APPENDIX 3-B

Regional Runoff and Pollutant Loading Technical Approach

Introduction

This Appendix details the regional-scale modeling methods employed to support a metrics-based approach to stormwater project prioritization for the County of San Luis Obispo Stormwater Resource Plan (SWRP). It includes the purpose and rationale for the modeling approach selected; the technical elements that distinguish this regional application from the more detailed, urban-area application on which it is based, and sample outputs and their intended usage to fulfill the needs of this SWRP.

Model alignment with regional management needs

Models are used to integrate the best scientific understanding of hydrology and pollutant transport to extend the utility of existing data, supporting estimates of stormwater impacts in locations or time periods for which there are no data. The use of urban hydrology and pollutant models to inform both short and long-term stormwater programmatic planning decisions is common (e.g., Elliot and Trowsdale, 2007; Zoppou, 2001; Lee et al., 2012; Rossman, 2013; Voskamp and Van de Ven, 2015). A key decision point is determining which model to use among the alternatives available. Model selection should be guided chiefly via the intended use of model outputs and the necessary degree of model detail for the identified management purposes (Leavesley et al. 2002). Considerations for model selection typically include resources available, required process detail representation, time step, and spatial resolution. Typically, the least complex model that reliably meets the anticipated application is best (Chandler 1994, Rauch et al. 2002, Dotto et al. 2012), since development, input data, and computational costs tend to be less.

In addition to practical considerations, model selection has scientific implications that can affect the ability to serve management purposes (see US EPA, 2009). Relatively complex modeling alternatives tend to have high input data requirements and numerous "free" parameters that require user calibration. Often, only a few input variables may contribute significantly to the outputs (Li et al. 2014). Such over-parameterization commonly results in a high degree of uncertainty in the model outputs due to subjective decisions required during the calibration process (Beven 1989, Beven 2001) and because parameter values often vary over time and space (Hossain and Imteaz, 2016). Inclusion of extraneous model components or parameters that do not result in a measurable output response may improve simulation performance, but they can fortify a model against discerning changes in a catchment over time (Beven 2001, Nandakumar and Mein 1997) or for testing heuristic management scenarios (Freni et al. 2011). Even where good hydrological data are available, such models are probably only sufficient to support reliable calibration of models of very limited complexity (Jakeman and Hornberger 1993, Gaume et al. 1998).

For stormwater resource planning, information about *where* impacts are most acute, and so where reduction benefits can be maximized, is critical because landscape heterogeneity creates substantial variation in both of these factors. Since there are no long-term runoff data at drainage scales finer than

regional watersheds (e.g., the entirety of the upper Salinas River watershed), approaches that rely strongly on calibration must lump landscape characteristics to that scale and thus provide very coarse spatial resolution. Such approaches often rely on Hydrologic Response Units (HRUs) to characterize this heterogeneity, but these HRUs are not generally contiguous in space, so the attributes that are location specific and contribute to runoff response within a drainage is not captured explicitly. Efforts to transition continuous simulation to spatially explicit grid-based calculations often suffer from difficulties associated with distributed parameter calibration (see Pignotti et al., 2017).

For stormwater planning purposes, hourly time-step estimates (often employed in continuous simulation models) may not be required to satisfy objectives; even annual time steps may often be sufficient. This also allows the use of decadal time-series, so that the model outputs bracket a wide range of plausible conditions, rather than having outputs tied to a shorter time period (albeit with finer time resolution) that is less likely to be representative of average long-term responses.

Detailed process representation of evapotranspiration, subsurface flow, stream hydraulics, and groundwater percolation are also not essential to meaningfully address most stormwater management questions and would also be impractical to apply throughout the entire region. Indeed, simpler approaches to hydrologic modeling have often shown comparable performance to more complex ones (e.g., Kokkonen et al. 2001; Perrin et al., 2001; Bormann and Diekkruger, 2003; Reed et al., 2004), particularly at annual time steps (Beck et al., 2017).

Recently developed decision support model alternatives

A full review of modeling approaches available is beyond the scope of this document, but suffice to say that there are many available that can be broadly classified as statistical, empirical, hydraulic, and hydrological that differ in their spatial and temporal resolution, functionality, water quality components, and accessibility (see Zoppou, 2017 for a recent review). Given the considerations detailed above, we begin with the bounding criteria that candidate models should provide (1) spatially explicit outputs via (2) relatively simple process representation on (3) annual time steps to efficiently (but adequately) satisfy stormwater management information needs. In addition, peer review, good documentation of how model equations are implemented, calibration procedures, and input data processing are required to provide transparency to model estimates used for decision making. Open source code is beneficial but not necessary to facilitate scrutiny by other experts, as long as the algorithms used in the model may be recreated based on readily available documentation. For example, computer code that controls user interfaces is not essential for detailed review, and it is relatively less accessible to most scientific or modeling experts.

Several simplified approaches have been recently developed in California to help communities comply with MS4 regulatory requirements, support stormwater resource planning and perform reasonable assurance analysis. These include the Stormwater Tool to Estimate Load Reductions (swTELR) developed in the Central Coast Region (Beck et al., 2017), the Regional Watershed Spreadsheet model developed for the San Francisco Bay Area (Wu et al., 2016), the Load Prioritization and Reduction model (LPR) developed for Santa Barbara County (Geosyntec, 2015), and the SBPAT model developed for the County of Los Angeles (Austin, 2010). Each of these are intended to be used as planning-level tools and share

similar elements, differing primarily in their input data treatment and execution. For example, each of these models employ a volume–concentration approach to calculating pollutant loads, wherein loads are calculated as the product of runoff and empirically estimated land-use or land-cover-based pollutant concentrations. This approach includes the simplifying assumption that unit area runoff for homogeneous areas has a constant concentration of pollutants, rather than the dynamic approach employed in continuous simulation models such as HSPF and SWMM that allows concentrations to vary over time steps as short as an hour.

Although these simplified approaches all share an equivalent conceptual foundation, they have significant differences that can guide the choice of the most suitable application for this SWRP. For example, the SBPAT model (http://www.sbpat.net/index.html) is essentially a GIS-based interface that requires coupling with the EPA's SWMM. As such it requires the expertise and data requirements of that underlying continuous simulation model. There is no documentation of the model algorithms, assumptions, functionality, required data inputs, or calibration procedure provided on the model website; nor is there any listing of publications featuring SBPAT that have been peer reviewed.

By comparison, the Pollutant Load Prioritization and Reduction Model (LPR) provides a simplified runoff accounting mechanism, but it still requires calibration to observed data. This disallows estimates at finer spatial resolution than the calibration scale (e.g. region-scale watersheds), since errors in one part of a drainage may be cancelled out by errors in another part; resulting in a calibrated parameter set that reflects these cancelling effects, rather than optimal values for the individual locations. A distinct advantage of LPR is that it provides pollutant loading for 12 different pollutants, based primarily on event concentration data collected in Southern California (e.g., Stein et al., 2007). The Regional Watershed Spreadsheet Model has a similar approach, but it uses spatially distributed rainfall inputs and focuses specifically on loadings of PCBs and mercury. The RWSM uses land use and impervious cover input data and monitoring data to specify characteristic runoff concentrations (Lent et al., 2011). Adequate calibration of pollutant EMC coefficients has proved difficult in the Bay Area watersheds, however, being a persistent source of uncertainty as estimates are strongly dependent on choice of calibration data sets (Wu et al., 2017). Both LPC and RWSM use runoff ratios for generation of average annual runoff, which is a very simple approach that provides no variation of runoff response to different rainfall intensities or volumes (Lent et al., 2011). The RWSM model in particular is very well documented, the methods of implementation have been transparently communicated, and its developers have included critical assessment and identification of performance deficiencies.

Although both LPC and RWSM are credible alternatives for this SWRP, we believe that their advantages (and shortcomings) are largely shared by swTELR. As significant discriminator, however, is that communities throughout the County of San Luis Obispo have adopted and are actively using swTELR to support MS4 permit requirements. Therefore, the most compatible approach to regional modeling of runoff and pollutant loading that meets the objectives of this SWRP is a variation of swTELR that will ensure efficient integration of regional outputs with those from municipalities and urbanized areas of the County that have already been developed. TELR has the additional advantage of using the National Resource Conservation Service Curve Number method (NRCS-CN) for runoff generation (USDA-NRCS, 1986), which provides variation of runoff response to different rainfall volumes. This contrasts to the

single-value runoff ratio method used in RWSM and LPC. This means that swTELR produces outputs that characterize the shape of the rainfall probability distribution more completely than can be accomplished with a single value, which can only represent the central tendency of that distribution. Similar to the other approaches described, swTELR does not provide outputs for a particular year but instead returns average annual response. This is adequate for management modeling objectives as defined for this plan and has been judged generally acceptable for stormwater management planning (Lent et al., 2011).

The original version of swTELR was developed for use in urban environments and has some shortcomings for use as a regional tool. Given the alignment of the model with the management objectives and its potential for seamless integration with the region's existing investment in more detailed stormwater modeling, however, we believe that the optimal solution is to borrow the runoff and routing algorithms from TELR and modify them appropriately for regional application. This also allows the adoption of useful elements from other modeling approaches as appropriate.

Regional application of TELR

Initial development of swTELR was in predominantly urbanized catchments covering approximately 100 acres (Beck et al., 2017). Its prior validation also emphasized urban-area applications, and so evaluating the accuracy and utility of the results for broader scale application is also necessary. These topics are addressed in turn.

Limitations of swTELR

Several limitations of swTELR have already been documented for swTELR (2NDNATURE, 2016) but do not necessarily provide barriers to use in regional applications. The NRCS Curve Number method (NRCS-CN) (USDA-NRCS, 1986) used in swTELR is a well-tested method, but it includes no detailed representation of physical hydraulic or soil processes and has shown mixed performance when compared with measured data (e.g., Hawkins, 1984). The NCRS-CN method does not consider rainfall intensity or duration, only total rainfall volume, and it assumes a uniform curve number to characterize runoff response for each land-use area. Confidence in the method, however, is provided by the fact that much more sophisticated and widely used models, such as the Soil Water Assessment Tool (SWAT), also employs curve numbers for runoff generation and can show comparable performance to other methods (e.g., King et al., 1999). The NRCS-CN method employed in swTELR strikes a middle ground of complexity between the simplest approaches, such as the use of single-value runoff ratios (Wu et al., 2017), and more complex continuous simulation models. Runoff routing and temporary storage in swTELR is represented only as a single parameter in the time-of-concentration calculations for stormwater movement towards centralized BMPs, so there is no explicit way to represent storage in the form of ponding. There is also no explicit representation of antecedent hydrologic conditions that may affect subsurface water movement, although the range of antecedent conditions is included in the curve number specification for each cover type. While these factors are important for predicting hourly hydrographs and flood forecasting, they have limited relevance for a regional planning application that considers only average annual responses.

Estimates of particulate pollutant loading in swTELR use total suspended solids (TSS) as a surrogate parameter, based on reviews of compiled data in the International National Stormwater BMP Database (http://www.bmpdatabase.org/index.htm) and the literature. Results are expressed in units of tons per acre per year. Extension to other pollutants, which is commonly done by many other such models, requires specifying runoff concentrations for those pollutants. This ought to be done with great caution, since even TSS, which is among the most often measured constituents, shows highly variable estimates for individual land uses and land cover types. Incorporation of other pollutants compounds what is already a substantial source of uncertainty; their inclusion in other models provides a false degree of precision for discerning loading response amongst individual constituents. Thus, extension of swTELR functionality to include additional pollutants is not a priority for this application (nor should it be for other such modeling efforts).

The primary modifications that have been made to apply swTELR at a regional scale application (*Regional TELR*; hereafter "*R-TELR*") are:

- Development of distributed rainfall inputs for the entire County
- Land-cover-based curve number specification in undeveloped areas
- Changes to runoff generation algorithms suitable for larger spatial scales
- Land-cover-based runoff concentrations suitable for larger spatial scales
- Incorporation of slope effects into the runoff and TSS loading calculations
- A simplified flow network to accommodate a more extensive drainage network

Given the availability of spatial datasets at the 30-meter pixel scale resolution, runoff generation can be calculated to match the scale of variation of those inputs. This requires processing of very large raster data sets, which is performed with functions written in the R Statistical programming language (https://www.r-project.org/) and Model Builder in ArcGIS Pro from ESRI (https://www.esri.com/en-us/home). Each step of the spatial modeling process is fully documented below; results are output in raster layers that are used for interim validation at each step of the processing.

Development of distributed rainfall inputs

Within urbanized areas, swTELR is driven by precipitation measurements from local rain gages (usually within an MS4 boundary), but the regional scale requires rainfall inputs in areas that are often far from rainfall gauge measurements. The PRISM interpolated rainfall data sets produced by Oregon State University (http://prism.oregonstate.edu/) provides a very good solution to estimate precipitating across the entire landscape. The PRISM climate group compiles climate observations from a wide range of monitoring networks, applies robust quality control and spatial interpolation techniques, and provides climate data at various spatial/temporal resolutions covering the period from the year 1895 to the present. The standard products available from the PRISM Group (e.g., monthly mean values) were not adequate since TELR requires several percentile values from a 30+ year rainfall record to specify precipitation inputs. Instead, a program was created using functions written in R to acquire the appropriate PRISM historical raster layers for each year for the period 1981-2016 and perform a series of raster data processing steps. After the 35-year sequence is acquired (12,775 raster layers), they were

stacked so that each 4 km² pixel represents a time series of values for that grid cell. From these layers, percentile values that describe the shape of the precipitation data distribution were calculated for each pixel and these values were used to drive runoff generation in Regional TELR.

Initial validation showed good correspondence between TELR inputs from local gauge data downloaded from the Western Regional Climate Center (https://wrcc.dri.edu/) and the PRISM-calculated percentile values (12.5, 50, 85, 95) for 15 Central Coast cities, with slightly lower estimates from the PRISM data (see Figure 3C-1). To correct the consistent bias towards underprediction of precipitation values form the interpolated PRISM data, a linear regression model was fit to these data to specify the bias correction via the equation shown in Figure 3C-1.
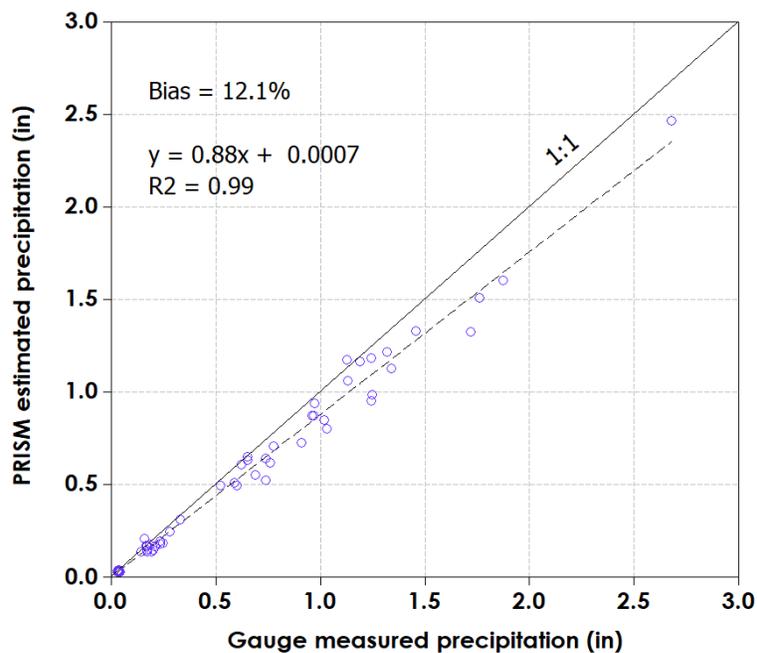

Bias = 12.1%

$y = 0.88x + 0.0007$
$R2 = 0.99$

1:1

Figure 3C-1. Correspondence between calculated percentile values for WRCC rain gauges and PRISM interpolated data for 15 Central Coast Cities.

Changes to runoff generation algorithms

The NRCS-CN method represents storage as an *initial abstraction*, which incorporates all losses before runoff begins, including water retained in surface depressions, water intercepted by vegetation, evaporation, and infiltration. Runoff does not begin until the initial abstraction has been exceeded. The initial abstraction is variable across the landscape but is highly correlated to the curve number (NRCS-USDA-1986). A value of to 5% was used in swTELR, as research indicates that this is most appropriate value for urbanized areas (Woodward et al., 2003; Lim et al., 2006; Shi et al., 2009), especially for the less-permeable hydrologic soil groups C and D (Jiang, 2001). This affects calculation of the maximum potential soil moisture retention after runoff begins, and in swTELR was adjusted based on model fitting

reported in the hydrologic literature (Hawkins et al., 2002; Lim et al., 2006). For R-TELR, the initial abstraction is set to 20% and the maximum soil moisture retention after runoff begins is returned to the original calculation method. Both of these components are implemented as originally specified in USDA-NRCS (1986).

Land-cover based curve number speciation in undeveloped areas

Higher runoff curve numbers generate more runoff per unit amount of rainfall. In urban environments, the curve number is determined in swTELR via the soil type and the amount of impervious coverage, with curve numbers increasing linearly with additional imperviousness. This method is less applicable to more rural areas, where there is usually very little impervious coverage and so other factors are more important for determining runoff generation, such as the nature of the vegetation cover (e.g., forest vs grassland). For example, in development of the RWSM, Lent et al. (2011) tested specification of runoff ratios using both percent impervious and NLCD land cover data and found variable performance depending on factors such as rainfall amounts, slope, and imperviousness. Following from this example, R-TELR adopts a two-branched spatial data processing approach, wherein the method of curve number depends on the level of impervious cover. For pixels with > 5% impervious cover (usually urbanized areas), R-TELR employs the same method as swTELR for specifying curve numbers based on NRCS soil class and percent impervious cover. Outside of urbanized areas we used the NRCS soil classes in conjunction with the National Land Cover Dataset (NLCD), with corresponding USDA-reported land cover-based curve numbers (USDA, 1986) to specify curve number values (Table 3C-1; e.g., Eslinger et al., 2012). In natural landscapes we expect soil and vegetation storage to be more important factors dictating runoff response than in urbanized environments, and the curve-number specification method reflects this understanding.

Table 3C-1. NLCD Land Cover and USDA starting curve numbers for NRCS soil types before adjustments for impervious coverage (USDA, 1986). CRCs are median values reported in 35 separate stormwater quality studies and the National Stormwater Quality Database (NSQD, 2015; http://www.bmpdatabase.org/nsqd.html).

NLDC Land Cover	NLCD Category#	USDA Cover Type	NRCS Soil Type CN			
			A	B	C	D
Developed, Hi-Intensity	24	Commercial and Business	89	92	94	95
Developed, Medium-Intensity	23	1/8 Acre Residential	77	85	90	92
Developed, Low Intensity	22	1/4 Acre Residential	61	75	83	87
Developed, Open Space	21	Open Space, Fair Condition	49	69	79	84
Cultivated Crops	82	Row Crops	67	78	85	89
Pasture/Hay	81	Open Space, Good Condition	39	61	61	80
Barren Land (Rock/Sand/Clay)	31	Fallow	77	86	91	94
Grasslands/Herbaceous	71	Pasture, Grassland, Range	30	58	71	78
Shrublands/Scrub	52	Brush	30	48	65	73
Forest (Deciduous/Evergreen/Mixed)	41, 43, 43	Woods	30	55	70	77
Wetlands (Woody/Emergent Herbaceous)	90, 92	-	0	0	0	0
Open Water	11	-	0	0	0	0

Land Cover based runoff concentrations

R-TELR requires specification of characteristic runoff concentrations (CRC) to land uses beyond those that can be classified as urban development. Similar to swTELR, R-TELR employs a simple volume-concentration approach, wherein

Pollutant Load (mass/time) = stormwater runoff (volume/time) * pollutant concentration (mass/volume)

This approach ignores the event-specific dynamics that depend on rainfall duration and intensity that have been linked to variations in pollutant concentrations throughout an event. For example, algorithms to represent pollutant build-up and wash-off over time are common in continuous simulation models (Freni et al., 2009; 2011; Mannina and Viviani, 2010; Hossain and Imteaz, 2016), which has been shown to improve pollutant modeling performance in some cases (Wang et al., 2011). An important disadvantage, however, is that parameters for these calculations are difficult to identify with precision or validate with sampling (Freni et al., 2009). While Monte Carlo sampling of the parameter space can improve parameter identifiability and (Strecker et al., 1990; Wagener and Kollat 2007; Freni et al., 2011), high degrees of uncertainty frequently persist in model outputs when calibration is required, even when performance is improved (Beven, 1989; Petrucci and Bonhomme, 2014). Other researchers have found that pollutant accumulation and generation on event time scales is extremely difficult to predict and that similar seasonal or annual results could be obtained using constant concentrations (Sage et al., 2015). At the average annual scale, these effects are substantially less important than the drainage

inputs and runoff volumes for explaining pollutant loads (Lee and Bang, 2000; Brezonik and Statelmann, 2002).

As in swTELR, the R-TELR pollutant loading module only pertains to particulate pollutants, as informed by total suspended solids (TSS) results. Particulate pollutant loading is used as the proxy measure for other pollutants, since entrainment and transport processes are similar for all particulates and large proportions of pollutants such as metals are often bound to particulate matter in runoff (Loganathan et al., 2013; Chen and Chang, 2014; Herngren et al., 2005; Sartor et al., 1972; Kayhanian et al., 2012). Strong correlations have been observed between particulates such as TSS and other water-quality constituents, including total organic carbon, nutrients, heavy metals, oil and grease (Kayhanian et al., 2012). The assumption of correspondence between particulates and other pollutants has been tested directly through targeted sampling programs that include TSS and a suite of other pollutants (2NDNATURE 2010a, 2010b, 2014; 2NDNATURE and nhc 2012, 2014), although we acknowledge that these experiments were done in primarily urbanized drainages. We expect TSS to be a less useful proxy for non-conservative constituents, such as nitrogen, that have different fate and transport properties. An alternative approach would be to use the Revised Universal Soil Loss Equation (RUSLE) to calculate sediment yields, but other researchers have found poor correspondence between measurements and RUSLE estimates at the watershed scale and have specifically recommend against using it as a planning tool (Boomer et al., 2008).

Similar to swTELR, R-TELR employs *characteristic runoff concentrations* (CRC's), which are defined as the expected average annual pollutant concentration generated from a land use in a particular condition across a range of event types (nhc et al., 2010). While similar to event mean concentration (EMC) values commonly applied in stormwater modeling (e.g., Butcher, 2003), CRCs are intended to be an annual volume-weighted average of EMC values. Outside of MS4s, land-cover types other than 'developed' usually dominate watersheds, and so this wider array of land cover types is captured by associating the full range of NLCD types with individual CRCs, analogous to how CRCs are specified for urban land uses. A literature search identified the best CRC values based on past measurements of Total Suspended Solids (TSS) for different land cover types. Table 3C-2 lists the median values for each land cover type obtained from a number of independent studies. For generation of particulate pollutant loads, R-TELR used the median value for each land cover type listed in Table 3C-2.

Table 3C-2. Rural land cover types and associated TSS measurements from various researchers. Median values reported, unless otherwise indicated. CUL = Cultivated, PAS = Pasture, Bar = Barren, GRA = Grasslands, SHB = Shrubland, FOR = Forest, WTL = Wetland.

Study	Rural Land Cover TSS (mg/L)						
	CUL	PAS	BAR	GRA	SHB	FOR	WTL
Adamus and Bergman, 1995	107	55	70	55	11	11	19
USGS, 2006	190						
Ackerman and Schiff, 2003	1191						
Tiefenthaler, et al. 2008	88						
Stein et al. 2007	112						
Tetra Tech, 2010 (mean)	355						
Line et al. 2002		143				113	
Line, 2015		422					
Line et el, 2016		350					
Bartley and Speirs, 2010	3104	259				26	
Packet, et al., 2009	612						
Jarvelein, 2014	580	40		40	40	40	
Line, 2003		65					

As previously noted, measured runoff concentrations show high variance within individual land cover types, and some land cover types have few measurements available. While our current literature search is not exhaustive, it should be noted that other approaches often rely on only a single source for specifying concentration values (e.g., Eslinger et al., 2012). For R-TELR we calculated the median TSS values for each land cover type, which helps reduce the effects of extreme values when characterizing central tendency. CRCs for urban land-use types used in swTELR are based on 23 literature studies, along with analysis of the National Stormwater BMP Database that includes thousands of individual measurements from hundreds of individual studies. For R-TELR, we binned each of the urban land-uses into one or more of the NLCD and calculated median values for each of those urban land uses (Table 3C-3).

Table 3C-3. Median concentration values for used for R-TELR CRCs. COM = commercial, IND = industrial, SFR = single family residential, MFR = multi-family residential, OTH = other HTR = high traffic road, MTR =moderate traffic road, LTR = low traffic road.

NLDC Land Cover	Class #	swTELR Urban Land Use	CRC (mg/L)
Developed, Hi-Intensity	24	HTR, MTR, IND, COM, MFR	104
Developed, Medium-Intensity	23	MTR, LTR, SFR, OTH	99
Developed, Low Intensity	22	LTR, SFR, OTH	88
Developed, Open Space	21	OTH	15
Cultivated Crops	82		355
Pasture/Hay	81		143
Barren Land (Rock/Sand/Clay)	31		70
Grasslands/Herbaceous	71, 72		48
Shrublands/Scrub	51, 52		26
Forest Deciduous/Evergreen/Mixed	41, 42, 43		33
Wetlands (Woody/Emergent Herbaceous)	90. 95		19

Incorporation of slope effects

Slope has a more important effect on runoff generation and subsequent pollutant loading in natural landscapes compared the urbanized environments where much of the cover is impervious surfaces. Runoff generation is affected by reduction of the initial abstraction (Fox et al., 1997; Chaplot and Bissonnais, 2003), a decrease in infiltration, and a reduction of the recession time of overland flow (Evett and Dutt, 1985). The NRCS-CN does not take slope into account because it was developed in cultivated landscapes, where slopes are generally less than 5%. Experiments on steeply sloping plots indeed show that they yield considerable more runoff (Sharma, 1986). Given the conceptual logic for incorporation of a slope parameter to the NRCS-CN method, a number of approaches to modification have been reported in the literature (Williams, 1995; Huang et al., 2006, Huang; Strehmel et al., 2014). While none of these have yet have been incorporated into the continuous simulation SWAT model, which also use the NRCS-CN, citing some mixed performance results (e.g., Ebrahimian et al., 2012), their potential for improving runoff and pollutant loading estimates is recognized in the recent model update documentation (USDA-NRCS, 2017).

Here, we employ the empirical method developed by Huang et al. (2006), who studied the effect of slope on runoff volumes under simulated rainfall for 11 years to modify the existing standard NRCS-CN method for land slope. They developed a slope adjusted CN empirical equation as follows:

$$CN_{2\alpha} = CN_2 \frac{322.79 + 15.68(\alpha)}{\alpha + 323.52}$$

…where CN_2 is the NRCS handbook for average moisture condition, $CN_{2\alpha}$ is the adjusted CN for a given slope, and A is slope (m·m^{-1}) between 0.14 and 1.4 (14-140%). Slope was calculated using a 30-meter pixel resolution digital elevation model (DEM) for San Luis Obispo County and the slope tool in ArcGIS

Pro. Slopes greater than 14% are within the domain of this CN adjustment and are shown in Figure 3C-2, with the steepest slopes generally occurring in the Southern Santa Lucia Mountains just east of the City of San Luis Obispo.
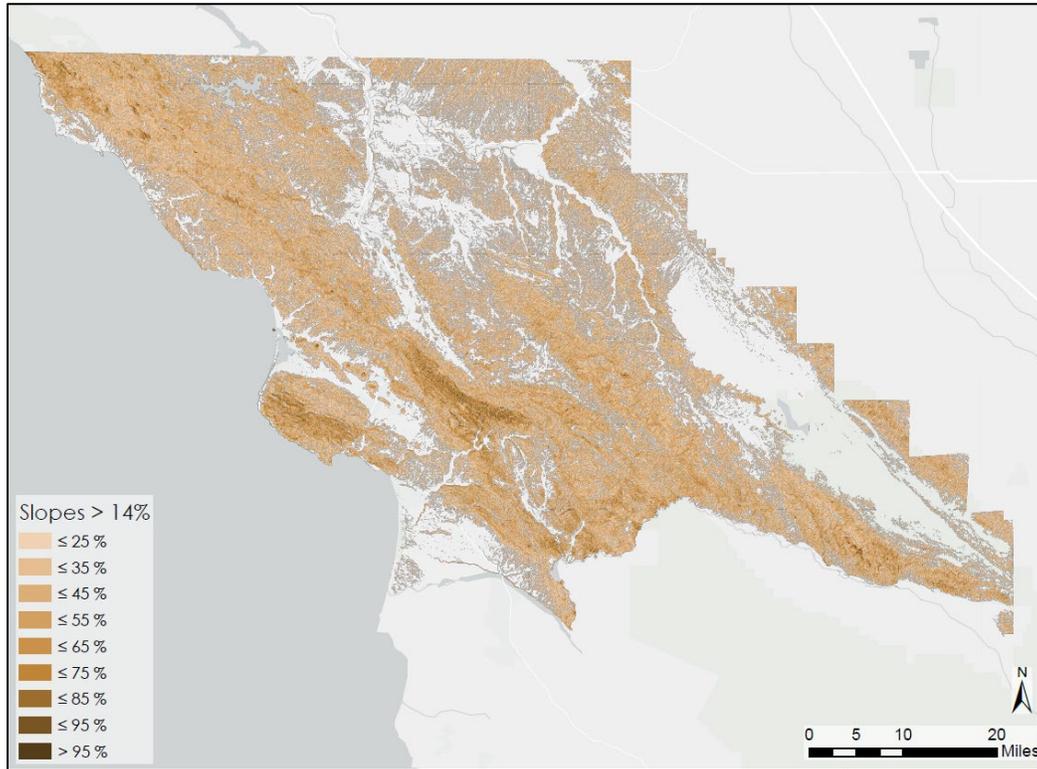

Figure 3C-2. Calculated slope from 30-m DEM for SLO County used for adjustment of curve numbers.

Thus, curve number calculated for each pixel in R-TELR were adjusted to incorporate the influence of slope on runoff generation throughout the County. The net result will be somewhat greater runoff generation and pollutant loading in these areas than would have occurred without this slope adjustment.

Simplified routing and spatial aggregation scale

Although the calculations in R-TELR are made at the 30-m pixel scale, they can be aggregated to larger areas, such as the CalWater "Planning Watershed" scale CalWater (v.2.2.1) (approximately 10,000 acres), for hydrologic routing (if required) and integration with other spatial datasets used to identify stormwater opportunities. Runoff outputs are shown at their full 30-m resolution in Figure 3C-3 with the Planning Watersheds overlaid. The highest average annual runoff values occur in densely urbanized areas with high proportions of impervious cover, such as the City of San Luis Obispo, and mountainous areas such as the Santa Lucia Range that tend to receive more rainfall and/or have steeper slopes. The gridded pattern than can be seen in Figure 3C-3 is due to PRISM rainfall grid, which at 4 km is much coarser than the NRCS Soils and NLCD land cover and impervious datasets (30 m).
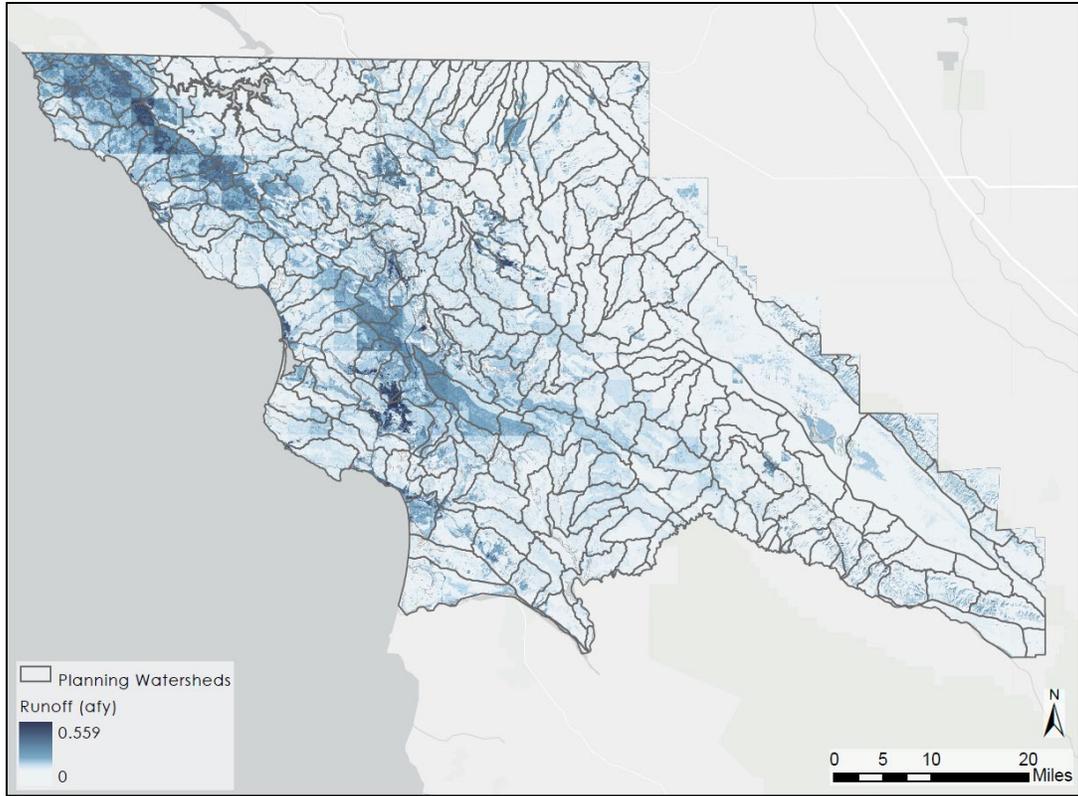
Figure 3C-3. Spatially distributed average annual runoff throughout the County, expressed in acre-feet per year per 30-m pixel.

These results can be aggregated into larger polygons to show area-normalized runoff and particulate loading (see Figure 3C-4 and Figure 3C-5 for the Salinas Watershed Group). These outputs are calculated for each of the Watershed Groups separately to illustrate relative runoff and pollutant loading impacts within each Watershed Group, and also for each Planning Watershed within the County collectively. Darker Planning Watersheds illustrate relatively higher estimated runoff and pollutant loading per unit drainage area, indicating higher potential for receiving water impacts. As anticipated, Planning Watersheds with high levels of human disturbance show greater runoff and pollutant loading. Those Planning Watersheds in the Upper Salinas that contain substantially urbanized areas, such as the City of Atascadero, show the greatest relative runoff volumes. Cultivated areas between Atascadero and Paso Robles include Planning watershed that fall into the highest pollutant loading category.
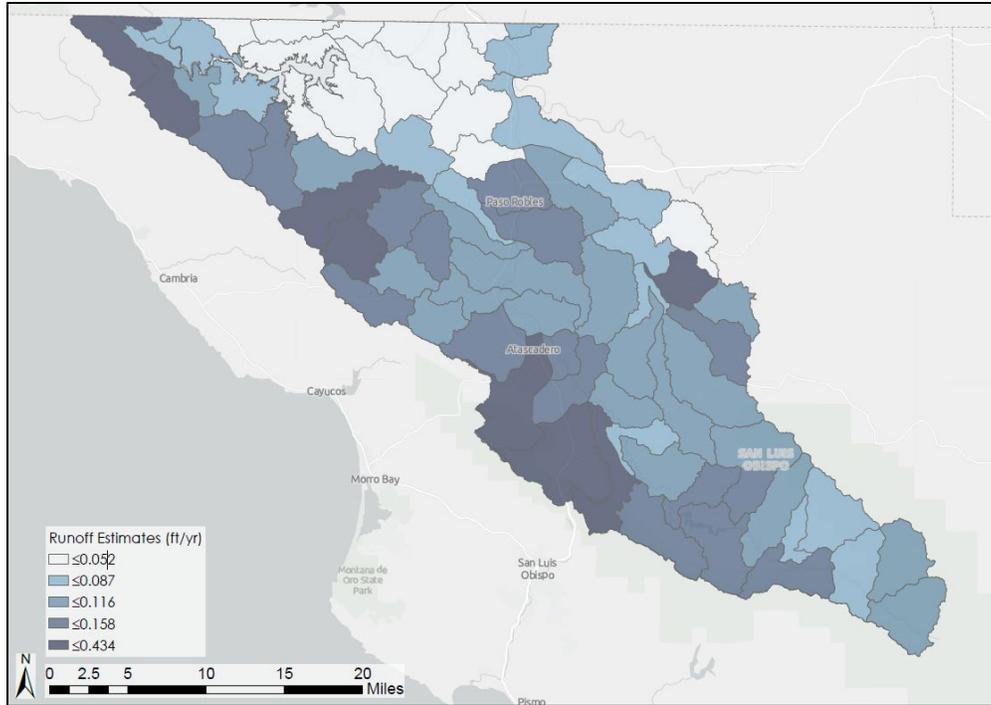
Figure 3C-4. Runoff estimates from R-TELR aggregated to the Planning Watershed scale for the Salinas Watershed Group.
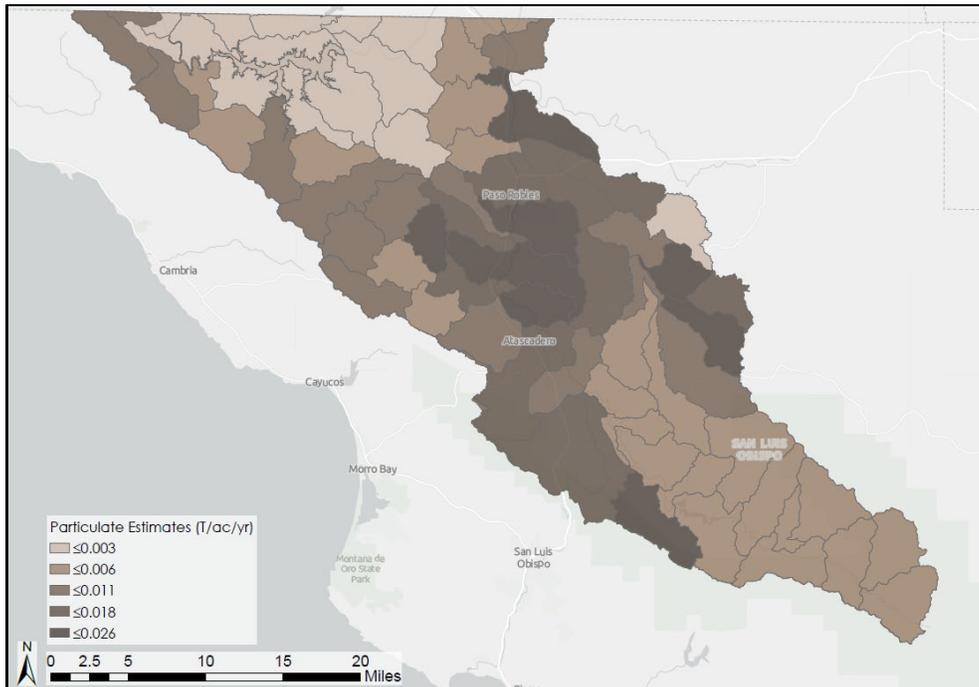

Figure 3C-5. Particulate pollutant loading estimated from R-TELR aggregated to the Planning Watershed scale for the Salinas Watershed Group.

In urbanized areas of the County with MS4 NPDES permits (shown as gray areas in Figure 3C-6), runoff and pollutant modeling using swTELR has been completed at the urban catchment scale (approximately 100 acres). Via swTELR, runoff is routed sequentially downstream from one catchment to the next. Since these urban catchment boundaries depend primarily on the stormwater infrastructure and urban hardscape, there is often poor alignment between these drainages and CalWater Planning Watersheds (see Figure 4). Consequently, runoff and pollutant modeling were performed separately at these two spatial scales and then combined to identify opportunities at these two nested spatial drainage scales. In this manner, projects located within a high priority Planning Watershed and also a high priority urban catchment would receive the highest opportunity score relative to these model-based metrics.
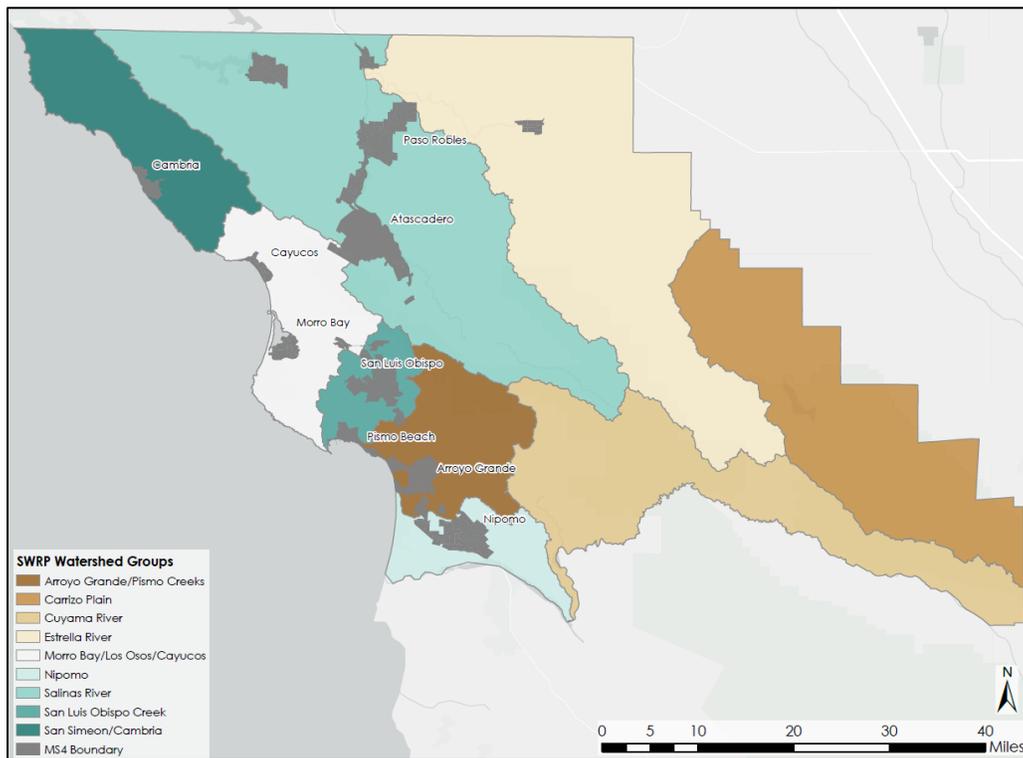

Figure 3C-6. Watershed Groups and MS4 areas within the County.

R-TELR Runoff Verification

Since TELR was developed and validated in primarily urbanized watersheds, full validation in watersheds with mostly undeveloped land-cover types has not yet been performed. Comparisons with the swTELR outputs primarily urbanized catchments shows good correspondence with no systematic bias and only random scatter that is primarily due to the distributed rainfall inputs and more granular soils data used in R-TELR (see Figure 3C-7). Outside of the urbanized catchments, where much of the area has impervious cover of < 5%, estimates from swTELR and R-TELR diverge more markedly, primarily due to NLCD land-cover-based curve number specification in these areas. This effect can be seen as data points that fall farthest below the 1-to-1 line, indicating much lower runoff predictions for R-TELR than for swTELR. Comparisons with swTELR outputs provide confidence that the runoff generation algorithms

are working as intended, but it still does not provide direct evidence of R-TELR model accuracy, which requires comparisons with measured data. The fact that the runoff generation algorithms used in R-TELR have been tested in many regional-scale applications as part of other modeling platforms (e.g., USDA SWAT), provides a good deal of confidence that the estimates may as reliable as any other model that functions on similar time and spatial scales. Nonetheless, comparison with measured data is a valuable exercise to determine the usefulness of estimates in a decision-making context (e.g., Wu et al., 2016).
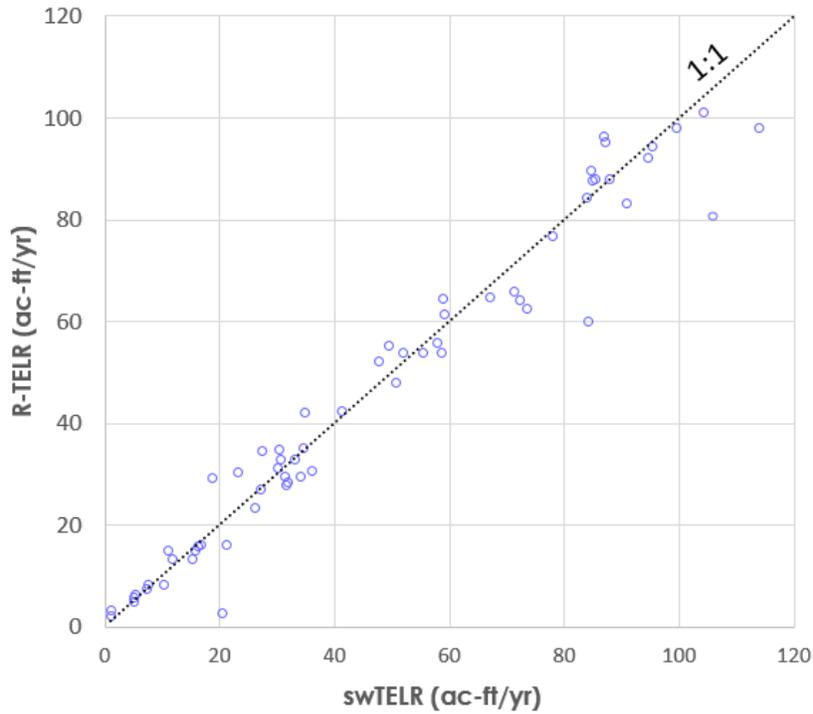

Figure 3C-7. Validation experiment results comparing swTELR outputs with those of R-TELR for 63 urban catchments within the City of Watsonville.

References

2NDNATURE, 2010a. PLRM v.1: Focused Stormwater Monitoring to Validate Water Quality Source Control and Treatment Assumptions. Final Phase I Technical Report. March 2010. 118 pp.

2NDNATURE, 2010b. Focused stormwater monitoring to validate water quality source control and treatment assumptions. Final Report prepared for U.S. Army Corps of Engineers, June 2010. 118 pp.

2NDNATURE, 2014. Aligning Stormwater Monitoring Datasets with Priority Management Questions. Final Technical Guidance Document. Prepared for the USFS Pacific Southwest Research Station. December 2014. 68 pp.

2NDNATURE LLC 2017. Stormwater Tool to Estimate Load Reduction (swTELR) Final Technical Document v1.1. March 2017

2NDNATURE and Northwest Hydraulic Consultants, 2012. Focused Stormwater Quality Monitoring to Inform Assumptions & Evaluate Predictive Capabilities of Existing Tools. Final Technical Report. Prepared for USFS Pacific Southwest Research Station. June 2012. 149 pp.

2NDNATURE and Northwest Hydraulic Consultants, 2014. Catchment-Scale Evaluation of Tahoe Stormwater Tools. Final Technical Report. Prepared for USFS Pacific Southwest Research Station. June 2014. 139 pp.

Austin, Lisa, et al. "Development of TMDL Implementation Plans (A GIS-Based Approach to Project Planning and Identification toward the Attainment of Water Quality Compliance for the Ballona Creek Watershed)." Proceedings of the Water Environment Federation 2010.11 (2010): 5162-5181.

Beck, N.G., Conley, G., Kanner, L., Mathias, M. 2017. An urban runoff model designed to inform stormwater management decisions. Journal of Environmental Management v 193: 257-269. http://dx.doi.org/10.1016/j.jenvman.2017.02.007\

Beven, K.J., 1989. Changing ideas in hydrology – the case of physically based models. Journal of Hydrology 105, 157-172

Beven, K.J., 2001 Rainfall-Runoff Modeling the Primer. Wiley, New York, USA. 360 pp.

Boomer, K.B., D.E. Weller, T.E. Jordan. 2008. Empirical models based on the universal soil loss equation fail to predict sediment discharge from Chesapeake Bay catchments. J. of Environ. Qual. 27:79-89. doi:10.2134/jeq2007.0094

Boorman, H. and B. Diekkruger, 2003. Possibilities and limitation s of regional hydrological models applied within an environmental change study in Benin (West Africa). Physics and Chemistry of the Earth 28: 1323-1332

Brezonik, P.L., Stadelmann, T.H. (2002) Analysis and predictive models of stormwater runoff volumes, loads, and pollutant concentrations from watersheds in the Twin Cities metropolitan area, Minnesota, USA. 36 (7) 1743-1757.

Butcher, Jonathan, 2003. Buildup, washoff, and event mean concentrations. Journal of the American Water Resources Association, 39(6): 1521-1528. DOI: 10.1111/j.1752-1688.2003.tb04436.x

Chaplot, V.A.M, Y.L. Bisonais, 2003. Runoff features for interrill erosion at different rainfall intensities, slope lengths and gradients in an agricultural loessial hillslope. Soil Science Society of America Journal, 67, 844-851.

Chandler, R., 1994. Modeling and nonpoint source pollution estimates in surface water management. MS Thesis, Univ of Washington, Seattle.

Chen, H.J., and H. Chang. 2014. Response of discharge, TSS and E. coli to rainfall events in urban, suburban and rural watersheds. Environmental Science Processes and Impacts. DOI: 10.1039/c4em00327f

Dotto, C.B.S., M. Kleidorfer, A. Deletic, W. Rauch, and D.T. McCarthy, 2014. Impacts of measured data uncertainty on urban stormwater models. Journal of Hydrology 508: 28-42. DOI:10.1016/j.jhydrol.2013.10.025

Elliot, A.H. and S.A. Trowsdale, 2007. A review of models for low impact urban stormwater drainage. Environmental Modelling & Software 22(3): 394-405. DOI:10.1016/j.envsoft.2005.12.005

Eslinger, David L., H. Jamieson Carter, Matt Pendleton, Shan Burkhalter, Margaret Allen. 2012. "OpenNSPECT: The Open-source Nonpoint Source Pollution and Erosion Comparison Tool." NOAA Office for Coastal Management, Charleston, South Carolina. Accessed [Month Year] at coast.noaa.gov/digitalcoast/tools/opennspect.

Evett, S.R., G.R. Dutt, 1985. Length and slope effects on runoff from sodium dispersed, compacted earth microcatchments. Soil Science Society of America Journal, 49, 734-738.

Fox, D.M., R.B Bryan, A.G. Price, 1997. The influence of slope angle on final infiltration rate for interill conditions. Geoderma, 80, 181-194.

Freni, G., G. Mannina, G. Viviani, 2011. Assessment of integrated urban water quality model complexity through identifiability analysis. Water Research 45:37-50

Geosyntec, 2015. Memorandum to County of Santa Barbara, Project Clean Water. Program Effectiveness Assessment and Improvement Plan, Load Prioritization Reduction Model (LPR) Model Guidance document. April, 2015, 27 pp.

Hawkins, R. H., 1984 A comparison of predicted and observed runoff curve numbers, Proceeding of Special Conference Irrigation and Drainage Division, Flagstaff Arizona, ASCE, New York, NY.

Hawkins, R.H., R. Jiang, D.E. Woodward, A.T. Hjelmfelt, and J.A Van Mullem, 2002. Runoff Curve Number Method: Examination of the Initial Abstraction Ratio. In: Proceedings of the Second Federal Interagency Hydrologic Modeling Conference, Las Vegas, Nevada. U.S. Geological Survey, Lakewood, Colorado. CD-ROM.

Herngren L., A. Goonektilleke, G. Ayoko, 2005. Understanding heavy metal and suspended solids relationships in urban stormwater using simulated rainfall. Journal of Environmental Management, 76, pp 149–158.

Hossain, I., M. Imteaz, 2016. Advances in Landscape Runoff Water Quality Modeling: A Review. Springer International Publishing. Chapter 12, pp 225-257.

Huang, M., J. Gallichand, Z. Want, M. Goulet, 2006. A modification to the Soil Conservation Service curve number method for steep slopes on the Loess Plateau of China. Hydrological Processes, 20, 579-589.

Jakeman, A.J., G.M. Hornberger, 1993. How much complexity is warranted in a rainfall runoff model? Water Resources Research 29, 2637-2649.

Kayhanian, M., B.D. Fruchtman, J.S. Gulliver, C. Montanaro, E. Ranieri, and S. Wuertz. 2012. Review of highway runoff characteristics: Comparative analysis and universal implications. Water Research 46(2012): 6609-6624.

King, K.W., Arnold, J.G., Bingner, R.L., 1999. Comparison of Green-Ampt and Curve Number Methods on Goodwin Creek Watershed Using SWAT. Transactions of the American Society of Agricultural Engineers, 42 (4) 919-925.

Kokkonen, T.S. and A.J. Jakeman, 2001. A comparison of metric and conceptual approaches in rainfall-runoff modeling and its implications. Water Resources Research 37 (9): 2345-2352.

Leavesley, G.H., S.L. Markstrom, P.J. Restrepo, R.J. Viger, 2002. A modular approach to addressing model design, scale and parameter estimation issues in distributed hydrologic modeling. Hydrological Processes 16, 173-187.

Lee, J.G., A. Selvakumar, K. Alvi, J. Riverson, J.X. Zhen, L. Shoemaker, and F. Lai, 2012. A watershed-scale design optimization model for stormwater best management practices. Environmental Modelling & Software 37: 6-18. DOI:10.1016/j.envsoft.2012.04.011

Lent, M.A. and McKee, L.J., 2011. Development of regional suspended sediment and pollutant load estimates for San Francisco Bay Area tributaries using the regional watershed spreadsheet model (RWSM): Year 1 progress report. A technical report for the Regional Monitoring Program for Water Quality, Small Tributaries Loading Strategy (STLS). Contribution No. 666. San Francisco Estuary Institute, Richmond, CA.

Lee, H.L., K.W. Bang, 2000. Characterization of urban stormwater runoff. Water Resources 34(6) 1773-1780.

Li, C., W. W. Wang, J. Xiong, P. Chen, 2014. Sensitivity analysis for urban drainage modeling using mutual information. Entropy 16, 5739-5752, doi:10.3390/e16115738

Lim, K. J., B. A. Engel, S. Muthukrishnan, and J. Harbor, 2006. Effects of initial abstraction and urbanization estimated runoff using CN technology. Journal of the American Water Resources Association 42: 629–643. DOI:10.1111/j.1752-1688.2006.tb04481.x

Loganathan, P., S. Vigneswaran, J. Kandasamy, 2013. Road-Deposited Sediment Pollutants: A Critical Review of their Characteristics, Source Apportionment, and Management. Critical Reviews in Environmental Science and Technology 43 (13): 1315-1348.

Mannina, G., G. Viviani, 2010. An urban drainage stormwater quality model: Model development and uncertainty quantification. Journal of Hydrology, 381, pp. 248-265.

Nandakumar, N., R.G. Mein, 1997. Uncertainty in rainfall runoff model simulations and the implications for predicting the hydrologic effects of land-use change. Journal of Hydrology 192 211-232.

Northwest Hydraulic Consultants Inc. (nhc), Geosyntec Consultants, Inc., and 2NDNATURE, LLC. 2010. Pollutant Load Reduction Model. Available at https://www.enviroaccounting.com/TahoeTMDL/Program/Display/ForUrbanJurisdictions. Accessed in May to September 2015.

Perrin, C., Michel, C., and Andreassian, V., 2001. Does a large number of parameters enhance model performance? Comparative assessment of common catchment model structures on 429 catchments, Journal of Hydrology, 242, 275–301.

Petrucci, G., C. Bonhomme, 2014. The dilemma of spatial representation for urban hydrologysemi-distributed modeling: Trade-offs among complexity, calibration, and geographical data. Journal of Hydrology 517, 997-1007.

Rauch, W., J.-L. Bertrand-Krajewski, P. Krebs, O. Mark, W. Schilling, M. Schütze, and P.A. Vanrolleghem, 2002. Deterministic modelling of integrated urban drainage systems. Water Science & Technology 45(3): 81-94.

Rossman, L.A., 2013. National Stormwater Calculator. Available at http://www.epa.gov/nrmrl/wswrd/wq/models/swc. Accessed in May to September 2015.

Reed S., V. Koren, M. Smith, Z. Zhang, F. Moreda, D. Seo, and DMIP Participants, 2004. The distributed model intercomparison project (DMIP): motivation and experiment design. Journal of Hydrology 298: 27-67.

Sage, J., C. Bonhomme, S. Ali, M. Gromaire. Performance assessment of a commonly used "accumulation and wash-off" model from long-term continuous road runoff turbidity measurements. Water Research, 78, pp 47-59.

Sartor, J., G. Boyd, F. Agardy, 1972. Water pollutants aspects of street surface contaminants. Journal of Water Pollution Control Fed, 46, pp 458–467.

Sharma, K.D. Runoff behavior of water harvesting micro-catchments. Agr, Water Manage. 11 (2), 137, 1986.

Stein, E., L. Tiefenthaler, L., Schiff, Kenneth, 2007. Sources, patterns and mechanisms of storm water pollutant loading from watersheds and land uses of the greater Los Angeles are, CA, USA. Southern California Coastal Water Research Project Final report. 103 pp.

Strecker, E., E. Driscoll, P. Shelley, D. Gaboury, J. Sartor, 1990. The U.S. Federal Highway Administrations Receiving Water Impact Methodology. The Science of the Total Environment, 93, pp 489-498.

Strehmel, A., K. Bieger, J. Jeong, B. Schmalz, N. Fohrer. Towards improvement of the water balance on steep slopes – development of a correction algorithm of the runoff curve number for slope angles up to 100%. International SWAT Conference, 2014. Porto de Galinhas, Brazil. August, 2014.

USDA-SCS (U.S. Department of Agriculture-Soil Conservation Service), 1986. Urban hydrology for small watersheds. Technical release 55, NTIS PB87-101580, 2nd edn. USDA SCS, Springfield, Virginia.

USDA-SCS (U.S. Department of Agriculture-Soil Conservation Service), 2017. Chapter 9.: Hydrologic Soil-Cover Complexes. National Engineering Handbook DRAFT Proposed CN Update. September, 2017. 50 pp.

US EPA, 2009. Guidance on the Development, Evaluation, and Application of Environmental Models. March, 2009, 99 pp.

Voskamp, I.M, and F.H.M Van de Ven, 2015. Planning support system for climate adaptation: Composing effective sets of blue-green measures to reduce urban vulnerability to extreme weather events. Building and Environment 83: 159-167. DOI10.1016/j.buildenv.2015.07.018.

Wagener, T., Kollat, J., 2007. Numerical and visual evaluation of hydrological and environmental models using the Monte Carlo analysis toolbox. *Environmental Modeling & Software,* 22, pp 1021–1033.

Woodward, D.E., R.H. Hawkins, R. Jiang, A.T. Hjelmfelt, Jr., J.A. Van Mullem, and Q.D. Quan, 2003. Runoff Curve Number Method: Examination of the Initial Abstraction Ratio. In Conference Proceeding Paper, World Water and Environmental Resources Congress 2003: pp. 1-10.

Zoppou, Christopher. (2001). Review of Urban Storm Water Models. Environmental Modelling & Software. 16. 195-231. 10.1016/S1364-8152(00)00084-0.

Wang, L., Wei, J., Huang, Y., Wang, G., Maqsood, I., 2011. Urban nonpoint source pollution buildup and washoff models for simulating storm runoff quality in the Los Angeles County. Environmental Pollution, 159, pp. 1932-1940.

Williams, J.R., 1995. Chapter 25: The EPIC model. 909-10002. In: Singh, VP (ed). Computer models of watershed hydrology. Water Resources Publications, Highlands Ranch, CO.

Wu, J., Gilbreath, A.N., McKee, L.J., 2017. Regional Watershed Spreadsheet Model (RWSM): Year 6 Progress Report. A technical report prepared for the Regional Monitoring Program for Water Quality in

San Francisco Bay (RMP), Sources, Pathways and Loadings Workgroup (SPLWG), Small Tributaries Loading Strategy (STLS). Contribution No. 811. San Francisco Estuary Institute, Richmond, California.