half-hourly rainfall estimates at 0.1° resolution from satellite passive microwave and infrared data. *J. Appl. Meteorol.* **43**, 576–594.

Tedesco, M., Pampaloni, P., Pulliainen, J. & Hallikainen, M. 2003 Classification and retrieval of dry snow parameters by means of SSM/I data and artificial neural networks. In: *Proceedings of the 2003 IEEE International Geoscience and Remote Sensing Symposium, Toulouse, France*. IEEE, New York. Vol. 1, pp. 330–332.

Tedesco, M., Pulliainen, J., Takala, M., Hallikainen, M. & Pampaloni, P. 2004 Artificial neural network-based techniques for the retrieval of SWE and snow depth from SSM/I data. *Remote Sens. Environ.* **90**, 76–85.

Trafalis, T. B., Richman, M. B., White, A. & Santosa, B. 2002 Data mining techniques for improved WSR-88D rainfall estimation. *Comput. Ind. Eng.* **43**, 775–786.

Vann, L. & Hu, Y. 2002 A neural network inversion system for atmospheric remote-sensing measurements. In: *IEEE Instrumentation and Measurement Technology Conference, Anchorage, AK*. IEEE, New York. pp. 1613–1615.

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