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Calibration of WRF-Hydro for Bhagirathi - Alaknanda Basin

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Abstract: ***Complemented with the coupling of the most sensitive and challenging interaction between terrestrial hydrology and atmosphere, the Bhagirathi-Alaknanda basin of the Garhwal Himalaya requires advanced dynamic and most comprehensively coupled atmospheric-hydrological models for simulation of streamflows. WRF-Hydro model which is enhanced by integrating most advanced set of hydrologic physics parameterization accounting for lateral water flow occurring on the land surface is the most compatible for this basin. This paper illustrates the development and the calibration of WRF-Hydro model through construction of flow matrices for different seasons.***

Keywords: ***WRF-Hydro Model Which Is Enhanced By Integrating***

I. INTRODUCTION

WRF-Hydro is the hydrological extension package to the Weather Research Forecast(WRF) model, which, running in entirely coupled or uncoupled modes, can fill in as an incorporated hydro-meteorological prediction framework. WRF-Hydro is designed to simulate land surface hydrology and energy states and fluxes using a variety of physics-based and conceptual approaches. All things considered, it is expected to be utilized as either a land surface model in both independent ("uncoupled" or "disconnected") mode and completely coupled (to an atmospheric model) mode. Both time-evolving "forcing" and static input datasets are requisite for model operation. The exact specification of both forcing and static data depends on the selection of model physics and component options to be used. The principal model physics options available in WRF-Hydro include the following: (i)1-dimensional (vertical) land surface parameterization, (ii) Surface overland flow, (iii) Saturated subsurface flow, (iv) Channel routing, (v)Reservoir routing.

Table 1: WRF-Hydro Model hydrological routing physics

Processes	Equations	Physics Options
Subsurface routing	$q_{i,j} = -T_{i,j} \tan\beta_{i,j} w_{i,j}$, $\beta_{i,j} < 0$	Surface exfiltration from saturated soil columns Lateral flow from saturated soil layers
Surface overland flow routing	$q_x = \alpha_x h^{\beta}$ $S_{fx} = S_{ox} - \frac{\partial h}{\partial x}$ (an example for the x direction)	Pounded water in excess of retention depth subject to over land flow 2-D diffusive wave overland flow
Channel routing	$Q = -\operatorname{sign}\frac{\partial z}{\partial x} K \sqrt{\left\lvert\frac{\partial z}{\partial x}\right\rvert}$ $K = \frac{C_m}{n} AR^{2/3}$	1-D diffusive wave One-way: overflow into channel No subsurface losses No overbank flow
Base flow	$Q_{basei} = C_i e^{\alpha_i z_i}$	Empirical, exponential storage-discharge model Base flow combined with overland flow

In a completely-coupled mode, the WRF-Hydro version 2.0 architecture dispenses the means to couple a hydrological model component to atmospheric models and other Earth System modelling architectures [Gochis et al., 2014] [3].

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While various options exist in WRF-Hydro for addressing land-surface column physics, the 1-D Noah land surface model ("Noah LSM") [Mitchell et al., 2004 [5]; Ek et al., 2003] has been utilized basically on the grounds that the Noah LSM gives land surface model consistency when it is run in both fully coupled mode with WRF or in standalone, uncoupled mode [2]. The Noah LSM computes the vertical fluxes of energy, i.e., sensible and latent heat, net radiation, and moisture (including canopy interception, snowpack accumulation and ablation, infiltration, infiltration-excess, deep percolation, ponded water depth, and soil thermal and moisture states). On each land surface model time step the penetration abundance, ponded water profundity, and soil dampness are disaggregated from the 1-D Noah LSM network.

(3 km in the current case) and contribution to a high goal directing matrix (300 m) by a period step weighted technique [Gochis and Chen, 2003] and then passed to the subsurface and overland stream terrain steering modules [4]. Saturated subsurface overflow routing, surface overland flow routing, channel and lake routing, and base-flow modules are assimilated in the WRF-Hydro framework.

The WRF-Hydro modelling system has been applied in several different and unique cases focusing on different hydro-meteorological forecasting and simulation problems [e.g., Gochis et al., 2014; Yucel et al., 2015; Senatore et al., 2015; Arnault et al., 2016] [1]. In both gauged and ungauged basins in the Black Sea region, this model successfully simulated flood events with reasonable accuracy [Yucel et al., 2015] [8]. Following multi-parameter automated calibration, for a simulation of full annual cycle of the Crati river basin in southern Italy, the WRF-Hydro system achieved Nash-Sutcliffe efficiency of 0.8 [Senatore et al., 2015] [6].

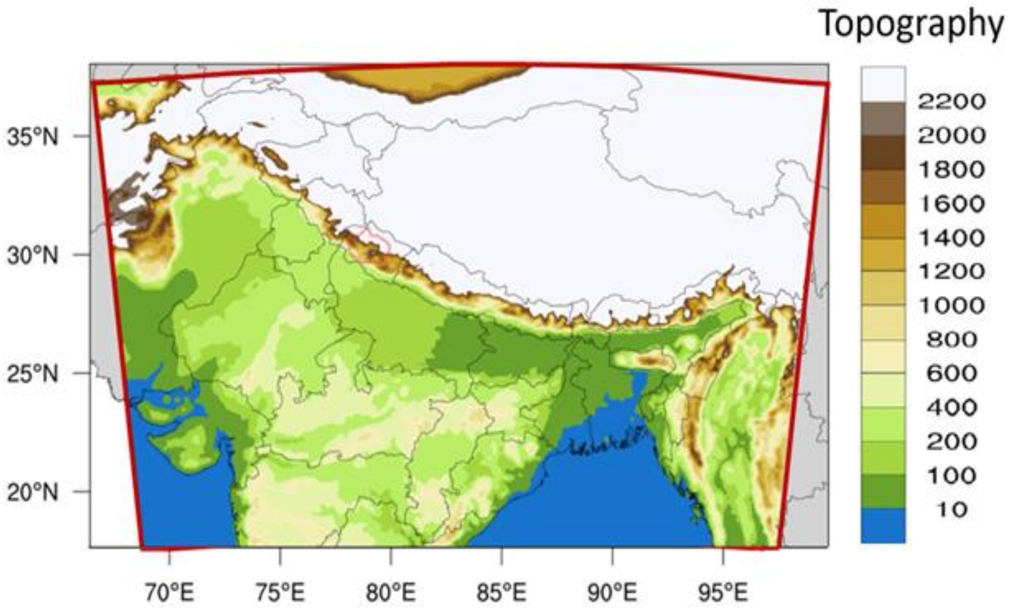

Figure 1. The full WRF-Hydro domain for the study

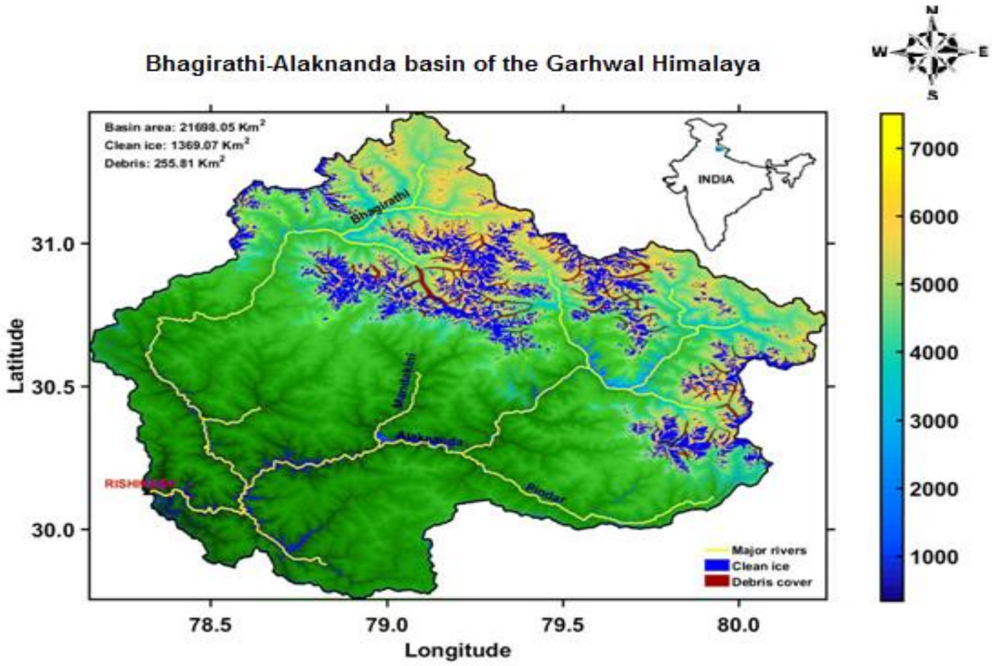

Figure 2. WRF-Hydro calibration basins

II. CLIMATE DATA

The meteorological forcing used for WRF-Hydro is the IMD gridded daily rainfall, and for the other meteorological fields (air temperature, humidity, solar radiation, and wind), the model is using the Global Ensemble Forecast System (GEFS) reforecast 6-hourly data. The model has been operated on a 3-hourly time-step, with the daily IMD precipitation temporally downscaled to the 3-hourly level. 3-hourly rainfall distribution pattern from GEFS has been used and then temporally disaggregated the IMD daily rainfall by conserving the rainfall volume.

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III. DATA REQUIREMENTS FOR WRF-HYDRO IN OPERATIONAL FORECASTING

The WRF-Hydro system is ideally constrained with sub-daily meteorological data, with a base time-step of 6 hours, albeit hourly information are best. The model is calibrated and configured using both IMD daily gridded observations and GEFS Reforecast data (zero-lag time) that is available at 3-hourly level. All the IMD and GEFS data have been mapped to 10 km WRF-Hydro domain in NetCDF format. In this experiment, the bias correction has not been done for WRF-Hydro inputs.

IV. CALIBRATION PROCESS

The WRF-Hydro model incorporates an automated calibration procedure that can be used to calibrate the model to every individual sub-basin or to aggregated basins. Within WRF-Hydro, the Dynamically Dimensioned Search (DDS) algorithm was appropriated (Tolson and Shoemaker 2007) [7].This is a search strategy in model parameter space, which is scaled to the maximum number of iterations specified by the user. In the initial iteration, the algorithm searches globally, and as the procedure approaches the maximum user-defined number of iterations, the search transits from a global to a local search.

DDS is an n-dimensional, heuristic, probabilistic global optimization algorithm for consistent, box-constrained (bound-constrained) optimization problems. DDS is designed to find good solutions quickly and requires least if any algorithm parameter tuning, but is not considered a global optimization model given the simulated annealing iteration limits. In the current study, the maximum number of iterations has been set to 200 for the WRF-Hydro calibration. Furthermore, plots of convergence are included in Figure.

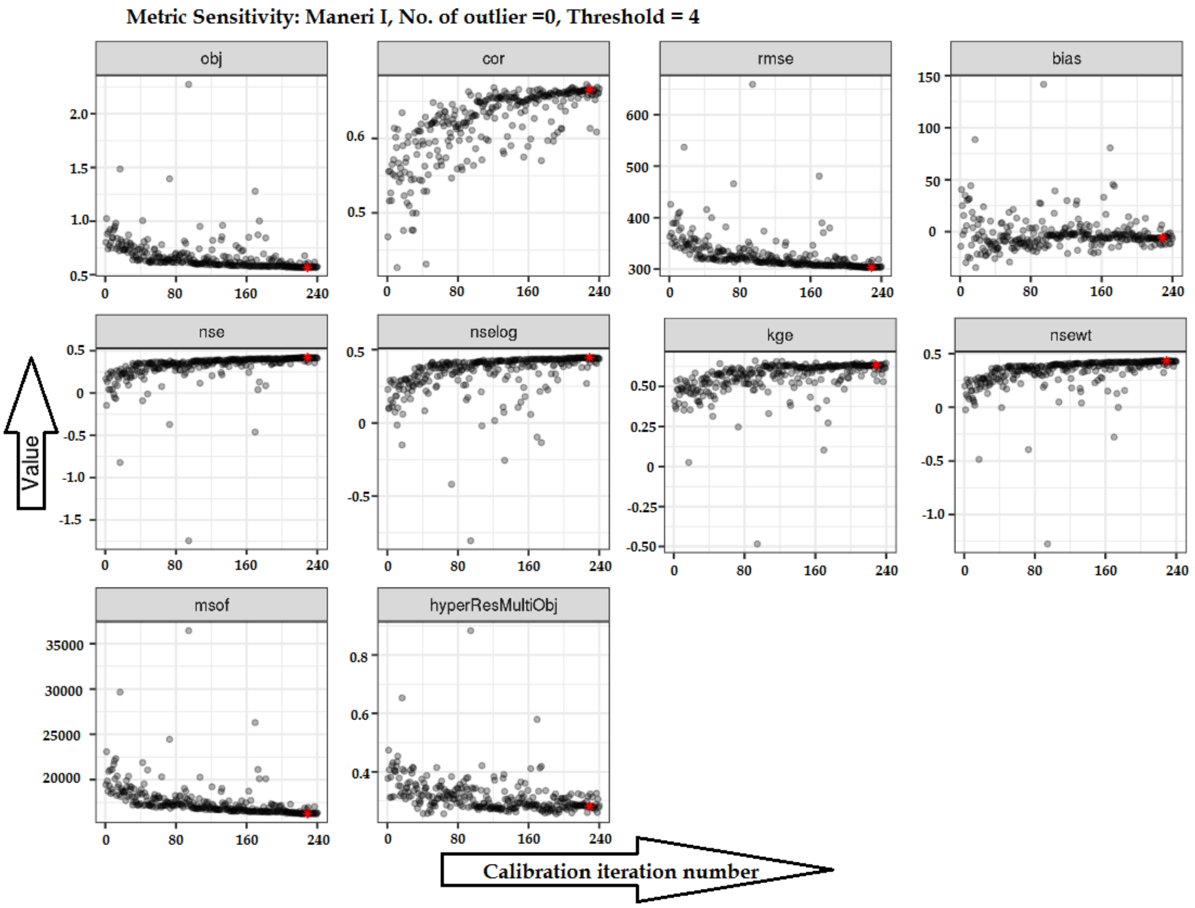

Figure 3 : Convergence Plots Over 240 Iterations For Each Parameter (Example for Maneri)

Calibration has been conducted for each incremental sub-basin unit. The Bhagirathi, for example, has been calibrated according to the following procedure:

1. Calibrating WRF-Hydro for the two upstream gauges, Maneri I and Maneri II.
2. Calibrating the model for Uttarkashi, calibrated upstream basins (i.e., Maneri I and Maneri II) has been masked out.
3. Masking-out Uttarkashi sub-basin and calibrate the model for Tehri gauge.

The list of important WRF-Hydro parameters to regionally calibrate WRF-Hydro is listed in Table 2.

The standard NSE emphasizes high flow performance of the model due to squared error terms. However, combining NSE of log-transformed streamflow with standard NSE provides an additional emphasis on low flows to account for background model bias. The objective function used for the calibration is provided in Equation 1, which uses an average of the NSE and NSELog. During calibration this single objective function is minimized.

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$$Objective\ function\ = 1 - \frac{(NSE+NSE_{LOG})}{2} \qquad (1)$$

NSE is the Nash-Sutcliffe Efficiency and NSE_{LOG} is the log-transformed NSE.

Before performing the calibration, WRF-Hydro has been "spun-up" for the selected basins (Figure), separately, from January 1, 2005, through January 1, 2018, period using the default model parameters. Using the model state of January 1, 2018, as the "warm start," the model calibration has been executed from January 1, 2005, through January 1, 2012. A separate 1-year spin-up from January 1, 2005, through December 31, 2005, has been considered for each iteration to match the model state to current conditions and suppress most instabilities from parameter changes. In spite of the fixed date ranges of calibration and validation, the model has been optimized involving only the reliable periods of perception for each particular site. The critical parameters of the WRF-Hydro related to soil, vegetation, runoff, snow, and groundwater and their description are provided in Table-1. Using the best parameters estimated in the calibration experiment the model has been evaluated over the associated reliable periods between January 1, 2012, and January 1, 2018.

Table 2: Calibrated WRF-Hydro parameters

Parameter name	Description	Unit	Calibration value ranges (Minimum, Maximum)
BEXP	Pore size distribution index	dimensionless	(×0.40, ×1.90)
CWPVT	Canopy wind extinction parameter for canopy wind profile formulation	m^{-1}	(×0.50, ×2.00)
DKSAT	Saturated hydraulic conductivity	$m\ s^{-1}$	(×0.20, ×10.00)
Expon	Exponent controlling rate of bucket drainage as a function of depth	dimensionless	(1.00, 8.00)
LKSATFAC	Multiplier on lateral hydraulic conductivity (controls anisotropy between vertical and lateral conductivity)	Unitless	(10.00, 10000.00)
MFSNO	Melt factor for snow depletion curve; larger value yields a smaller snow cover fraction for the same snow height	dimensionless	(×0.25, ×2.00)
MP	Slope of Ball-Berry conductance-to-photosynthesis relationship	Unitless	(×0.60, ×1.40)
REFKDT	Surface runoff parameter, increasing REFKDT decreases surface runoff	Unitless	(0.10, 4.00)
RETDEPRTFAC	Multiplier on retention depth limit	Unitless	(0.10, 20000.00)
RSURFEXP	Exponent in the resistance equation for soil evaporation	dimensionless	(1.00, 6.00)
SLOPE	Linear scaling of "openness" of bottom drainage boundary	0-1	(0.00, 1.00)
SMCMAX	Saturation soil moisture content (i.e., porosity)	volumetric fraction	(×0.80, ×1.20)
VCMX25	Maximum carboxylation at 25°C	$umol\ m^{-2}\ s^{-1}$	(×0.60, ×1.40)
Zmax	Maximum groundwater bucket depth	mm	(10.00, 250.00)

Note: '×' in the values denote that the calibration parameter is a multiplier on the default value.

V. CALIBRATION AND VALIDATION RESULTS

Table 3 to Table 5 present a summary of the calibration and validation statics for the 10 gauging sites for the WRF-Hydro model.

Table 3: All-Season WRF-Hydro performance metrics

		All-Season									
		Calibration					Validation				
Basin	Subbasin	MAE	NSE	KGE	NSE_Abs	Prsn. Corr	MAE	NSE	KGE	NSE_Abs	Prsn. Corr
Alaknanda	Tapovan	117.27	0.42	0.58	0.52	0.65	132	0.36	0.66	0.45	0.67
Alaknanda	Joshimath	104.18	0.28	0.47	0.38	0.56	103	0.1	0.56	0.34	0.62
Alaknanda	Rudraprayag	304.24	0.34	0.57	0.44	0.71	493	0.39	0.6	0.37	0.73
Alaknanda	Srinagar	454.90	0.21	0.46	0.12	0.51	692	-12.9	-3.37	-2.02	0.53
Alaknanda	Devprayag	134.62	0.41	0.37	0.46	0.72	116	0.37	0.38	0.4	0.63
Bhagirathi	Maneri I	145.47	0.40	0.44	0.29	0.58	62	0.18	0.48	0.2	0.56
Bhagirathi	Maneri II	156.38	0.48	0.61	0.32	0.61	151	-0.02	0.27	0.05	0.48
Bhagirathi	Uttarkashi	149.72	0.51	0.46	0.40	0.74	134	0.57	0.71	0.44	0.76
Bhagirathi	Tehri	141.35	0.30	0.54	0.34	0.55	198	0.06	0.54	0.33	0.56
Bhagirathi	Rishikesh	139.37	0.51	0.53	0.32	0.65	177.43	0.41	0.45	0.45	0.69

Table 4: Monsoon-Season Performance Metrics

		Monsoon Season (months)									
		Calibration					Validation				
Basin	Subbasin	MAE	NSE	KGE	NSE_Abs	Prsn. Corr	MAE	NSE	KGE	NSE_Abs	Prsn. Corr
Alaknanda	Tapovan	227.25	0.36	0.48	0.38	0.67	239.60	0.23	0.54	0.31	0.61
Alaknanda	Joshimath	207.16	0.17	0.28	0.24	0.48	211	0.03	0.48	0.29	0.58
Alaknanda	Rudraprayag	597.32	0.27	0.55	0.29	0.62	895	0.26	0.54	0.3	0.67
Alaknanda	Srinagar	792.35	0.11	0.32	0.15	0.39	1189	-12.2	-2.67	-1.77	0.46
Alaknanda	Devprayag	324.18	0.27	0.31	0.32	0.62	329	0.26	0.28	0.26	0.49
Bhagirathi	Maneri I	187.53	0.21	0.14	0.24	0.65	156	0.23	0.12	0.32	0.79
Bhagirathi	Maneri II	175.45	0.23	0.39	0.31	0.63	124	0.17	0.45	0.15	0.59
Bhagirathi	Uttarkashi	226.34	0.28	0.51	0.21	0.55	211	-0.19	0.24	-0.12	0.47
Bhagirathi	Tehri	236.65	0.42	0.46	0.41	0.69	179	0.49	0.67	0.54	0.71
Bhagirathi	Rishikesh	853.38	0.34	0.43	0.36	0.57	912.24	0.39	0.41	0.46	0.63

Table 5: Lean-Season performance metrics

		Lean Season (months)									
		Calibration					Validation				
Basin	Subbasin	MAE	NSE	KGE	NSE_Abs	Prsn. Corr	MAE	NSE	KGE	NSE_Abs	Prsn. Corr
Alaknanda	Tapovan	36.44	-3.19	-0.27	-0.44	-0.04	26.2	-5.83	-2.12	-0.5	0.32
Alaknanda	Joshimath	27.23	-0.59	0.17	-0.11	0.21	32.7	-0.14	-0.31	0.02	-0.02
Alaknanda	Rudraprayag	42.40	0.32	0.38	0.09	0.58	48.3	-1.82	-0.23	-0.66	-0.05
Alaknanda	Srinagar	168.66	-0.19	-0.18	0.07	0.27	137	-3.96	-0.97	-1.81	0.19
Alaknanda	Devprayag	92.24	0.47	0.51	0.29	0.54	58.2	-0.45	0.31	-0.03	0.38
Bhagirathi	Maneri I	16.56	0.12	0.01	0.32	0.41	11.8	-0.07	0.23	0.21	0.34
Bhagirathi	Maneri II	24.65	0.42	0.71	0.28	0.60	17.8	-0.67	0.23	-0.24	0.41
Bhagirathi	Uttarkashi	69.25	0.56	0.66	0.31	0.66	74.4	-0.11	-0.25	-0.38	0.39
Bhagirathi	Tehri	87.23	-5.21	-0.34	-2.18	0.17	112.5	-3.56	-0.22	-0.57	0.41
Bhagirathi	Rishikesh	339.45	-19.13	-2.08	-4.24	0.21	454.82	-14.27	-1.85	-1.98	0.27

VI. CONCLUSION

Predominated with frequent occurrence of hydro-meteorological hazards and flanked by sparsely distributed observational systems, the Bhagirathi-Alaknanda basin deserves the most sensitive performance of the coupled atmospheric-hydrological dynamic model of WRF-Hydro for reliable hydrologic prediction. The configuration of WRF- Hydro was applied in the finest resolution grid where the surface and subsurface flow were computed. The calibration process was performed for all season in each sub-basin. Results showed that the correlation coefficient between the observed and simulated discharges has been found higher than 0.75 for all prevailing seasons. Thus these calibrated parameters could be used from every scientific team that wants to perceive on hydrologic prediction of Bhagirathi-Alaknanda basin.

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REFERENCES

1. Arnault, J., S. Wagner, T. Rummler, B. Fersch, J. Bliefernicht, S. Andresen, and H. Kunstmann, 2016: Role of runoff–infiltration partitioning and resolved overland flow on land–atmosphere feedbacks: A case study with the WRF-Hydro coupled modeling system for West Africa. J. Hydrometeor., 17, 1489–1516, https://doi.org/10.1175/JHM-D-15-0089.1.
2. Ek, M.B.; Mitchell, K.E.; Lin, Y.Y.; Rogers, E.; Grunmann, P.; Koren, V.; Gayno, G.; Tarpley, J.D. Implementation of Noah land surface model advances in the National Centres for Environmental Prediction operational mesoscale Eta model. J. Geophys. Res. 2003, 108, 8851.
3. Gochis, D.J., Yu, W., Yates, D.N., 2014. The WRF-Hydro Model Technical Description and User's Guide, Version 2.0. NCAR Technical Document. 120 pages. Documentation, Model Code and ArcGIS Pre-processing Tools available online at: < http://www.ral.ucar.edu/projects/wrf_hydro/ >.
4. Gochis, D. J., & Chen, F. (2003). Hydrological Enhancements to the Community Noah Land Surface Model (No. NCAR/TN-454+STR). University Corporation for Atmospheric Research. doi: https://doi.org/10.5065/D60P0X00

5. Mitchell, K. E., et al. (2004), The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system, J. Geophys. Res., 109, D07S90, doi: https://doi.org/10.1029/2003JD003823
6. Senatore, A., G. Mendicino, D. J. Gochis, W. Yu, D. N. Yates, and H. Kunstmann, 2015: Fully coupled atmosphere-hydrology simulations for the central Mediterranean: Impact of enhanced hydrological parameterization for short and long time scales. J. Adv. Model. Earth Syst., 7, 1693–1715, https://doi.org/10.1002/2015MS000510.
7. Tolson, B. A. , & Shoemaker, C. A. . (2007). Dynamically dimensioned search algorithm for computationally efficient watershed model calibration. Water Resources Research, 43. doi: https://doi.org/10.1029/2005WR004723
8. Yucel, I., A. Onen, K. K. Yilmaz, and D. Gochis, 2015: Calibration and evaluation of a flood forecasting system: Utility of numerical weather prediction model, data assimilation and satellite-based rainfall. J. Hydrol., 523, 49–66, https://doi.org/10.1016/j.jhydrol.2015.01.042.

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