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Calibration of a SWAT Hydrologic Model for the Tamer Watershed in Northern Iran

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SWAT2005 (Soil and Water Assessment Tool) was used to simulate runoff and investigate the effect of various rain-gauge stations on the results of the model in Tamer watershed in northern Iran. The calibrated model will be used to predict the impact of different management operations on the runoff, sediment, and nutrient loads in the 1524 km^2 watershed. SUFI2 version 2.1.5 was used to calibration and performs uncertainty analysis of the model. The watershed studied included two climate and rain gauge stations Tamer and Golidagh. Tamer is located at the very end of the watershed and Golidagh is located at the top of the watershed. The model was run with Golidagh rain gauge station for the years 1999-2005 and with Tamer rain gauge station for the years 1990-1993. The calibration and validation of the model was performed for the years 1990-1993. The results showed that the model had reliably simulated runoff in both of stations. Four factor were considered in judging the model performance of runoff: *P-factor*, *R-factor*, R^2 and *NS*. The respective values of each were, respectively, 0.65, 1.2, 0.55 and 0.55 for calibration and 0.56, 1.2, 0.77 and 0.7, respectively for validation.

KEYWORDS: SWAT, uncertainty analysis, SUFI-2, runoff, rain gauge station, Iran

Introduction

Soil erosion causes economic, social and environmental problems. According to past studies, Asia suffers more than other continents from soil erosion, and Iran is one of the worst affected countries in Asia (Dregne, 1992; FAO, 1994). The mean annual erosion rate in Iran is estimated to be about 2500 t km^{-2}, which is 4.3 times more than the mean erosion rate in the world (Ahmadi et al., 2003). Also, available information shows that 59% of 17 large basins studied in Iran have been severely degraded (Ahmadi et al., 2003).

In recent years, mathematical models of watershed hydrology and transport processes have been employed to address a wide spectrum of environmental and water resources problems. The Soil and Water Assessment Tool, SWAT, (Arnold et al., 1998) was developed to predict the effects of different management practices on water quality, sediment yield and pollution load in watersheds. This is a computationally efficient simulator of hydrology and water quality at various scales. The program has been used in many international applications (Arnold and Allen, 1996; Narasimhan et al., 2005; Gosain et al., 2006; Abbaspour et al., 2007; Yang et al., 2007; Schuol et al., 2008a, b; Faramarzi et al., 2009). Arnold et al. (2000) applied SWAT with the addition of a streamflow filter and recession methods for regional estimation of baseflow and groundwater recharge in the upper Mississippi River basin. The results showed a general tendency for SWAT to under-predict spring peaks and to overestimate autumn streamflow compared to measured monthly data during both calibration and validation periods. Abbaspour et al. (2007) used SWAT to simulate all related processes affecting water quantity, sediment and nutrient loads in the Thur watershed in Switzerland. Their study indicated excellent results for discharge and nitrate, and quite good results for sediment and total phosphorus.

Very little information is available on sediment and river discharge in northen Iran therefore the main goal of this study is to model sediment and river discharge at Tamer watershed. To model sediment yield we intended first to calibrate hydrology while tuning discharge related parameters. Considering the fact that in the Tamer watershed hydrometric station, the sediment data were measured once or twice a month, the model was calibrated mostly using daily discharge data and then sediment parameters were slightly tuned for a better sediment simulation result.

As distributed hydrological modeling is subject to large uncertainties, the definition and quantification of model uncertainty has become the subject of considerable research in recent years. To fulfill this demand, researchers have developed various calibration-uncertainty analysis techniques for watershed models. These include Bayesian inference methods, such as: the Markov chain Monte Carlo (MCMC) method (Kuczera & Parent, 1998; Vrugt et al., 2003; Yang et al., 2007); generalized likelihood uncertainty estimation (GLUE) (Beven & Binley, 1992); parameter solution (ParaSol) (van Griensven & Meixner, 2006); and sequential uncertainty fitting (SUFI-2) (Abbaspour, et al., 2007). We used the program SUFI-2 in the SWAT-CUP package (SWAT Calibration Uncertainty Programs) (Abbaspour, et al., 2010) to calibrate the Tamer model.

Material and Methods

Description of the study area

The Tamer watershed, with an area of about 1524 km^2, is located in the north-east of the Gorganrud basin in Golestan province in Iran (Figure 1). The elevation ranges from 132 m at the outlet of the watershed to 2141 m in the mountainous areas. The mean annual temperature is 17.8°C and the mean annual precipitation is 496.4 mm. approximately 50% of the land is used for agriculture. The major crops are wheat and watermelon. More than 30% of the watershed is covered by forest, and the small part is covered by pasture and orchard.

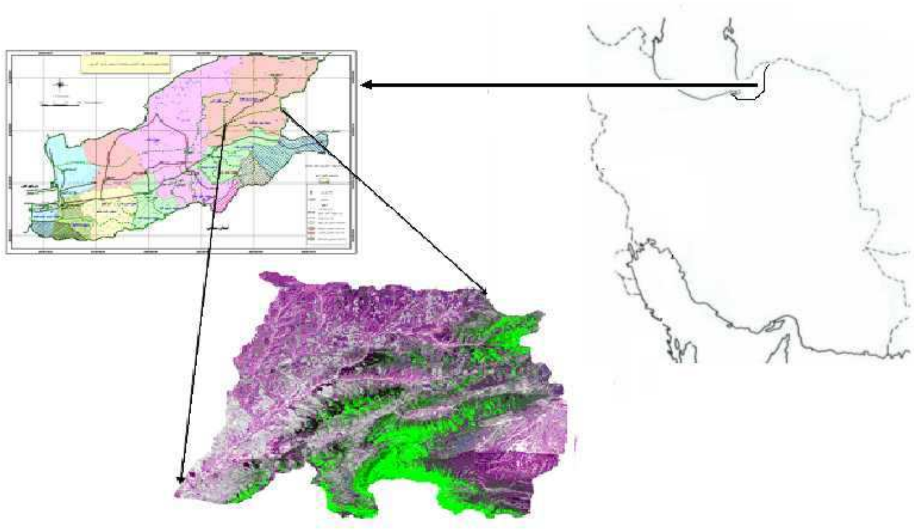

Figure 1 . Location of the Tamer watershed

Description of SWAT

SWAT is a basin-scale, continuous time model that operates on a daily time step and evaluates the impact of management practices on water, sediment and agricultural chemical yields in ungauged basins (Arnold et al., 1998). The model's major components include weather, hydrology, erosion, soil temperature, plant growth, nutrients, pesticides, land management, channel and reservoir routing. In SWAT, the watershed is divided into multiple sub-basins, which are then further sub-divided into hydrological response units (HRUs). These units consist of homogeneous landuse, management and soil characteristics. The water balance of each HRU is represented by four storage volumes including: snow, soil profile (0–2 m), shallow aquifer (typically 2–20 m) and deep aquifer (>20 m). The SWAT provides two methods for estimating surface runoff: the SCS curve number and the Green-Ampt infiltration method. In this study, we used the SCS curve number method. The peak runoff is an indicator of the erosive power of a storm and is used to predict sediment loss. The SWAT calculates the peak runoff rate with a modified rational method (Chow et al., 1988). Lateral subsurface flow in the soil profile (0–2 m) is calculated simultaneously with percolation. A kinematic storage routing that is based on the degree of slope, slope length and saturated hydraulic conductivity is used to predict lateral flow in each soil layer. Lateral flow occurs when the storage in any layer exceeds field capacity after percolation. Groundwater flow contribution to total streamflow is simulated by creating shallow aquifer storage (Arnold & Allen, 1996). Percolation from the bottom of the root zone is considered as recharge to the shallow aquifer. In SWAT, there are three methods for estimating potential evapotranspiration: Priestley & Taylor (1972), Penman-Monteith (Monteith, 1965) and Hargreav & Samani (1985). Water flow is routed through the channel network using the variable storage routing method or the Muskingum river routing method. Sediment yield in SWAT is estimated with the modified soil loss equation (MUSLE) developed by Williams & Berndt (1977).

Description of SUFI-2

In this research, various SWAT parameters related to discharge were estimated using the SUFI-2 algorithm (Abbaspour et al., 2007). In SUFI-2, uncertainty is defined as the discrepancy between measured and simulate variables. To account for this uncertainty, we therefore need to capture the measured data, except the outliers, in the predicted results. Therefore, SUFI-2 combines calibration and uncertainty analysis to find parameter uncertainties that result in prediction uncertainties bracketing most of the measured data, while producing the smallest possible prediction uncertainty band. Hence, these parameter uncertainties reflect all sources of uncertainties, i.e. conceptual model, inputs (e.g. rainfall), and parameter. In SUFI-2, uncertainty of input parameters is depicted as a uniform distribution, while model output uncertainty is quantified at the 95% prediction uncertainty (95PPU). The cumulative distribution of an output variable is obtained through Latin hypercube sampling. The SUFI-2 model starts by assuming a large parameter uncertainty (within a physically meaningful range), so that the measured data initially fall within the 95PPU, then decreases this uncertainty in steps while monitoring the *P-factor* and the *R-factor*. The *P-factor* is the percentage of data bracketed in the 95% prediction uncertainty (95PPU) calculated at the 2.5% and the 97.5% intervals of the simulated variables. This factor indicates the goodness of the calibration result. The *R-factor*, on the other hand, captures the level of uncertainty of the calibrated model, as a smaller 95PPU band indicates smaller model uncertainty. In each iteration, previous parameter ranges are updated by calculating the sensitivity matrix, and the equivalent of a Hessian matrix (Neudecker & Magnus, 1988), followed by the calculation of a covariance matrix, 95% confidence intervals of the parameters, and a correlation matrix. Parameters are then updated in such a way that the new ranges are always smaller than the previous ranges, and are centered around the best simulation (for more detail see Abbaspour et al., 2007). Because this analytical approach considers a band of model solutions (95PPU) instead of a best fit solution, the goodness of fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures instead of the usual R^2 or Nash-Sutcliffe coefficient NS (Nash & Sutcliffe, 1970), which only compare two signals. An ideal situation would lead to a *P-factor* approaching 100% and an *R-factor* approaching zero. In the current study, we used Arc-SWAT (Olivera *et al*., 2006), where ArcGIS (version 9.2) environment is used for project development. Spatial parameterization of the SWAT model is performed using SUFI-2 for a combined calibration and uncertainty analysis of the SWAT models.

Model parameterization and application

The SWAT-CUP program allows parameter aggregation on the basis of hydrological group, soil texture, land use, sub-basin number, and slope formulated as:

x__<parname>.<ext>__<hydrogrp>__<soltext>__<landuse>__<subbsn>__<slope>

where x__ is a code to indicate the type of change to be applied to the parameter. If replaced by v__ it means the default parameter is replaced by a given value; while a__ means a given quantity should be added to the default value, and r__ means the existing parameter value is multiplied by (1 + a given value); <parname> is the SWAT parameter name; <ext> is the SWAT file extension code for the file containing the parameter; <hydrogrp> is the soil hydrological group (A, B, C or D); <soltext> is the soil texture; <landuse> is the landuse category; <subbsn> is the sub-basin number, and <slope> is the slope delineation. Any combination of the above factors can be used to describe a parameter identifier, thus providing the opportunity for a detailed parameterization of the system. Omitting the identifiers <hydrogrp>, <soltext>, <landuse>, <subbsn>, and <slope> allows global assignment of parameters.

The data used in study are as follows:

i. Digital elevation model (DEM) obtained from the Golestan regional water office with a spatial resolution of 50 m

ii. Digital stream network at the 1:75 000 scale, produced by the Natural Resources Department of the Cartographic Centre of Iran

iii. Soil and landuse maps, at a scale of 1:100 000, produced by the Natural Resources Department of the Cartographic Centre of Iran. The soil map includes 17 types of soil.

iv. Climate data records from 2 rain gauges and 1 air temperature gauges over a period of 16 years (1990–2005); data were obtained from the Golestan regional water office.

The Tamer watershed was subdivided into 23 sub-basins and 94 HRUs. The model was calibrated twice. Once using Golidagh rain gauge station in 1999-2005 period and the second time by using Tamer rain gauge station in 1990-1993 period. Data from the Tamer hydrometric station in the Tamer watershed were used for calibration in 1999-2005 and validation in 1990-1993. In Tamer watersheds, the Hargreaves method was used to estimate evapotranspiration, and the Muskingum routing method was selected to route water through the channel network. The SWAT model was initially calibrated based on the monthly measured discharge data. The objective function was formulated using the *NS* coefficient. Sediment data were based on collected grab samples, which were used to measure suspended solids. Because these grab samples were the only available data for model calibration, the main calibration was performed using discharge data and then by fitting sediment parameters to obtain a better sediment simulation

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Results and discussion

An initial sensitivity analysis resulted in the choice of parameters that were calibrated as listed in Table 1. The results of monthly discharge calibration at Tamer are shown in Figure 2. *R-factor*=1.2, *P-factor* =0.65, *NS*=0.56, and R^2= 0.56, which represent a good calibration result.

An extreme flow event in August 2005 was underestimated but other peaks were satisfactorily captured. Error in the rainfall input data may be one reason for underestimation. The model in March and April overestimates the flow because irrigating extractions from the streams in the watershed were not properly accounted for because of lack of information. Validation results are shown in Figure 3 where the statistics of *P-factor*=0.56, *R-factor*=1.2, R^2=0.77, and *NS*=0.70 indicate adequate validation results.

In the next step we calibrated daily discharge in preparation for sediment calibration. In this attempt the model clearly does not reproduce the extreme events as illustrated in Figure 4. For daily discharge calibration, we obtained *NS*=0.1, R^2=0.1, *R-factor*=0.49, and *P-factor*=0.6. For the validation period in Figure 5, we obtained *NS*=0.3, R^2=0.38, *R-factor*=0.68, and *P-factor*=0.5. The reason of the low coefficient for *NS* is the weakness of the model in simulating the peak runoff. As these were the best daily calibration results, we used this model to simulate sediment. The following statistics were obtained for sediment calibration (Figure 6): *P-factor*=0.5, *R-factor*=0.42, *NS*=0.13, and R^2=0.13, and for validation (Figure 7) we obtained *P-factor*=0.36, *R-factor*=0.03, *NS*=0.07, and R^2=0.82. A reason for the inability of SWAT to model sediment peaks properly is that the flow peaks were not represented well in the model s well as the loess nature of the soil, which erodes quite easily. In the next step we will consider using hourly rainfall to better capture the short duration high intensity rainfall events characteristic of the region.

Table 1. Description of SWAT2005 input parameters selected for runoff and sediment calibration

*Parameter names**	*defenition*	*Initial range*		*Final range*	
		min	max	min	max
r__CN2.mgt	SCS runoff curve number for moisture condition II	-0.3	0.5	-0.87	-0.47
r__CN2.mgt	SCS runoff curve number for moisture condition II	-0.5	0.3	-0.5	-0.3
r__SOL_BD().sol	Soil bulk density (g/cm^3)	0.04	0.3	-0.13	0.26
r__SOL_BD().sol	Soil bulk density (g/cm^3)	-0.1	0.1	-0.19	-0.09
r__SOL_AWC().sol	Soil available water storage capacity (mmH$_2$O/mm Soil)	0.4	1.4	0.15	0.55
r__SOL_AWC().sol	Soil available water storage capacity (mmH$_2$O/mm Soil)	-1.0	-0.7	-0.96	-0.76
r__SOL_K().sol	Soil conductivity (mm/hr)	0.15	1.15	0.62	1.02
r__SOL_K().sol	Soil conductivity (mm/hr)	-1.0	-0.03	-0.65	-0.25
v__ALPHA_BF.gw	Base flow alpha factor (days)	0.0	0.5	0.04	0.12
v__ALPHA_BF.gw	Base flow alpha factor (days)	0.0	0.5	0.26	0.46
v__RCHRG_DP.gw	Deep aquifer percolation factor	0.0	1.0	0.0	0.08
v__RCHRG_DP.gw	Deep aquifer percolation factor	0.0	1.0	0.9	1.0
v__EPCO.hru	Plant uptake compensation factor	0.07	0.7	0.01	0.05
v__ESCO.hru	Soil evaporation compensation factor	0.5	1.0	0.74	0.94
v__OV_N.hru	Manning,s n value for overland flow	0.01	0.7	0.39	0.59
v__CH_N2.rte	Manning,s n value for the main channel	0.09	0.22	0.05	0.13
v__CH_K2.rte	Effective hydraulic conductivity in the main channel (mm/hr)	122.0	216.0	187.0	227.0
v__SPCON.bsn	Channel sediment routing	0.001	0.01	0.006	0.007
v__SPEXP.bsn	Exponent for calculating sediment re-entrained in channel	1.0	1.5	1.17	1.25
v__PRF.bsn	Peak factor for sediment routing channel	0.0	2.0	0.65	0.85
v__APM().bsn	Peak factor for sediment routing sub-basin	0.5	2.0	0.7	1.0
v__CH_EROD.rte	Channel erodibility factor	0.0	0.6	0.25	0.35
v__CH_COV.rte	Channel cover factor	0.0	1.0	0.2	0.3
r__USLE_K().sol	USLE soil erodibility factor	0.0	0.65	0.01	0.3
r__USLE_K().sol	USLE soil erodibility factor	0.0	0.65	0.2	0.4

* v__: means the default parameter is replaced by a given value, and r__: means the existing parameter value is multiplied by (1 + a given value)

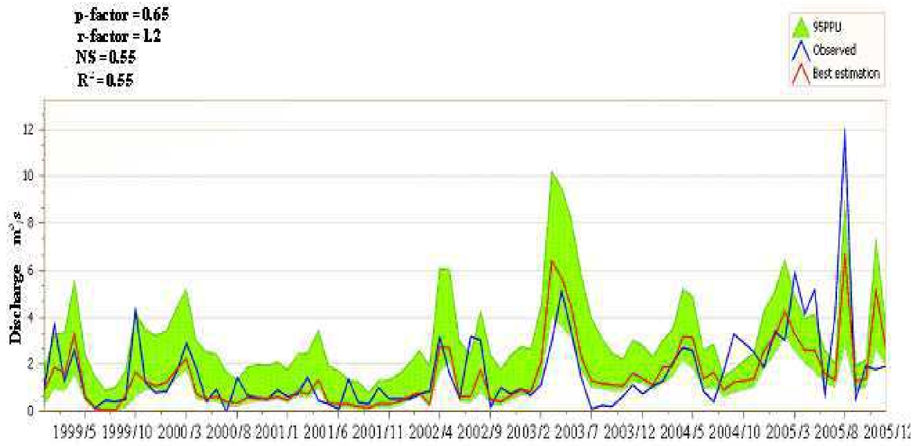

Figure 2. Monthly calibration results

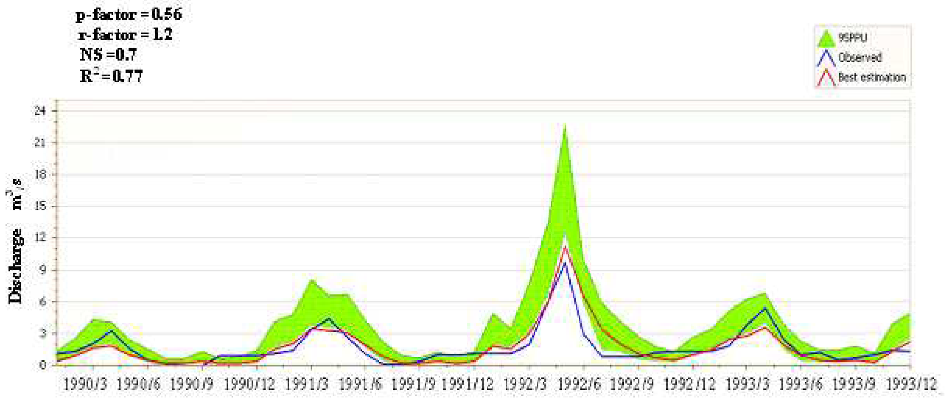

Figure 3. Monthly validation results

Conclusion

The SWAT model was applied to Tamer watersheds in northern Iran to predict runoff and sediment. Monthly calibration and validation of discharge was quite satisfactory. However, daily calibration and validation of discharge produced unsatisfactory accounting of the peak flows. The daily model was further used to simulate sediment. After calibrating for influential sediment parameters, the model results were still not satisfactory. We concluded that the main reason for poor sediment results is the poor capturing of the storm peaks by the flow model, which in turn results from the inadequate description of the rainfall in the region. In further research we will use hourly rainfall data to better capture the extreme frontal rainfall events characteristic of the region.

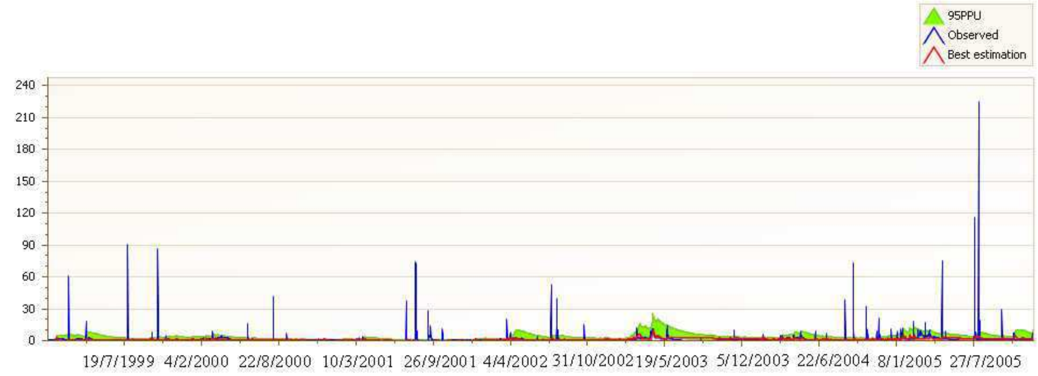

Figure 4. Daily river discharge calibration

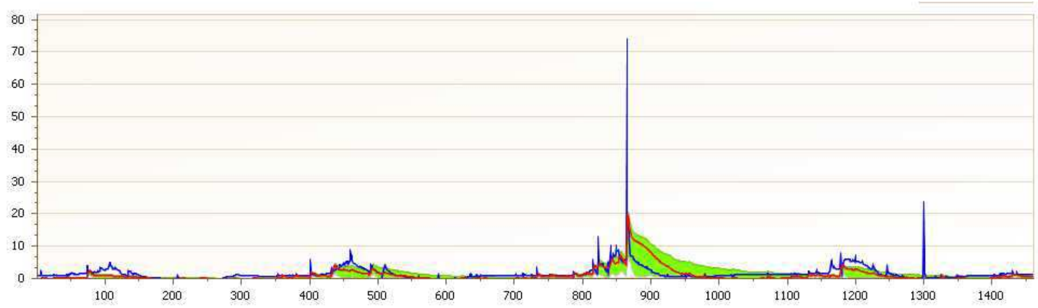

Figure 5. Daily river discharge validation

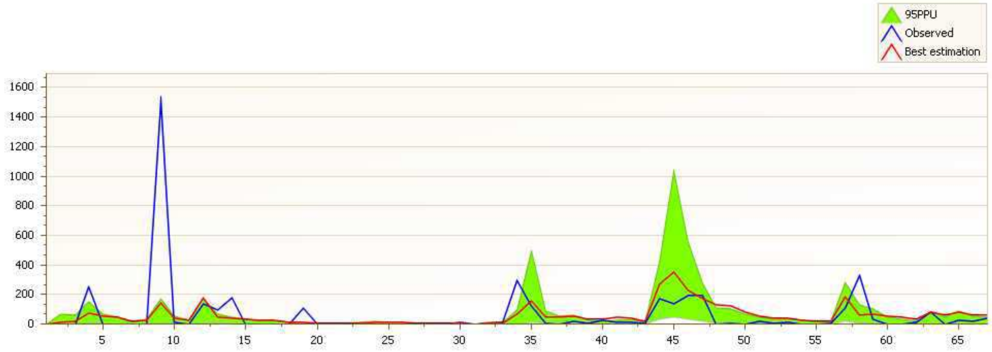

Figure 6. Daily sediment calibration

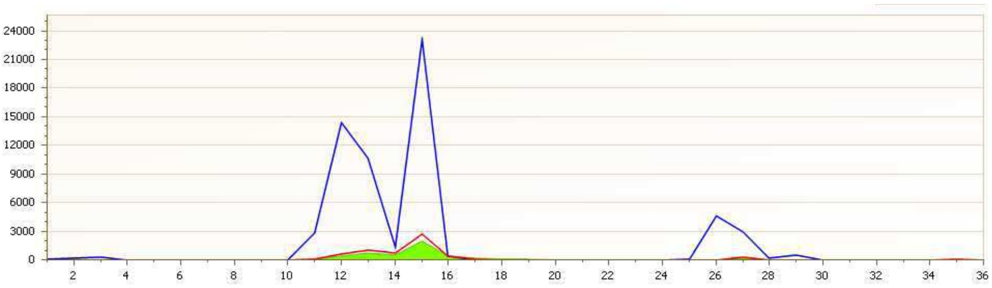

Figure 7. Daily sediment validation

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